Development of Context-Sensitive Accessibility Indicators:

A GIS-based Modelling Approach for Cape Town

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Declaration

I, **Imuentinyan Aivinhenyo**, hereby declare that the contents in this research thesis are my original work. Any quotation from or description of the work of others is acknowledged by reference to the sources, whether published or unpublished.

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Signature: ______________________ Date: 30 August 2019

Abstract

Adequate public transport infrastructure and services are essential to facilitate access to basic opportunities, such as jobs, healthcare, education, recreation or shopping, especially in low-income cities where the majority of the low-income population have no access to the car. In the context of transport exclusion and urban poverty, access and accessibility metrics can serve as good indicators for the identification of transport-disadvantaged zones or population groups in a city. In Cape Town, accessibility-based planning is being embraced by the authority as a means of addressing the planning defects of the past apartheid regime, which created a city that is spatially fragmented by race and income levels. Among the agenda outlined in its 5-year Integrated Transport Plan of 2013-2018, is the need to develop a highly integrated public transport network in which all households would have equitable access to the public transport system, especially for the majority of the urban poor who reside in the city outskirts far from major economic centres. Although planning efforts are being made to redeem the defects of the past, there is still the need for tools and indicators to understand the current situation, as well as to further aid planning and decision making about land-use and transport. The objective of this research, therefore, is to develop suitable indicators of accessibility, identify possible spatial and socioeconomic drivers of accessibility and evaluate equity in the distribution of accessibility benefits for various population groups in Cape Town.

In the study, transport network data of Cape Town are utilised to develop GIS-based indicators of network access and origin accessibility to various opportunities like jobs, healthcare and education, across various modes of travel. An Access Index measures public transport service presence within a zone, based on route and stops availability. The index is used to compare the coverage levels provided by each mode of public transport in the city. Also, an Accessibility Index is proposed, that measures the number of opportunities 'potentially reachable' within a specified 'reasonable' travel time. A key consideration in measuring accessibility by public transport is the monetary cost of overcoming distance, based on the pricing structure that exists in Cape Town. Equity in accessibility is further evaluated both vertically and horizontally. Vertical equity is evaluated using a proposed Accessibility Loss Index, which analyses the potential implication of affordability and budget restrictions on accessibility, based on the income level of the poor households. GINI type of measures is also proposed to evaluate horizontal equity across the various population groups for various travel modes. To further understand the likely drivers of accessibility, an exploratory OLS regression technique is employed to investigate the relationship between accessibility and a combination of socioeconomic and built environment features of the study area.

The study reveals among other things that potential accessibility achievable by car is far higher than that achievable by public transport. The paratransit mode provides the most extensive access coverage, and the highest level of accessibility among all the public transport modes investigated. However, this mode shows to be one of the most expensive options of travel, especially for low-income households who are likely to be restricted by travel monetary budgets. The train turns out to be the most affordable travel option, although the level of accessibility achievable with the train is much lower compared to the paratransit or regular bus. From a vertical equity perspective, the consideration of transport affordability drastically reduces the opportunity space and potential accessibility for the poorest population group compared to the higher income groups. The study further interrogates the distance-based tariff model of public transport services in Cape Town, which it considered to be detrimental to the welfare of poor households, regarding the potential to access essential opportunities.

The contribution of this study to the body of research on accessibility is twofold: methodological and contextual. On the methodological dimension, it presents a GIS-based approach of modelling accessibility both for the car and for a multimodal public transport system that combines four modes; bus, train, BRT and a minibus taxi (paratransit). It also builds on existing gravity-based potential accessibility measure by incorporating an affordability dimension. The consideration of affordability adds a further layer that enables vertical equity evaluation by judging the potential for destination reachability by the monetary out-of-pocket cost of travel. This approach is considered to be more sensitive to the context of low-income cities like Cape Town, where low-income household’s daily travel decisions are likely to be more guided by monetary cost.

Keywords: Accessibility; Transport Equity, Public Transport; Inequality; Cape Town.

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Publications

Parts of the content of this dissertation have appeared in the following:

Book Chapter

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Journal Article

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Peer-reviewed conference papers

3. Aivinhenyo, I., Zuidgeest, M. and van Ryneveld, M. (2016) 'Measuring Destination Accessibility by Public Transport Incorporating User Affordability- a case of Cape Town, South Africa', *Proceedings 14th World Conference on Transport Research (WCTR), Shanghai, China, July 2016.*

4. Aivinhenyo, I. and Zuidgeest, M. (2017) 'Mapping Job Accessibility by Car and Public Transport in the city of Cape Town, South Africa', *Proceedings 2017 World Symposium on Transport and Land Use Research (WSTLUR) Brisbane, Australia, July 2017.*

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Acronyms

2SFCA – Two-Step Floating Catchment Area

BRT – Bus Rapid Transit

CBD – Central Business District

CoCT – City of Cape Town

CTSDF – Cape Town Spatial Development Framework

DoT – Department of Transport

GABS – Golden Arrow Bus Service

IDP – Integrated Development Plan

IRT – Integrated Rapid Transit

ITP – Integrated Transport Plan

LUPTAI – Land Use and Public Transport Accessibility Index

MBT – Minibus Taxi

NBD – Northern Suburb Business District

OLS – Ordinary Least Squares

PT/PuT – Public Transport/Public Transit

PTAL – Public Transport Accessibility Level

SAL – Structural Accessibility Layer

SBD – Southern Suburb Business District

SDF – Spatial Development Framework

SIM – Spatial Interaction Model

SNAPTA – Spatial Network Analysis for Public Transport Accessibility

TAZ(s) – Traffic Analysis Zone(s)

TCT – Transport for Cape Town

TDA – Transport Development Authority

TDI – Transport Development Index

Chapter 1

Introduction

Measures of accessibility have been widely used for evaluating transport systems' integration with land uses. They are measures of the extent to which a transportation system is serving the population in providing access to essential opportunities, such as jobs, healthcare, education, shopping, recreation, among others. Van Wee et al. (2013) regard accessibility measures as indicators of the impact of land-use and transport development policy plan on the functioning of society in general. They are also tools for recognising mobility needs and for identifying service gaps (Mamun and Lownes, 2011), and can be applied at various spatial scales, including the local neighbourhood level and regional level.

While the concept of accessibility as a planning measure has gained wide attention over the past few decades, with most of the existing research originating from developed countries, countries in the Global South, including South Africa, are only recently starting to embrace it as a subject of discourse both in academia and in planning practice. In Cape Town, for example, accessibility has been recognised as one of the city's planning goals. Planning policy documents, such as the Spatial Development Framework (City of Cape Town, 2010b), the Integrated Development Plan (City of Cape Town, 2013c), and the Integrated Transport Plan, ITP (City of Cape Town, 2013e) all include access and accessibility among desired planning outcomes. The 2013 ITP, for example, states the need to develop a highly integrated public transport network in which all household would have access to public transport (City of Cape Town, 2013e).

Despite the growing attention and recognition of accessibility as a planning objective in South Africa, and Cape Town, in particular, little attempt has been made to develop indicators of accessibility that reflects the unique South African context of inequality, segregation, and urban poverty. The overall aim of this research is, therefore, to develop interpretable spatial accessibility models from existing theory, taking into account the socioeconomic characteristics of households, understand the possible drivers of accessibility and evaluate equity in accessibility as it affects the various population groups.

The remaining parts of this chapter are structured as follows; Section (1.1) presents the research background and problem context. This gives rise to the problem statement presented in Section (1.2), the research objectives in Section (1.3) and research questions in Section (1.4). The relevance and contribution of the research are discussed in Section (1.5), while the final Section (1.6) presents an outline of the entire thesis.

1.1 Problem Context

Cities of South Africa are experiencing rapid urban growth. Population growth, migration and a host of other factors are giving rise to a continuous expansion of the urban landscape. Such expansion, however, is accompanied by opportunities and challenges: opportunities for economic development on the one hand, environmental and social challenges on the other. A common phenomenon associated with urban expansion - where there is little or no compact nor mixed-used development - is that activity and population centres become more spatially distributed and dispersed from each other. A typical resultant effect is longer trip distances and increased travel costs between origins and destinations. In the case of Cape Town, the increasing separation is not only a fall-out of the natural urban growth process[1] but also from past planning policies of the apartheid era.

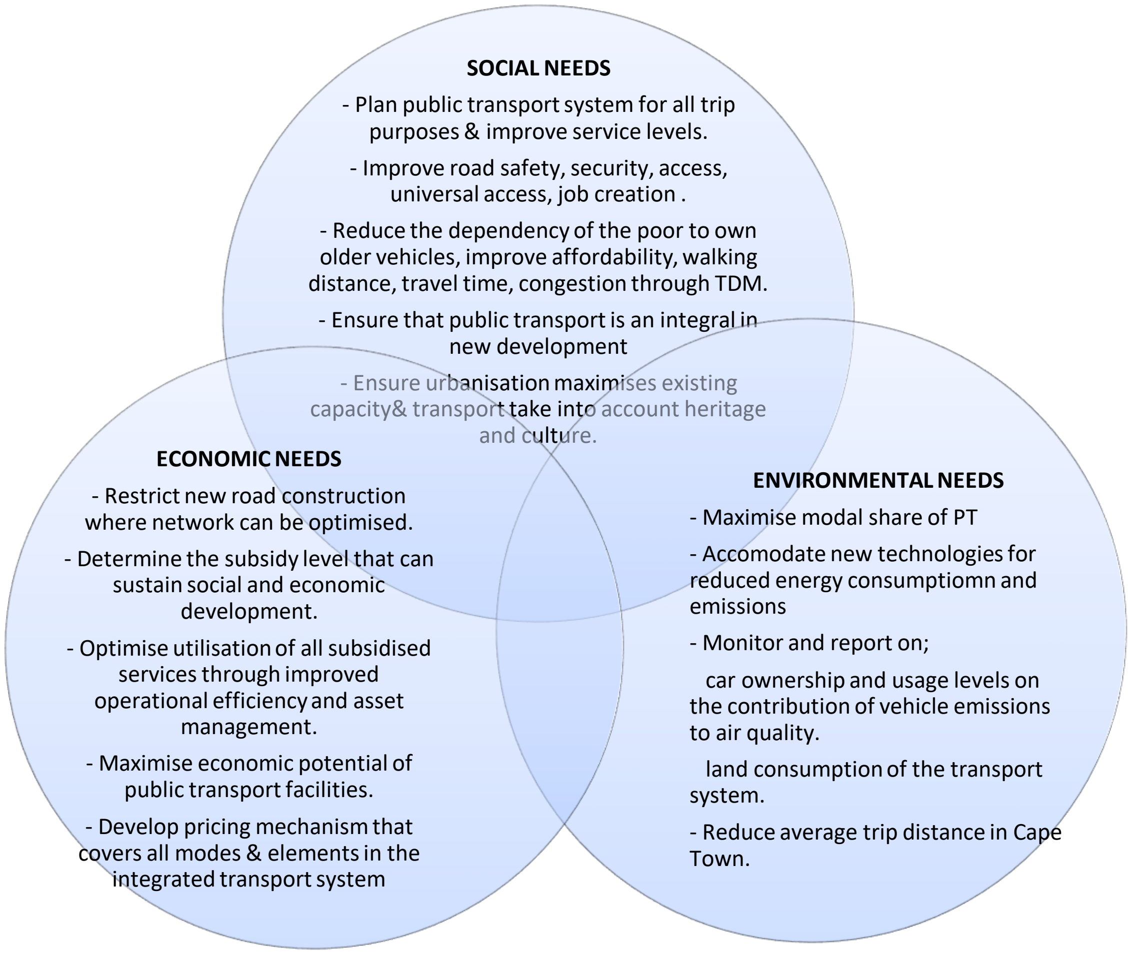
The apartheid planning system, through the Group Areas Act of 1950 (Parliament of the Republic of South, 1950), resulted in urban landscapes which are highly dispersed and segregated by race and income, with buffers of open, undeveloped land created between various human settlements (Visser, 2001). As a result of the zoning system, the majority of the low-income residential population, mainly those of coloured and black race, were confined to the urban outskirts in settlements commonly referred to as ‘townships’, which are relatively far from the Central Business District (CBD) and other economic hubs in the city (Christopher, 1987). The economic segregation created by the apartheid system in South Africa, which has been a subject of many studies (for example, Donaldson 2001; Visser 2001; Christopher 1987), can be viewed in terms of the limitations created in the ability or capacity of people to access opportunities or engage in desired activities. The most affected group, in this case, are the low-income dwellers who reside far from major economic centres. The underlying implication for such households, who also, mostly rely on public transport for mobility, is longer travel distances to access these opportunities like jobs,

[1] With annual population growth rate of about 3% per annum, and growth of about 30% within last decade, based on StatsSA census report of 2011.

healthcare facilities or schools, and consequently, more vulnerable to transport-related social exclusion (see Section 2.2).

In the post-apartheid governance era, however, several initiatives have been put in place to redeem the defects of past planning, guide integrated development and promote social equality. A number of policy frameworks and strategies aimed at reconstructing the South African cities and delivering basic needs to the poor have emerged both at the local and national levels (Visser, 2001). The Cape Town Spatial Development Framework (SDF) and the Integrated Development Plan (IDP) are examples of key initiatives by the City of Cape Town to guide an all-inclusive urban and economic growth in Cape Town (City of Cape Town, 2013d). Within the Integrated Development Plan, the need for a well-integrated transportation system to facilitate access to opportunities in all parts of the metropolis has also been recognised. Planning goals outlined in the Integrated Transport Plan (ITP) are geared towards the development of a viable, accessible and efficient public transport system capable of serving all parts of the city and providing an alternative to the use of the automobile (City of Cape Town, 2013e). Among the strategies highlighted in the CTSDF include the establishment of an integrated grid-based movement and the creation of an efficient, integrated city-wide public transport system that supports the accessibility grid (City of Cape Town, 2010b). The phased implementation of the BRT/IRT system in the city, in addition to the existing bus, minibus taxi and rail services, is evidence of the effort spent on improving public transport city-wide.

The goals of the city in terms of transport improvement are guided by the ‘Triple Bottom Line’, categorised under economic, social and environmental needs. This is depicted in Figure 1-1.



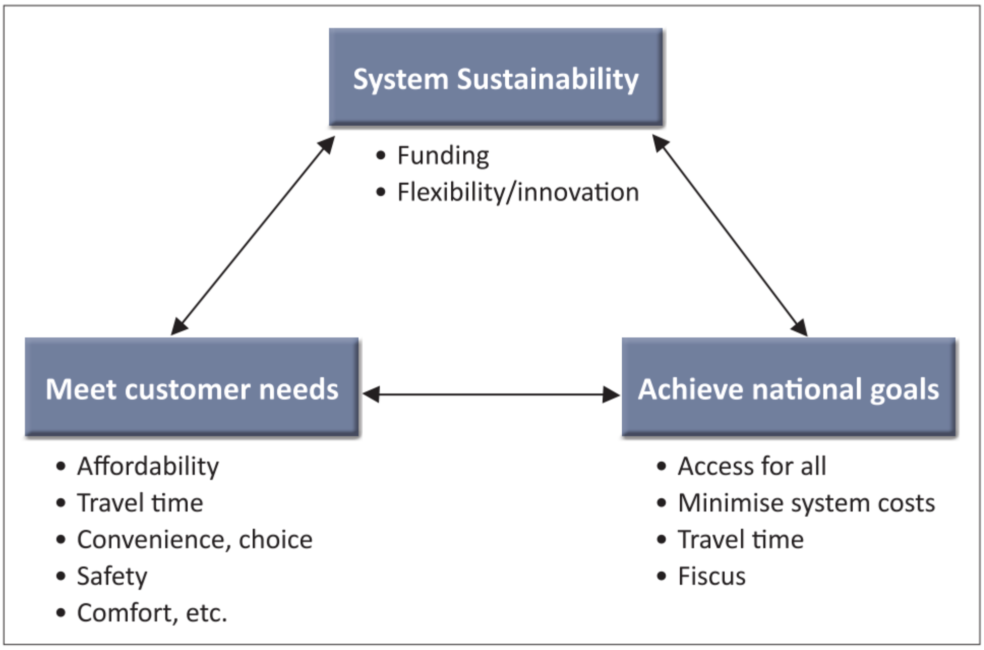
Source: City of Cape Town, 2013

Figure 1-1: Transport Needs- Triple Bottom Line.

Towards addressing some of the identified needs, short, medium and long term visions have been set by the city's Transport and Urban Development Authority (TDA) to improve transportation city-wide, through the development of an integrated transport network (City of Cape Town, 2013e). Among the objectives set to be realised are;

- ✓ *To plan an efficient and viable relationship between land uses, supporting infrastructure and transport for the sustainable development of the city region.*
- ✓ *To have integrated, intermodal, interoperable, responsive and car competitive public transport for the benefit of the community.*
- ✓ *To facilitate a fully integrated and well-maintained infrastructure network along with related facilities, and to manage and enable the utilisation of this major asset appropriately and effectively.*
- ✓ *To develop a public transport system that is easily accessible to every household.*

Most of the objectives being pursued at the city level are also in line with national-level objectives, as reflected in various policy and strategic frameworks, for example; the Moving South Africa Action Agenda of 1999 (Department of Transport, 1998), which is being updated in 2018. The key objectives from the 'Action Agenda' as summarised in Luke & Heyns (2013) are presented in Figure 1-2 below.



Source: Luke & Heyns (2013)

Figure 1-2: Public Transport Objectives

Figure 1-2 shows that the national objectives for public transport services are centred on improving accessibility by creating a sustainable system that would be efficient (in terms of travel time cost), while also meeting user needs (in terms of affordability, safety, comfort, among others).

In line with current global trends on sustainable urban transportation planning which have stressed the need to move towards accessibility-based planning (Holst 1979; Cervero 2005a), it can be seen that planning goals, both at the city and national levels above, are geared towards improving accessibility and equity through promotion of a well-integrated transport system that allows people to travel and participate in activities. There is, therefore, on one hand, the need for accessibility metrics to support planning, considering that effective planning can only be done around what can be effectively measured. On the other hand, considering that indicators will only point to the existing state of accessibility, there is also the need to understand what could be done to improve the accessibility experience of the least-advantaged residents or population groups.

1.2 Research Problem Statement

Martens (2016) considered a fair transportation system as that which provides a sufficient level of accessibility to all under most circumstances. It can also be considered as a system that is accessible to residents, irrespective of their place of residence, gender, race or social (income) class. In other words, it is a system that is both available and affordable; and does not exclude users by virtue of their ability to pay. In Cape Town, despite the ongoing efforts of the authority at improving access to public transport for residents, affordability is still considered a major issue, especially for the urban poor. Public transport is generally priced by distance travelled, and due to the spatial configuration of the city, the low-income households bear a high burden of travel costs. Authors' preliminary analyses of the Cape Town Household Travel Survey data of 2013, for example, show that low-income households spend an average of about 27% of their income on travel to work (see Chapter 4, Section 4.6). It has also been commonly reported that total monthly expenditure on travel for all trip purposes for low-income households amounts to about 40% of monthly income, well above the national planning benchmark of about 10% of income, as specified in the 1996 White Paper on National Transport Policy of South Africa (Department of Transport, 1996).

A high travel cost burden for households can limit the reachability of opportunities and induce urban poverty. Urban poverty is often characterised by cumulative deprivations and can be drawn along five distinct dimensions; income/consumption, health, education, security and empowerment (Baharoglu and Kessides, 2002). Adequate measures are therefore needed to evaluate these levels of deprivation. However, most of the existing accessibility measurement approaches do not take the wide disparity in income level among a population into account.

1.3 Research Objectives

The aim of this research is to develop context-sensitive accessibility indicators that consider not only the transport supply characteristics but also the user socioeconomic characteristics as reflected by income and affordability of transport services. The need for context-sensitive solutions for land use and transport in South African cities have also been emphasized by Beukes et al. (2011) whose work focused on developing decision support tool for multimodal road planning in Cape Town.

Based on the problem context and issues discussed in Section (1.2), this research is set out to achieve two major objectives; (1) to develop spatial indicators of accessibility to evaluate the land use and transport system of Cape Town (2) to evaluate equity in accessibility as it affects the various population groups in Cape Town. In addition to these two objectives, a sub-objective is to further explore ways of improving accessibility through an understanding of the likely drivers of accessibility.

The accessibility indicators consider the multimodal public transport system in Cape Town and are derived from existing location-based accessibility theory discussed in the literature. Under the main objectives mentioned above are several sub-objectives, which include;

i. To undertake a review of existing literature on accessibility and existing approaches and measures of public transport accessibility, building a knowledge base to inform the research method.
ii. To develop a GIS-based model of the multimodal public transport system of Cape Town suitable for accessibility evaluation.
iii. To develop context-sensitive and interpretable indicators of accessibility suitable for land use and transport planning, with key consideration of both the transport supply characteristics and user affordability of transport services. Context-sensitive implies that the measures are informed by, or is reflective of the key issues in Cape Town. Ease of interpretability is with respect to the communication of the indicators and its applicability for planning and decision making.
iv. Evaluate equity in accessibility to basic opportunities like jobs, healthcare facilities and schools in the city of Cape Town.
v. Investigate possible built environment and socioeconomic drivers of accessibility
vi. Suggest planning policies and strategies that could be implemented towards improving accessibility and equity for the urban poor.

1.4 Research Questions

Based on the problem statement and research objectives outlined above, the key questions addressed in this thesis are;

i. What is the relationship between social exclusion, transport affordability and accessibility?
ii. How can affordability be incorporated within the traditional accessibility measures?

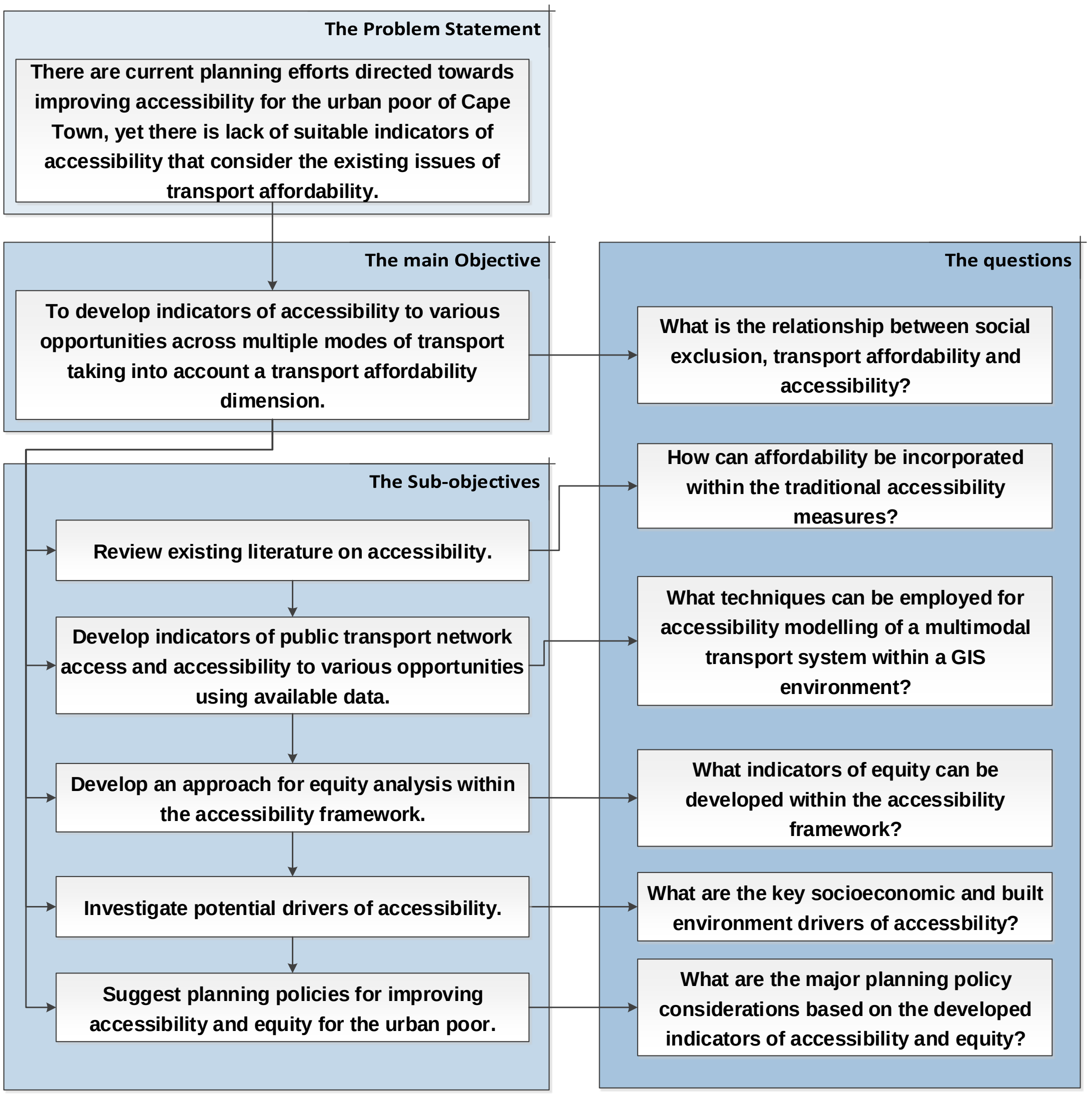
iii. How should a multimodal public transport system be modelled within GIS for accessibility computation?

iv. What indicators of equity can be developed within the accessibility framework?

v. What are the major socioeconomic and built environment drivers of accessibility?

vi. What are the key planning policy considerations /recommendations based on the developed indicators of accessibility and equity?

The connection between the research problem statement, research objectives and research questions is further shown in Figure 1-3 below:



Source: Author

Figure 1-3: Connection between problem statement, objectives and research questions

The flow chart (Figure 1-3) shows the main objective of research stemming from the research problem statement. Under the main objective are several sub-objectives, and every sub-objective is associated with a specific research question.

1.5 Research Concept

The conceptual representation of the research highlighting the major objectives is presented in Figure 1-4 below:

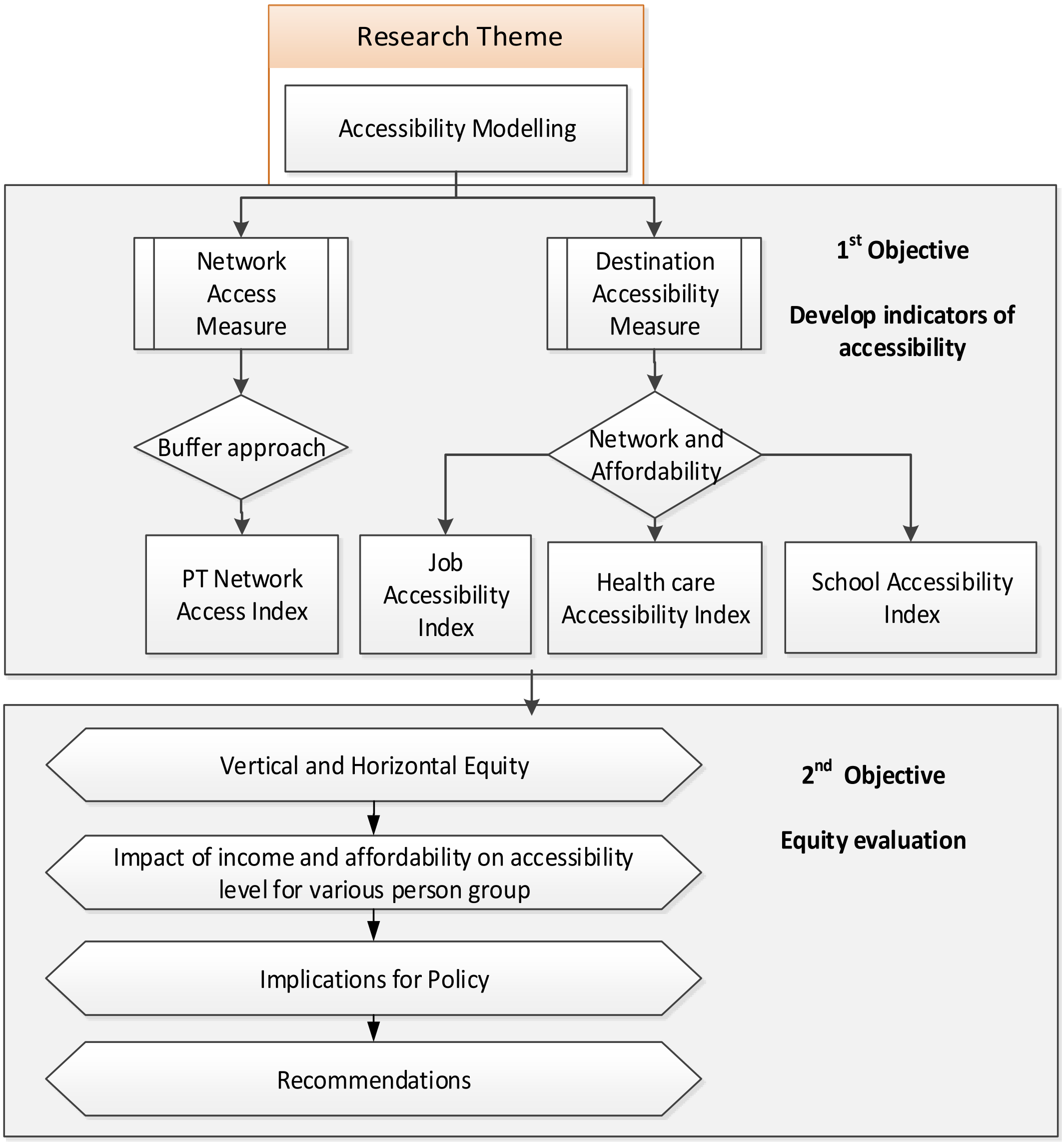


Figure 1-4: Conceptual representation of research

As mentioned in Section (1.3), the entire research is framed around two broad objectives; developing accessibility indicators and evaluating equity in accessibility levels for different user groups in Cape Town, based on affordability considerations. To achieve the first objective, two metrics; a network access metric that measures the level of access to a public transport system, and an accessibility metric that measures the potential for accessing opportunities, are developed. Three kinds of opportunities are considered; jobs, healthcare facilities and schools. The second objective of the research is to develop a method for evaluating equity in accessibility for various population groups. Specifically looking at the impact of income and affordability of transport on accessibility level, as it affects households across the various income groups. In addition to the two main objectives, a sub-objective of the research is to understand possible drivers of accessibility and propose some strategies that could be implemented to improve accessibility and equity for the urban poor.

1.6 Motivation, Relevance, and Contribution to Knowledge

This research is motivated by the notion that strategies and policies of urban development have a direct impact on the quality of life experienced in our cities (Bt Omar, 2006). Accessibility research has a potentially useful role to play in the planning of transport infrastructures and services in the context of developing cities. Handy & Niemeier (1997) had pointed out that accessibility has been in the transportation planning discourse, even though it has not been translated into performance measures or more concretely direct planning efforts and policies. As such, the goal of this research is to develop context-sensitive, intuitive and easy-to-interpret indicators of accessibility suitable for the South African context. Considering some of the key issues of transport discussed in the previous sections, such indicators will find application in transport system evaluation and have the potential to inform urban planning policies and decision making.

As a contribution to knowledge, the research builds on existing theoretical frameworks for measuring and evaluating accessibility, by incorporating an affordability dimension in the accessibility equation. Most of the existing measures are based on the transport supply characteristics without consideration of the socioeconomic composition of the trip makers. In this study, the inclusion of user affordability as a component of accessibility measurement is seen to be relevant to the context of low-income cities like Cape Town, where the cost of transportation is a huge burden, and the ability to pay is likely to be a factor determining the ability to access opportunities.

1.7 Thesis Structure

The entire thesis is presented in eleven chapters;

Chapter one presents the introduction which gives a brief background to the research and its significance to current urban transportation and land use planning in the city of Cape Town. The chapter also discusses the research problems, objectives as well as motivation for the research.

Chapter two provides further background for the research and makes a case for the development of accessibility indicators for Cape Town. This chapter discusses (in brief) the broader issues of transport equity and transport-related social exclusion as well as some measurement/evaluation frameworks from literature. Issues of urban poverty and fragmentation in South African cities like Cape Town are also discussed.

Chapter three presents a review of literature on the theory and evolution of spatial interaction models and the concept of accessibility. It discusses the various components and existing measures of accessibility to various kinds of opportunities as developed by researchers over the years. The various components of public transport accessibility are also discussed.

Chapter four presents the case study description, which is the city of Cape Town. It includes a brief socio-demographic overview of Cape Town and its public transport system. Also discussed, is the land use system and some relevant policy/strategic frameworks for transport and land use at the national and local levels. A mapping of the population and income distribution, as well as distribution of key opportunities relevant for this research (jobs, healthcare and education facilities) in the study area. is also presented.

Chapter five presents the first part of the research methodology, which discusses the various measures of access and accessibility, as well as a detailed description of the data and sources.

Chapter six is the second part of the methodology, which deals with the impedance decay functions estimation, a vital component of the gravity-based accessibility measures. Impedance functions are estimated for travel by various modes of public transport as well as for the car, using the 2013 Cape Town Household Travel Survey data. Also discussed are some statistical background on the theory of density estimation as the basis for impedance decay function estimation. Other aspects of this chapter include the trip-length frequency distributions for various modes and a comparison of various decay function types and parameter estimates. Decay patterns are also compared across modes for the various user groups.

Chapter seven is the third part of the methodology which presents GIS-based modelling of the multimodal public transport system of Cape Town. This includes detailed GIS techniques for preparing the network elements (route lines and stops) of the four modes of public transport considered (bus, BRT, train and minibus) in other to create a multimodal network dataset that takes into account, both intra-modal and inter-modal transfers. Also discussed are some of the limitations and assumptions made concerning modelling a multimodal public transport system within the ArcGIS. platform

Chapter eight reports the results, which presents the network access indicators as well as the accessibility indicators for the three opportunity types (jobs, healthcare and education). Also presented in this chapter is a schedule-aware analysis of accessibility based on the General Transit Feed Specification (GTFS) data of the BRT system of Cape Town.

In **Chapter nine,** the indicators of potential accessibility presented in chapter 8 are further applied in an exploratory regression analysis aimed at understanding potential drivers of accessibility. The regression technique utilises a stepwise procedure to find a combination of the most significant variables that explain the measured job accessibility for the case of travel by car and public transport. Understanding the variables that have a direct relationship with accessibility can further inform specific planning measures and strategies for improving accessibility.

Chapter ten presents an evaluation of equity in measured accessibility. It proposes some indicators such as the Accessibility Loss Index, Lorenz curves and Gini coefficients as suitable measures of vertical and horizontal equity across and within the various population groups.

Chapter eleven concludes the entire research. It summarises the major findings of the research and the implications for policy on land use and transport in Cape Town. Also highlighted are the limitations encountered with model development and recommendations for future improvement.

A schema of the chapters described above is presented in Figure 1-5, showing the flow between the major elements within each chapter.

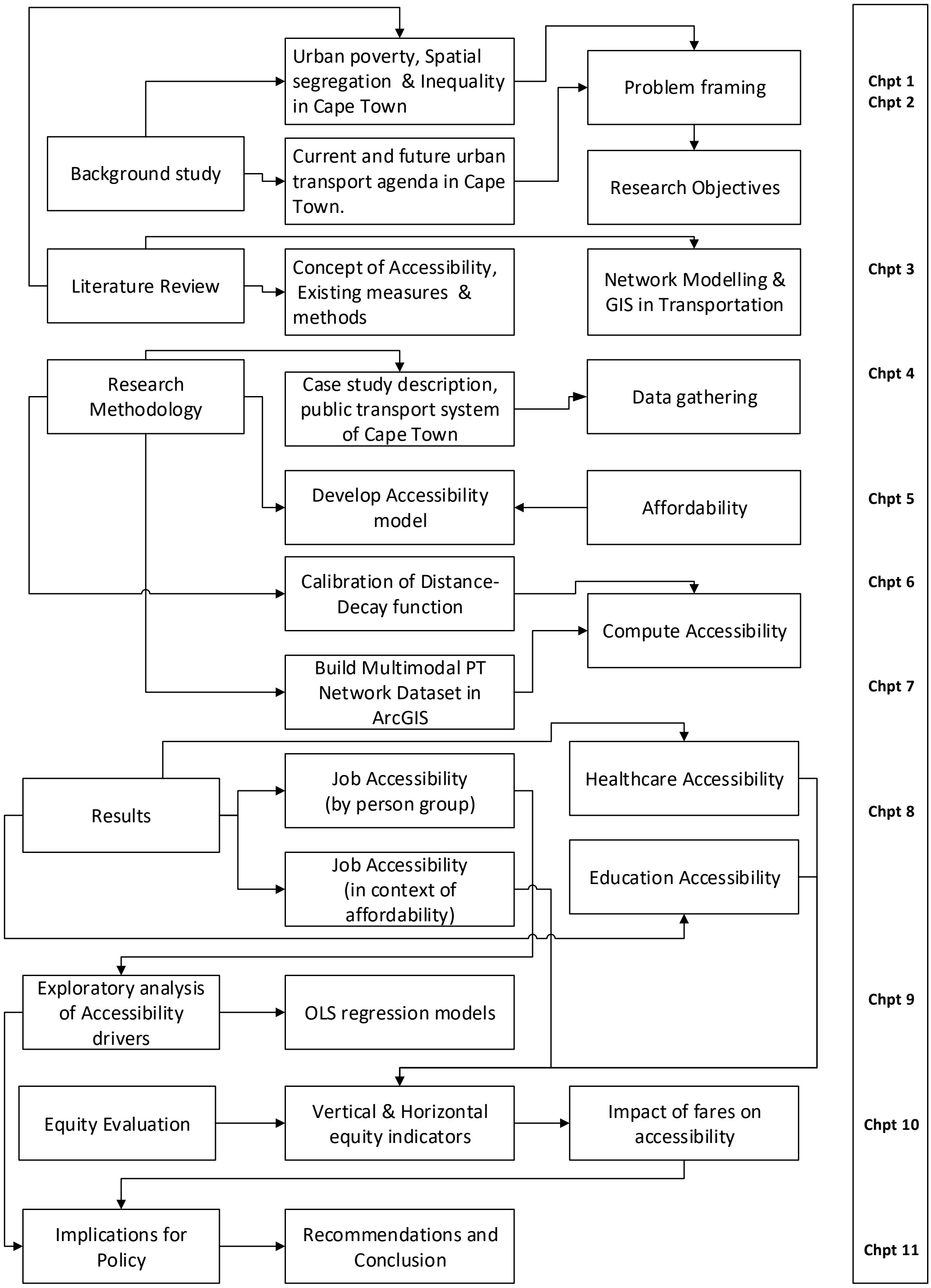


Figure 1-5: Thesis Structure

Chapter 2

Social Exclusion, Transport Equity and Accessibility

"Genuine equality means not treating everyone the same but attending equally to everyone's different needs." — Terry Eagleton, Why Marx Was Right

2.1 Introduction

In the introductory chapter, a research theme on accessibility, framed from the problem context (Section 1.1) was presented. The context reflects some of the critical transport and land-use challenges facing South African cities like Cape Town. In line with the identified issues, the first objective of this research is to develop accessibility indicators to essential opportunities. The second objective is to evaluate further the level of equity that exists in the distribution of accessibility as it affects various population groups. Equity issues arise when there are levels of unfairness or perceived unfairness in the distribution of resources or opportunities among individuals or groups of individuals within a given population of interest. As Talen (1998) had stated, equity, in the purest sense, can only be achieved after society has arrived at a general agreement about what is fair, a state which is virtually impossible to attain.

The focus of this chapter is, therefore, to provide a succinct discourse around some concepts that describe 'fairness' (or unfairness), especially as it relates to transport provision and land use. Among the concepts being discussed here are social exclusion, transport poverty, transport equity, affordability, and their connection with accessibility. Considering the broad nature of these concepts, this chapter intends to only provide an overview, to highlight the link with some of the problems presented in the introductory chapter as it relates to the Cape Town context.

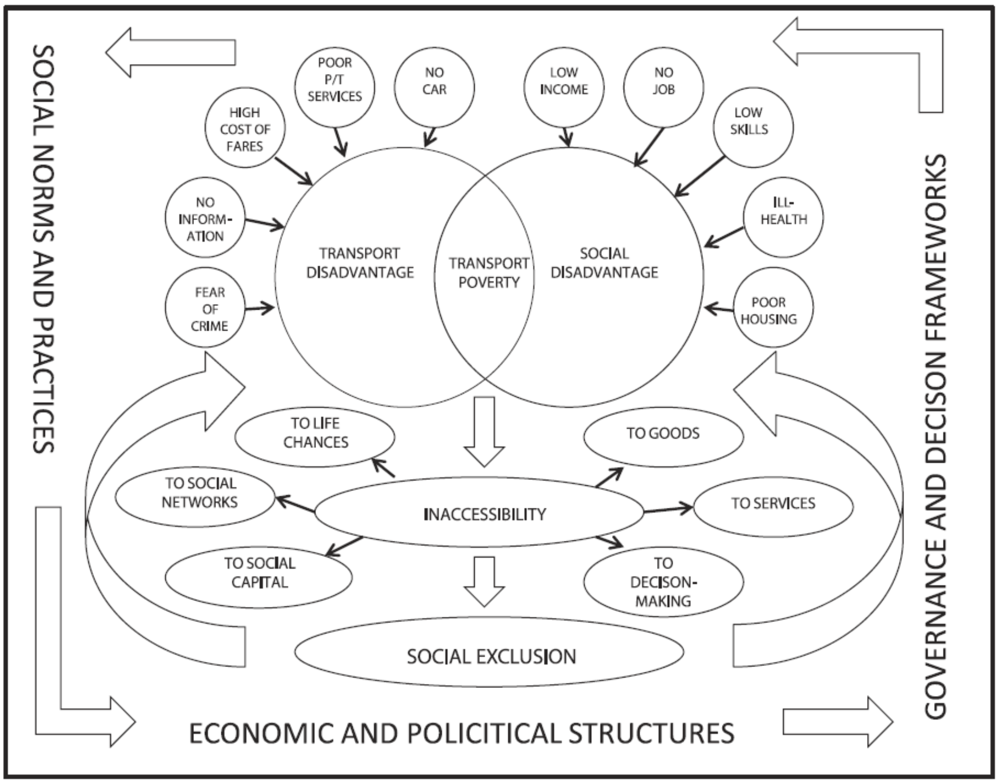
2.2 Social Exclusion, Poverty and the Link with Accessibility

The United Kingdom Social Exclusion Unit (SEU) regards social exclusion as 'what can happen when people or areas suffer from a combination of linked problems such as unemployment, poor skills, low incomes, poor housing, high crime, poor health and family breakdown' (ODPM, 2004, p 2). The concept of social exclusion has been known to feature in European social policies and discourse since the 1970s (Mackett & Thoreau, 2015; Rawal, 2007), and a good number of research projects (Stanley &

Lucas, 2008; Kaltheier, 2002) have in recent years, explored the dimensions of social exclusion and the factors that contribute to it.

Sen (2000) state that the concept of social exclusion must be examined in relation to its usefulness in understanding the nature of poverty and identifying the causes of poverty. Bradshaw et al. (2004) further describe the various domains of social exclusion to include; income and poverty, employment, education and skills, health inequalities, housing, and transport. Social exclusion in the context of transport (otherwise known as transport-related social exclusion) is discussed in Stanley & Lucas (2008), who examined its history, scope and the implication for social policy in transport.

The connection of transport to social exclusion has been viewed in terms of the limitations or barriers created when people are prevented from engaging in work or education, healthcare and a host of other desired activities (Social Exclusion Unit, 2003; Mackett & Thoreau, 2015). The barrier is usually a result of a lack of, or insufficiency in the supply side of transportation, either in terms of infrastructure or services. Stanley & Lucas (2008) state that social exclusion and transport in the United Kingdom, for example, are being primarily linked through the concept of accessibility. The relationship existing between transport and social exclusion as illustrated by Lucas (2012), is as shown in Figure 2-1.



Source: Lucas (2012)

Figure 2-1: Illustrating the relationship between transport disadvantage, social disadvantage and social exclusion

In the illustration above, Lucas (2012) highlights some of the key factors contributing to transport and social disadvantage to include high cost of transport fares, low incomes, poor public transport service, lack of jobs, low skills, lack of access to the car, amongst others. Most of these factors can also be associated with the situation of most South African cities including Cape Town. While these factors may be regarded as the general factors contributing to social exclusion, for the case of South Africa, other local factors such as past land-use planning patterns under the apartheid regime, feature as significant factors that have also contributed, to a large extent in creating social exclusion amongst the population.

Further, from Lucas (2012) illustration above, social exclusion is seen as a direct result of inaccessibility to opportunities. Therefore, from a transport perspective, social inclusion can be achieved through the enhancement of access to opportunities. The established link between transport and social exclusion have thus led to suggestions of adopting a social welfare approach (Lucas, 2004) to the planning and delivery of transport solutions, as lack of transport is considered as a social policy issue.

In the context of developing countries, transport-related social exclusion and its relationship with poverty have been on the policy agenda over the past few decades. In the late 1990s, the World Bank in partnership with the Department for International Development (DFID) commissioned a study to look at the relationship between transport and poverty, as well as possible instruments for inclusion in poverty-reduction strategies (Booth, Hanmer, & Lovell, 2000). In Nepal for example, the debate on social exclusion has found its way into National policy discourse, with social inclusion forming one of the four pillars of Nepal's Poverty Reduction Strategy Whitepaper of 2003 (Rawal, 2007).

In the local South African context, the issues of social exclusion and segregation (as noted in Chapter 1), have been discussed in various studies (Christopher 1987; Donaldson 2001; Visser 2001; Meiring et al. 2018). These studies attribute transport-related social exclusion to the past apartheid planning regime which created a high level of segregation among the population. An outcome of that planning era is that low-income neighbourhoods were located in peri-urban settlements (also known as townships), which are considerably farther away from major economic centres when compared to affluent neighbourhoods. The overall implication is that low-income earners tend to bear high transport costs due to the relatively long travel distance to these main opportunity centres like the Central Business Districts, which is affecting their access to goods, services and activities. As such, affordability adds another vital dimension to accessibility and thus social exclusion. Therefore, analysis of accessibility should incorporate a poverty dimension. Stokes (2015), however, considered transport poverty as a notion that is quite difficult to define, due to the controversy surrounding it, as to whether the 'real' issue exists. It is based around the idea that low incomes and poor accessibility can lead to disproportionate spending on transport to access basic services or lead to suppression of trips. One of the key objectives of this research is, therefore, to contribute to the question of 'whether a real issue exists' in the context of Cape Town South Africa, from an accessibility point of view.

2.3 Accessibility as a Measure of Transport Equity

Based on the illustrated relationship between transport disadvantage and social exclusion as discussed in Section 2.2 above, the overall goal of any functional transport system would, therefore, be to facilitate accessibility to vital opportunities and services for its population. In a 'perfect' city system, from an equity perspective, every member of the society would ideally enjoy equal levels of accessibility to such opportunities (Martens, 2016). However, due to the multidimensional complexities of cities (occasioned by often-conflicting planning objectives), it is rarely the case to have such perfection. The implication of this is that, in the real sense, it would be practically impossible for every member of society to enjoy equal levels of accessibility.

In the context of social exclusion and urban poverty, accessibility analysis provides a framework for identifying the level at which urban residents are being disconnected from opportunities such as jobs, healthcare, education, amongst others. Transport provision can, therefore, be evaluated from an accessibility perspective to reflect the levels of transport opportunities available to various persons or person groups and also the level at which certain groups of persons are excluded or transport-disadvantaged.

The issue of transport disadvantage (Schwanen *et al.*, 2015) is, however, not only a function of the lack of transport resource as it relates to the spatial orientation of the system regarding proximity to residents or their destinations. It also has to do with the question of how equitable such transport provisioning or distribution is. The definition of ‘equitable’ here relates to whether people of different income classes can equally access the system in terms of its affordability. This view is in line with Talen (1998), who stated that ‘defining equity without regard to the socioeconomic status may offer equality of opportunity, but leaves in place the inequalities of the existing social structure’ (Talen 1998, p. 24). In other words, one cannot talk about equity without considering things such as the income characteristics of the population. In a similar vein, if accessibility is regarded as a transport equity issue, its measurement must also take into account the income characteristics of the population. According to Talen (1998), in terms of planning, equitable distribution has to do with locating resources or facilities so that many different spatially defined social groups as possible can benefit, or rather, have access. While achieving such equitable distribution of transport resources or opportunities is a goal of paramount importance to planners, it has nevertheless, been a challenge for planners and policymakers. Inequities in the distribution of costs and benefits of transport infrastructure and services can lead to the production/reproduction of social inequalities and exclusion in a city (Manderscheid, 2009).

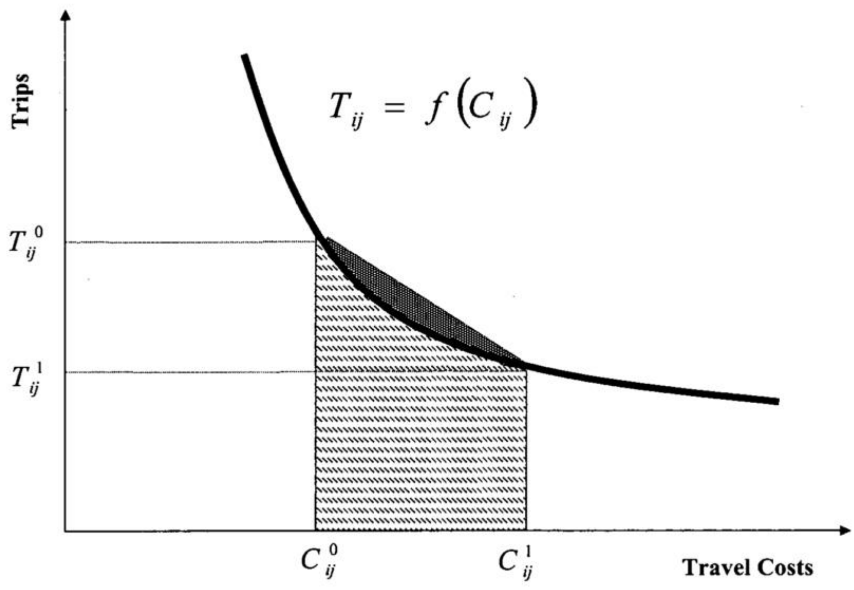
Several authors have employed the accessibility framework for evaluating equity and social exclusion. Guzman et al. (2017), emphasised the role of accessibility in addressing social and spatial inequalities and developed zone-based accessibility indicators to evaluate equity in employment and education in the city of Bogota, Colombia. Their approach utilised the potential accessibility measure, and they evaluated equity across population groups defined by income level. Their results revealed a ‘strong distributional effect of the socio-spatial and economic structure of the city’ (Guzman et al. 2017, p.236). Preston & Rajé (2007) suggested a combined matrix of area accessibility, area mobility and individual mobility as a possible schema for identifying both concentrated and scattered manifestations of social exclusion.

Non-work accessibility has also been used as part of the indicators of social equity. Grengs (2015), for example, developed non-work accessibility indicators to show how non-work accessibility varies among social groups of a city in the US. The authors found that low-income households and vulnerable social groups, which include African Americans and Hispanics, experience advantage in physical access to certain types of non-work activities such as childcare facilities, religious organisations and hospitals. The same social group were found to be distinctively disadvantaged in accessibility to other kinds of activities such as shopping and supermarkets, as a result of low access to private vehicles.

2.4 Transport Tariff & Affordability impact on Accessibility

With accessibility considered as a measure of transport equity (as discussed in Section 2.3), it can, therefore, be inferred that factors affecting accessibility, also have a resultant effect on equity. Among such factors that are of relevance in this study are; the monetary cost or tariff of transport, income and the ability-to-pay. Previous studies such as Bocarejo *et al.*, (2014) have made an attempt at incorporating monetary travel cost and affordability within accessibility measurement.

From the economic literature on travel (Paulley et al. 2006; Jara-Díaz 1997; Litman 2013), income is recognised as one of the critical factors that influences travel consumption, with budgets available to households imposing limitations on their total consumptions outlay for specific goods and services. Thus, income has been found to be a significant factor in virtually all empirical demand analyses. Considering that tariffs or user fares are fundamental to the operations of any public transport system, the price of transport is one of the critical factors determining the amount of travel people make (Paulley *et al.*, 2006). In other words, an increase in fares would generally result in a decrease in patronage, assuming an elastic relationship between the cost of service and demand for service. This relationship between demand (number of trips taken) and price (cost of trips) is depicted in Figure 2-2.



Source: Primerano (2004)

Figure 2-2: Trip demand with a change in travel cost

Figure 2-2 shows the elastic relationship between the number of trips and the cost of trips between locations i and j, whereby a change in cost from C_{ij}^{0} to C_{ij}^{1} results in a change in number of trips from T_{ij}^{0} to T_{ij}^{1}. While this might hold based on economic theory, users' response to fares changes is also usually dependent on the value they place on the trip.

If potential accessibility of a particular location i to destination j is taken as a proxy of potential demand attracted to location j from i, then it could be inferred that household income and consequently, travel expenditure/budget outlay, has a direct influence on accessibility potential. Thus, budget and affordability should be accounted for in the measurement or evaluation of accessibility.

While affordability has been recognized as one of the factors that impact on accessibility (Litman 2012), most of the existing accessibility measures have often ignored this component, with focus directed more on the transport network and service supply characteristics. Such analysis implies that the potential for interaction or engagement in opportunities is assumed to be wholly dependent on spatial access of the transport facilities, as well as the travel impedance from the origin of interest to the opportunity destination. With such focus on the system component, the human and social component of the system such as the ability-to-pay has often been ignored.

Transport affordability can be described as the financial burden individuals and households bear in purchasing transport services (Fan and Huang, 2011). A user's ability to pay for transport services (affordability) plays a role in determining if potential opportunities can be reached, and the number of trips that could be made based on the proportion of income that could be expended on transport services. Therefore, if affordability is regarded as a constraint to trip making, a measure that quantifies such affordability should be recognized within the accessibility model.

In this study, the consideration of affordability is seen to be relevant in the analysis of accessibility in low-income cities. A high affordability level would have an increasing effect on potential accessibility while low affordability should have a decreasing effect. In the case of a highly fragmented city like Cape Town where certain parts of the city are predominantly low-income areas while others are predominantly high-income, an analysis of accessibility based on the transport supply characteristics and the variation in income has more relevance to planning policies aimed at reducing transport-related social exclusion and promoting equity.

In developing a framework for defining and measuring transportation affordability, Fan & Huang (2011) described various elements affecting transportation affordability. They categorised those elements into three groups; household socio-demographic characteristics, the built environment, and the policy environment. The effect of household socio-demographics is seen in terms of how the household income levels determine the financial resources available to spend on goods and services (including transportation). Affordability of transport has been measured using different approaches. Traditional measures have usually been in terms of the proportion of household income expended on transportation (Fan & Huang, 2011; Gómez-Lobo, 2007), which can be represented as the transport affordability index (AI_h) for households h, as expressed by Equation (2-1) below:

$$\text{Index of Affordability}(AI_h) = \frac{\text{Transport Expenditure } (TE_h)}{\text{Income } (y_h)} \cdot 100\% \quad \text{(2-1)}$$

An expanded representation of Equation (2-1), as discussed in Gómez-Lobo (2007), is given in terms of the number of work trips made by household members, with the household's transport expenditure given by:

$$TE_h = \sum_{l=1}^{N_h} x_l \left(p_{l,}y_h\right) \cdot p_l \tag{2-2}$$

where x_l is the number of trips taken by household member l in a month, expressed as a function of the average price per trip for household member l, p_l, and the household monthly income y_h. N_h is the number of persons in the household *h*. It is assumed that the average price paid per trip could vary for every member of the household.

Substituting Equation (2-2) in (2-1), the Affordability Index (AI_h) now becomes,

$$AI_h = \frac{\sum_{l=1}^{N_h} x_l \left(p_{l,}y_h\right) \cdot p_l}{y_h} \tag{2-3}$$

In this study, the affordability of public transport is considered in terms of the proportion of monthly household income spent on commutes to work for the lowest income population. More details on the incorporation of affordability within potential accessibility measures are discussed in the methodology (Chapter 5).

2.5 Chapter Conclusion

A survey of literature for this chapter has revealed that 'social exclusion' is, indeed, a broad term that is quite multi-dimensional (Levitas et al. 2007), with numerous domains and drivers (Bradshaw *et al.*, 2004). This chapter has only provided an overview of this concept, with the idea of identifying the critical aspects of transport that contribute to social exclusion and making the connection with accessibility.

From the literature, there is some consensus that accessibility finds a direct connection to evaluating transport-related social exclusion and urban poverty. In line with this notion, the realisation of cohesive societies, will, in part, depends on combatting social exclusion (Meiring et al. 2018). Further, the illustration provided by Lucas (2012) in Figure 2-1 reveals some elements of transport disadvantage which could lead to inaccessibility, deprivation and resultant social exclusion. One of such elements of relevance to this study is income and affordability of fares.

The potential impact of fares on accessibility has been described in Section 2.4 and is hinged on the notion that high tariffs could lead to suppression of trips, which could further result in exclusion from activity participation. This can be tied to what Sen (2000) had described as 'capability deprivation' whereby the exclusion of the poor from participation in, or access to essential opportunities and activities, is considered as instrumental to poverty (Sen 2000).

For the case of Cape Town, a highly segregated city, where the vast majority of its population falls within the low-income and lower-middle-income category, accessibility can provide a useful framework for evaluating some of its numerous transport-related social issues. Considering that public transport is still the primary mode of commute for the low-income population, there is the need for accessibility indicators that relate accessibility in space with the socioeconomic characteristics of the individuals, such as their income level and ability to pay for public transport services. By combining the accessibility framework with Sen's analytical framework of 'capability deprivation' (Sen 2000), the potential risk of social exclusion for the least-advantaged group can, therefore, be evaluated using accessibility metrics.

Accessibility is also identified as a measure of transport equity. In other words, the benefit or fairness of a transportation system can be judged by the level of accessibility it enables or facilitates for various population groups. The evaluation of equity in transport can, therefore, be considered as an evaluation of its accessibility benefits for residents. Although, equity, just like social exclusion, is multi-dimensional and can be a difficult concept to analyse. The difficulty, according to Litman (2016), is due to the fact that equity itself, is of various types, and often involves numerous potential impacts and many possible ways of classifying individuals. More details on equity evaluation are presented in Chapter 10 of this thesis.

The next chapter (Chapter 3) presents a review of literature on accessibility and spatial interaction modelling.

Chapter 3

Review of Spatial Interaction Modelling & Accessibility

"Everything is related to everything else, but near things are more related than distant things." – Waldo Tobler

3.1 Introduction

The topic of 'accessibility' has generated a large amount of research over the years. While most of the research still apply the theory of spatial interaction based on John Stewart's principles of social physics (Stewart, 1947) developed from the 17th century Newtonian gravitational framework (Sen & Smith 1995; Batty 2007), new studies and methods are continuously being developed to reflect and accommodate different study contexts and data. This chapter presents a review of the accessibility concept from its earlier foundations towards the modern multi-dimensional construct it is today. It discusses the traditional measures of accessibility, and then, looks at a modal dimension of accessibility with a focus on public transport.

The opportunities dimension of accessibility is also discussed, looking specifically at the frameworks and case studies on job, healthcare and education accessibility, which are the three major opportunities considered in this research. The state of accessibility research in South Africa is also discussed. The chapter concludes with a summary discussion and synthesis of the existing tools and methods, which further guides the remaining parts of the thesis. In essence, the literature review attempts to answer the following key questions; *what is accessibility and what common models of accessibility currently exist? what are the key components and variables to be considered in public transport accessibility analysis? Are the existing techniques suitable for the Cape Town context which is characterised by segregation, poverty and inequality? What are the limitations of these techniques concerning the study context? What are the cases for and against the spatial gravity-based potential interaction model in comparison with other models?*

3.2 Overview of Spatial Interaction Modelling

Spatial interaction in a broad sense encompasses any movement over space resulting from a human process (Haynes and Fotheringham, 1984). According to the definition of Batty (2007), spatial interaction '*is the representation and simulation of flows of activity between locations in geographical space*' (Batty 2007, p1). Spatial interaction modelling (also known as SIM) has for long been recognised, especially in geography, where it was first applied as gravity modelling in the early part of last century (Roy, 2004). SIM models were and are still used to determine the influence of spatial separation between different geographic locations. In transport analysis these locations are often regarded as trip origins and destinations, sometimes aggregated into zones.

Roy (2004) regards spatial interaction as a hierarchical choice process which involves two key aspects; location decisions and travel decisions. The illustration given by the author involves a worker residing in a particular location in a city, and a particular job existing elsewhere in the same city. The first step in the interaction of these two parties is the negotiation of a bilateral employment contract between the worker identified by his or her place of residence and the employer identified by his or her place of business. The second step in the interaction process involves the daily commuting by the employed worker to and from his or her place of work. The understanding of these two aspects - location and travel - forms the basis for understanding the dynamics of spatial interaction. While the location decision enables the understanding of land use decisions and the spatial allocation of land use for housing or employment, the travel decision, on the other hand, enables the understanding of the implication on the transportation system.

The terms spatial interaction modelling and gravity modelling are in most cases used interchangeably, but there are however considerable differences between the two (Griffith and Fischer, 2013). Spatial interaction models include not only gravity-based models but also other similar models that have been derived using statistical mechanics and entropy maximisation approaches (Wilson, 1967). In other words, the gravity models are only one of the numerous spatial interaction models available.

The Spatial Interaction Model attempts to relate quantitatively, the components of the spatial interaction system (Miller and Shaw, 2001) and can be formulated using a general function notation as:

$$t_{ij} = f(\mu v_i, \alpha w_j, \beta c_{ij}) \tag{3-1}$$

Where;

t_{ij} is the flow between origin centroid i and destination centroid j

v_i is a variable summarizing the attributes of origin i that influences its trip outflow

w_j is a variable summarizing the attributes of destination j that influences its trip inflow

c_{ij} is the travel cost from i to j.

μ, α, β are parameters that reflect the relative effects of origin attributes, destination attributes and travel costs on the flow between the origin-destination (O-D) pair.

The origin variable, v_i and the destination attractiveness variable w_j can be functions of several attributes that are calibrated as part of the modelling process. The parameters are usually calibrated from data on these variables and an origin-destination flow matrix (Miller and Shaw, 2001).

Spatial interaction models of the gravity type can be unconstrained or constrained. In unconstrained models the total flow is directly based on the number of opportunities in the zones, whereas in the constrained versions of these models the actual interaction is based on the trip numbers predicted or known to originate from or arrive at the zones (Hall 1975; Ortuzar & Willumsen 2011). Constrained models can further be (1) production constrained (2) attraction constrained (3) production-attraction or doubly constrained (Herijanto and Thorpe, 2005).

Unconstrained models are simply the Equation (3-1) above. In production constrained models, the total number of flows leaving an origin, O_i is already known, and the model is constrained by the relationship:

$$\sum_j t_{ij} = O_i \tag{3-2}$$

Whereas, in the attraction constrained models, the trips reaching destinations j, D_j is known, and the flows is constrained by:

$$\sum_i t_{ij} = D_j \tag{3-3}$$

In the doubly-constrained models, both the origin and destination flows are constrained in the model (Torrens, 2000), and the predicted flows simultaneously satisfy the constraints given by Equation (3-2) and (3-3) above.

Several methods exist for estimating spatial interaction models, and the choice of method is usually dependent on the available data (Herijanto and Thorpe, 2005). Most of the methods are discussed in detail in Ortuzar & Willumsen (2011).

The unconstrained model uses a relatively simple computation method and is most suitable for situations where there are incomplete production and attraction data (Herijanto and Thorpe, 2005). These models can be calibrated by transforming the equation into logarithmic form and estimating the parameters by regression methods (Hall, 1975). The single and double constrained models, on the other hand, require more complex approaches to match the estimated and observed trip production or attraction rates for individual zones (Herijanto and Thorpe, 2005), and thus the calibration techniques are more sophisticated.

Further, among the debate on spatial interaction modelling, as discussed in Roy (2004) is the issue of the use of aggregate versus disaggregate models, with spatial interaction models commonly and dismissively assigned to the aggregate category (Roy 2004). Roy (2004) argue that such debate is usually based on a false premise, noting that the so-called aggregate SIM models usually divide the analysis into market segments at a more refined level. The determination of the spatial unit of analysis is also a critical consideration in SIM, considering that spatial data can be made available at various levels of aggregation. Associated with this, is the modifiable areal unit problem, MAUP (Jelinski & Wu 1996; Viegas & Martinez 2009), which is a source of statistical bias that results from spatial data aggregation. As noted by Viegas & Martinez (2009), the results obtained from any study on spatial data are not independent of scale, and the aggregation effects are implicit in the choice of the zonal boundaries. As such, attention must be paid to modifiable boundaries and scale issues in zone definition for spatial analysis. The next section of this chapter focuses on the concept of accessibility, which is based on the theories of spatial interaction.

3.3 The Accessibility Concept in Urban Transportation

3.3.1 Definitions of Accessibility

The concept of accessibility has long been central to a host of urban and regional transportation research endeavours (Koenig 1980: Martellato & Nijkamp 1996; Páez et al. 2012). Most researchers (Gould 1969; Handy 2002; Geurs et al. 2006; Van Wee et al. 2013), have agreed that it is not an entirely easy and straight-forward concept to define. It has, nevertheless, been operationalised in several ways, and a variety of meanings attributed to it (Geurs & Wee 2004; Lei & Church 2010). The definitions of accessibility that have been given by various authors so far are highly related and are tied to the individual perspective from which accessibility is being viewed.

One of the earliest and most cited definition is that of Hansen (1959) who defined it as ‘the potential of opportunities for interaction’ or ‘the intensity of the possibility of interaction’ (Hansen 1959, p.73). This is also related to the definition put forward by Páez et al. (2012), who see accessibility as the potential to reach spatially dispersed opportunities, for example, for employment, recreation, shopping, social interaction, etc. Cervero (2005) defined it as an indicator of the ability to efficiently reach oft-visited places. Geurs & Ritsema van Eck (2001) defined ‘access’ as the amount of effort for a person to reach a destination or the number of activities which can be reached from a specific location. Other notable definitions in literature include; ‘the inherent characteristics (or advantage) of a place with respect to overcoming some form of spatially operating source of friction’ (Dalvi and Martin, 1976); ‘the ability or freedom of individuals to decide whether or not to participate in different activities’ (Burns, 1979); ‘the benefits provided by a transportation/land-use system’ (Ben-Akiva and Lerman, 1979), ‘measure of an individual’s freedom to participate in activities in the environment’ (Weibull, 1980) and ‘an individual’s ability to reach desired goods, services, activities and destinations’ (Litman 2003; Litman 2014). A temporal dimension was also added by Bhat et al. (2002b) to the definition of accessibility which they describe as the ease of individuals to pursue desired activities at desired locations, by the desired mode and at the desired time.

Van Wee et al. (2013), however, gave a more elaborate definition to accessibility which they defined as the extent to which land use and transport systems enable individuals to reach activities or destinations by means of a (combination of) transport mode(s) at various times of the day (perspective of persons), and the extent to which land-use and transport systems enable companies, facilities and other activity places to receive people, goods and information at various times of the day (perspectives of locations of activities). This definition, similar to that of Bhat (2002), also incorporates attractiveness of the land use, attributes of the transport system, characteristics of the trip makers as well as the temporal dimension of the accessibility.

Accessibility has also been defined from a purely behavioural framework. In the definition proposed by Cascetta et al. (2016), accessibility is seen as ‘the expected number of opportunities available for a subject to perform an activity, where “available” means that the opportunity is perceived as a potential alternative to satisfy one’s needs, and can be reached given the spatiotemporal constraints of the individual’s schedule’ (Cascetta et al. 2016, p.45).

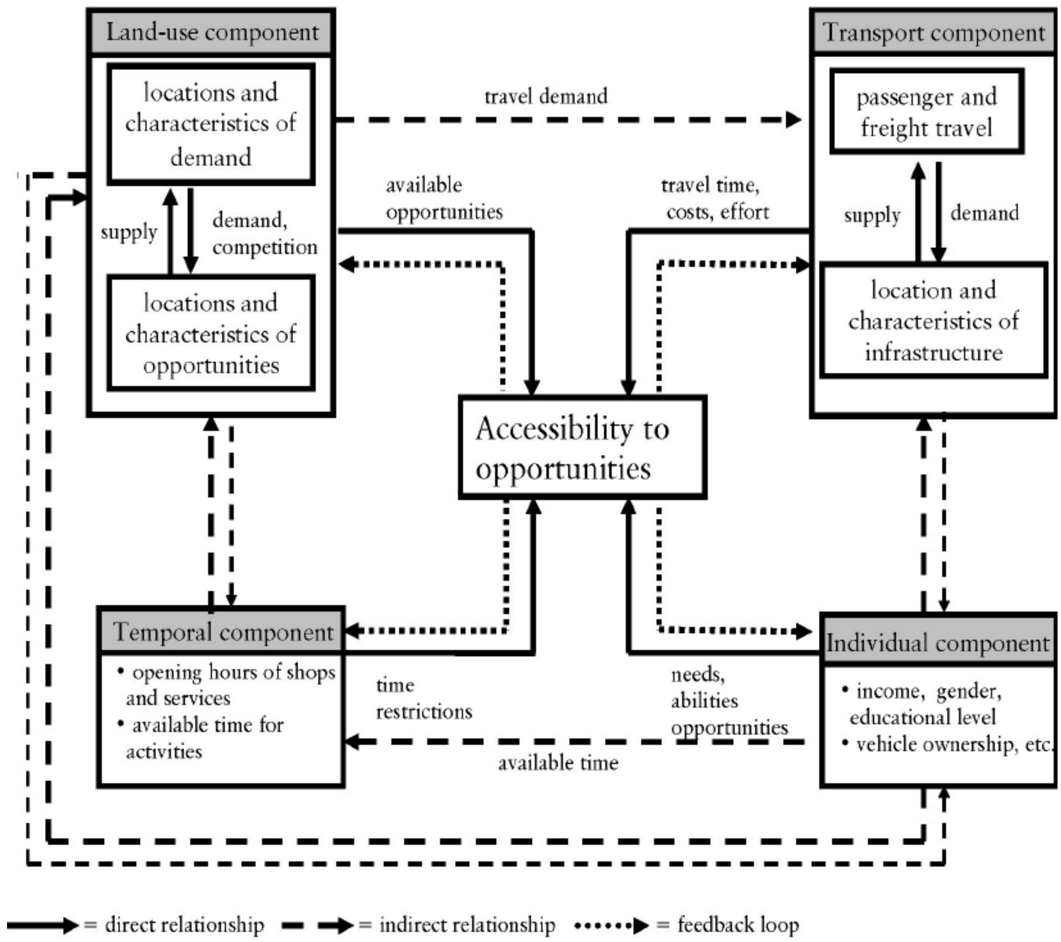
Irrespective of these variants of definitions, indicators of urban accessibility have generally been regarded as tools to aid transport planners, operators and local authorities in decision-making regarding transport network, transport service and land use planning (Koenig 1980; Hull et al. 2012; Silva 2012). In line with this, several countries have over the years incorporated accessibility measures in their transportation planning process (Bhat, Handy, Kockelman, Mahmassani, Gopal, *et al.*, 2002a). In the United Kingdom, the use of accessibility in the analysis of new transportation projects is mandated at the federal level as part of the nation's sustainability efforts (Hardcastle and Cleve, 1995). Other countries like the Netherlands (Hilbers and Verroen, 1993) and Spain (Jadraque *et al.*, 1996) have also continued to explore the inclusion of accessibility measures in urban transportation analyses. Concerning the accessibility versus mobility planning discourse (Handy, 2002), measures of accessibility have been seen as useful complements, and eventually, alternatives to traditional mobility measures (Cerdá, 2009). The concept of accessibility has also been used to develop decision support tools, for example, the Structural Accessibility Layer (SAL) for urban mobility management developed by Silva (2012), the PTAL Index developed for Transport for London (Transport for London, 2010), as well as the LUPTAI tool developed by Pitot et al. (2006).

Halden et al. (2005) identify several ways in which accessibility has been applied in planning. Most include access to opportunities such as jobs (Hanson & Schwab 1987; Ha et al. 2011; Bocarejo & Oviedo 2012; Cheng & Bertolini 2013a; Hu 2016; Cervero et al. 1995; Reggiani et al. 2011; Ha et al. 2011; Tilahun & Fan 2014), healthcare (Luo & Wang 2003; Luo & Qi 2009; Mcgrail & Humphreys 2014), education (Zhuo 2012; Chin & Foong 2006), or retail (Farber et al. 2014; Widener et al. 2015). Other application areas of accessibility include; investigating travel mode options (Jin, Beimborn and Greenwald, 2005) and automobile ownership rate (Thompson 2001), distribution of transport impacts and linkages with public policy (Hensher *et al.*, 2012).

3.3.2 Components of Accessibility

Through the examination of various accessibility measures, definitions and instruments (tools), several authors have identified the various components that constitute accessibility. Dalvi & Martin (1976) in their accessibility study of car-owning households in inner London, identified three elements as critical to modelling accessibility. The first is the individual component which incorporates the purposes, preferences, decision-making processes as well as their sensitivity to travel costs and comfort. The second component is the opportunities set available, while the third component is the ability of the transport system to overcome the spatial separation. A similar categorisation is given by Geurs & Ritsema van Eck (2001) who identified four components of accessibility as; *land-use, transportation, temporal and individual components*.

The land use component (also regarded as the activity component in Handy & Niemeier (1997) reflects the amount, quality and spatial distribution of opportunities (such as jobs, shopping, healthcare, recreational facilities) supplied at each destination. The transport component describes the transport system expressed as the disutility for an individual to cover the distance between origin and destination using a given type of travel mode. The amount of travel time (including waiting and parking), the fixed and variable costs of travel, and efforts (including reliability, level of comfort, accident risk) are all considered. The temporal component reflects the availability of opportunities at various times of the day, as well as the time available for individuals to participate in certain activities. The individual component reflects the needs (depending on age, income, educational level, household structure), the abilities (depending on people's physical condition, availability of travel modes) and opportunities (depending on people's income, travel budget, educational level) (Van Wee *et al.*, 2013). The relationship between the various components of accessibility as illustrated by Geurs & Van Wee (2004) is shown in Figure 3-1.



Source: Geurs & Van Wee (2004)

Figure 3-1: Relationship between components of accessibility

From the relationship described above, it follows that a holistic accessibility measure should 'ideally' incorporate each of these components. However, as pointed out by Geurs & van Wee (2004), the various attributes within each of these components are rarely captured in totality in most accessibility measures used in practice. Existing measures usually focus on specific components, as will be discussed further in Section (3.4).

Litman (2014), further highlights the various factors affecting accessibility, and their current level of consideration in most accessibility measurement/evaluation studies. These factors, as summarised in Table 3-1, include; transport demand and activity, mobility, transport options, user information, integration terminals and parking, affordability, mobility substitutes, land-use factors, transport network connectivity, transport system management and prioritisation.

Accessibility is also known to be affected by design of infrastructure, such as; public transport routes and stops (Yigitcanlar *et al.*, 2007), issues of reliability of timetable and perception of safety (Tyler, 1999). It has also been related to the qualities of the transportation system (for example travel speed) and of the land use system, such as density and mix (Bertolini and Clercq, 2003).

Table 3-1: Factors affecting accessibility

Factors	Description	Current Consideration	Improvements
Transport Demand	The amount of mobility and access people and businesses would choose.	Motorized travel demand is well measured, but non-motorized demand is not.	More comprehensive travel surveys and analysis of travel demands.
Mobility	Travel speed and distance.	Primarily evaluates motor vehicle traffic speeds and vehicle mileages travelled.	More comprehensive evaluation of mobility by other modes.
Transport Options (modes)	The quality (speed, convenience, comfort, safety, etc.) of transport options including walking, cycling, public transit, etc.	Motor vehicle travel speed and safety are usually considered, but other modes and other travel factors are often overlooked.	More multi-modal evaluation (speed, convenience, comfort, safety, etc. of walking, cycling, transit, etc.)
User information	Availability of reliable information on mobility and accessibility options.	Sometimes considered for certain modes or locations, but seldom comprehensive.	More comprehensive and integrated information to help users navigate transport systems.
Integration	The degree of integration among transport system links and modes.	Automobile transport is generally well integrated, but not connections between other modes.	More integrated planning to improve travellers' ability to connect between system components.
Affordability	The cost to users relative to their incomes.	Automobile operating costs and transit fares are usually considered.	Getter evaluation of transport costs relative to users' incomes.
Mobility Substitutes	Telecommunications and delivery services	Not usually considered in	Consider mobility substitutes as part of the transport system.

	that substitute for physical travel.	transport planning.	
Land Use Factors	Land use density and mix.	Usually considered in land use planning, but less in transport planning.	Measure how land-use factors affect travel distances and costs.
Transport Network Connectivity	Density of connections between roads and paths, and therefore the directness of travel between destinations.	Transport planning is starting to consider roadway connectivity impacts on accessibility.	Measure how roadway connectivity affects travel distances and costs.
Transport Management	How transport management affects accessibility.	Limited consideration.	Consider how various transport management strategies affect access.
Prioritisation	Strategies that favour more efficient travel activity.	Limited consideration.	Consider transport prioritization strategies.
Inaccessibility	The value of inaccessibility and isolation.	Not generally considered in transport planning.	Recognise the value of sometimes limiting access.

Adapted from: Litman (2014)

From Table 3-1, it could be seen that current research on accessibility measurement only considers a limited number of these factors; with mobility, transport mode options, network and land-use factors being the most often considered. While affordability has also been recognised by Litman (2014) as a factor that determines accessibility, most measures have failed to incorporate it within the accessibility measurement. In quantifying accessibility, say by public transport in the context of a low-income society, such as Cape Town, this component of affordability becomes even more crucial, and thus, should be considered.

3.4 Traditional Measures of Accessibility

The broad framework under which accessibility has been measured is still defined by ‘the ease of reaching or being reached’ by a transport system (Halden *et al.*, 2005).

Although different approaches have been developed in describing and measuring accessibility, most of the accessibility measures fall within the broad categories described by Geurs & van Wee (2004), who categorised accessibility measures into four distinct types; *location-based, infrastructure-based, person-based and utility-based measures*.

3.4.1 Location-based measures

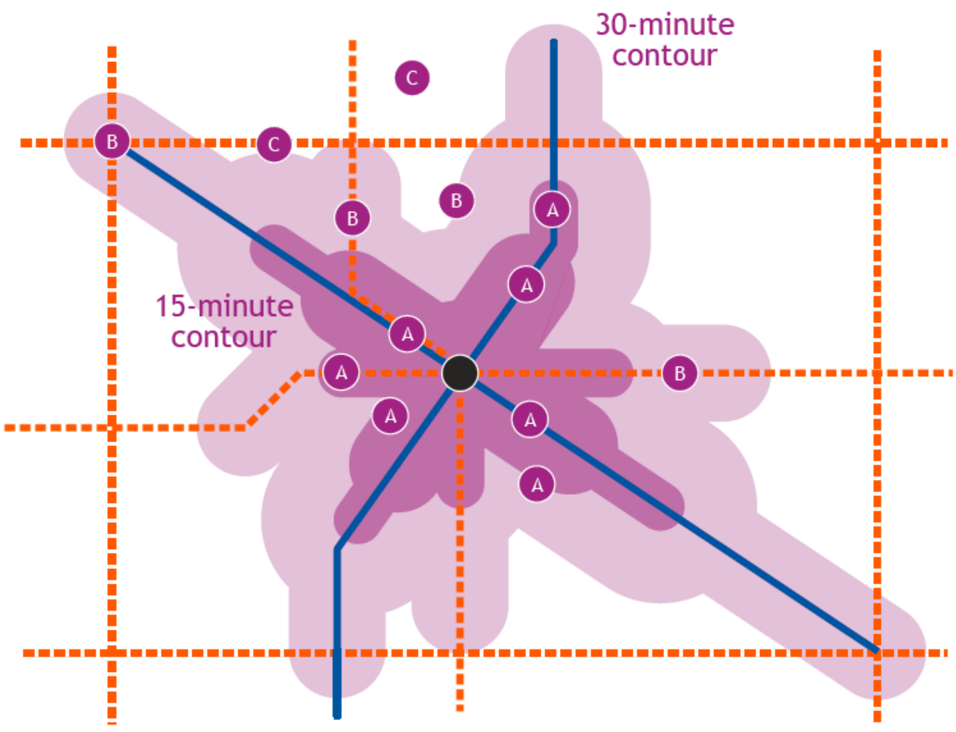
Location-based measures are among the earliest accessibility measures to be developed (Cerdá, 2009), and they analyse accessibility at locations on a macro level (Van Wee *et al.*, 2013) say of a zone or neighbourhood. This type of measure has been regarded as useful in comparing the accessibility levels of one location to another. Accessibility is usually measured for a single transportation mode, while the same equation can be applied several times for various modes (Cerdá, 2009). The measures are useful in identifying under-served zones or zones that lack the necessary infrastructure that enables accessibility. The two popular kinds of location-based measures described in the literature are distance-based measures and potential accessibility measures.

Distance-based measures

As described by Geurs & Wee (2004), distance-based measures, also regarded as connectivity measures, represent the simplest kinds of location-accessibility measures, and they give the degree to which two places are connected. These measures often find use in land-use planning as standards for the maximum travel distance (or travel time) to a given location or a transport infrastructure (Geurs & Wee 2004). In other words, distance measures consider the distance between the origin of interest and the different opportunities to be reached, and in most cases, the metric is interpreted in terms of the distance to the closest opportunity among the set of available opportunities. Some studies such as Makrí & Folkesson (2000) have also suggested the use of average distance from all origins to a particular destination, or the average distance to all destinations from any particular origin. Estimation of distance is usually done using; Euclidean distance, network or topological distance, network travel time with constant speed and dynamic network travel times (Geurs & Van Wee 2004; Malekzadeh 2015). Euclidean distance is only an approximation and is useful for aggregated analysis where sufficient details of the transport network or services characteristics are unavailable. Its deficiency lies in the fact that it ignores the actual topography of the area and the potential barriers to access. Using network or topological distance, however, resolves such deficiency. The use of network travel time or dynamic network travel time permits the evaluation of accessibility across various modes of travel which are characterised by different operational speeds.

Contour measures

Contour measures (Wachs & Kumagai 1973; Vickerman 1974; O'Sullivan et al. 2000a; Arce-ruiz et al. 2012) are a form of distance-based measures where accessibility to more than two possible destinations are analysed. As described by Geurs & Wee (2004), these measures (also known as isochronic, cumulative opportunities or proximity count measures) count the number of opportunities that can be reached within a given travel time, distance or costs (fixed costs), or measure the average or total time or cost required to access a fixed number of opportunities (fixed opportunities). Figure 3-2 below gives an illustration of contour measures for two travel time thresholds of 15 minutes (points A) and 30 minutes (points B) from an origin point in a network, represented by the black dot.



Source: Scheurer & Curtis (2007)

Figure 3-2: Illustration of the contour measure

Points A and B in Figure 3-2 above represent destinations reachable within 15 minutes and 30 minutes respectively. Contour measures, as illustrated, give an idea of the number of choices (opportunities, destination choices) within reach from a specific location. For example, the number of shopping malls, clinics, schools, among others, that can be accessed within a specified travel time, and from which residents could make a choice (Handy *et al.*, 1997).

Contour measures have also been applied in studying job dynamics within a region. El-Geneidy & Levinson (2006) applied the measure in a longitudinal analysis to track changes in job and residents' accessibility levels over a 10-year period for travel by the automobile in parts of the United States. Their measure was further utilised in investigating the effect of job accessibility on home sales, in which they found a positive and statistically significant correlation.

The contour accessibility measure is formulated below as a specific form of the gravity measure (discussed in next section), where the impedance function takes the form of a binary value (Handy & Niemeier 1997; Koenig 1980):

$$A_i^{c_{\max}} = \sum_{j=1}^{n} O_j \ B(c_{ij}) \tag{3-4}$$

with:

$$B(c_{ij}) = \begin{cases} 1 & \text{if } c_{ij} \leq c_{max} \\ 0 & \text{otherwise} \end{cases} \tag{3-5}$$

where;

$A_i^{c_{\max}}$ is the accessibility measured at location i, within a threshold travel cost, $c_{\max}$ given in terms of distance or time;

O_j is the opportunities in destination location j;

n is the number of destinations;

$B(c_{ij})$ is a binary variable equal to 1 if zone j is within the predetermined threshold of cost (distance or time), and 0 otherwise (Koenig, 1980). In other words, for any threshold of travel time or distance chosen, opportunities further away from such threshold are simply not included in the computation of accessibility.

The selection or utilisation of contour measures, just as any other measure, is dependent on the relevant policy objectives being pursued. As such, travel distance thresholds, for example, are often aligned or made consistent with policy goals. One of the major advantages of contour measures as suggested in Geurs & Ritsema van Eck (2001) is their ease of interpretation, as they do not make implicit assumptions about a person's perception of transport or the opportunities of interest, as well as the interaction of these two components. Proponents of other measures of accessibility such as the utility-based measures (Ben-Akiva & Lerman 1979; Dong et al. 2006; Cascetta et al. 2016) have however attributed these characteristics rather as limitations of the contour measures. One argument is that opportunities are considered equal, regardless of the travel cost associated with reaching them. For example, jobs within reach of travel time threshold of say 30 minutes are all considered equally. Another criticism is that travellers' preferences and behaviours are not captured by these measures, as all opportunities are considered to be equally desirable. These measures are also not able to capture the interacting effect of land use and transport attributes as well as the variable sensitivity of travellers to different kinds of opportunities (Geurs and van Wee, 2004). Despite these limitations and criticisms, these measures have been applied in numerous studies in a simplified manner to evaluate issues of equity in accessibility to social infrastructures (public goods) as well as evaluating changes in accessibility influenced by the transportation infrastructure (Handy et al. 1997; Cerda 2000).

Potential (Gravity) Measure

This kind of measures, also known as the gravity-based measure, is considered one of the most popular among the available measures of accessibility (Pirie, 1979), and have been widely applied in urban and geographical studies since the 1940s (for example Stewart 1947; Hansen 1959; Vickerman 1974; Salze et al. 2011; Papa & Coppola 2012; Gulhan et al. 2014). They estimate the accessibility of a particular zone i to all other zones j in which smaller or more distant opportunities provide diminishing influences (Geurs and van Wee, 2004). In other words, these measures weigh opportunities, usually the quantity of an activity (say, number of employment) by travel impedance, usually a function of travel distance, time or generalised cost (Handy *et al.*, 1997). The number of opportunities at one particular destination node, discounted by the distance (or cost) to access the node from some reference point (origin), is a measure of the relative accessibility of opportunities at the destination node (Pirie, 1979).

The accessibility measure, also popularly regarded as the Hansen measure is formulated as:

$$\mathrm{A}_i = \sum_{j=1}^{n} f(c_{ij})\, O_j \qquad (3\text{-}6)$$

where:

A_i is accessibility measured from origin location i;

c_{ij} is travel cost, given in terms of distance, time, or generalised cost in moving from i to j;

O_j is the amount of opportunities at destination j;

$f(c_{ij})$ is an impedance/deterrence function that usually takes the form of negative exponential or power function. This function can also be regarded as monotonously decreasing distance/time/generalised cost, c_{ij} weighting that provides an estimate of trip makers' sensitivity to, or perception of distance, time or generalised cost.

Some variants of the Hansen measure (Equation 3-6) above have been given in literature (for example, Jones 1981), where the index is either normalised or weighted by the quantity of opportunities as shown in Equations (3-7) and (3-8) below. These are regarded as the normalised and the population-weighted Hansen measure (Jones, 1981). The normalised measure is given by:

$$\mathrm{A}_i = \frac{\left[\sum_{j=1}^{n} f(c_{ij})\, O_j\right]}{\sum_{j=1}^{n} O_j} \tag{3-7}$$

The underlying difference between Equations (3-6) and (3-7) above is that Equation (3-6) presents accessibility as an absolute number of weighted aggregated opportunities across zones, while Equation (3-7) presents those opportunities as a proportion of total opportunities available in the entire area of interest. The job accessibility measure proposed in this study is a form of the normalised Hansen measure. More of this is discussed in Chapter 5.

Another variant is the population-weighted Hansen measure, which is represented as:

$$\mathrm{A}_i = P_i \sum_{j=1}^{n} f(c_{ij}) O_j \tag{3-8}$$

where P_i is the population of the zone i.

This type of measure associates accessibility with the opportunity which the inhabitants of the study area collectively possess to participate in a set of activities (Jones, 1981).

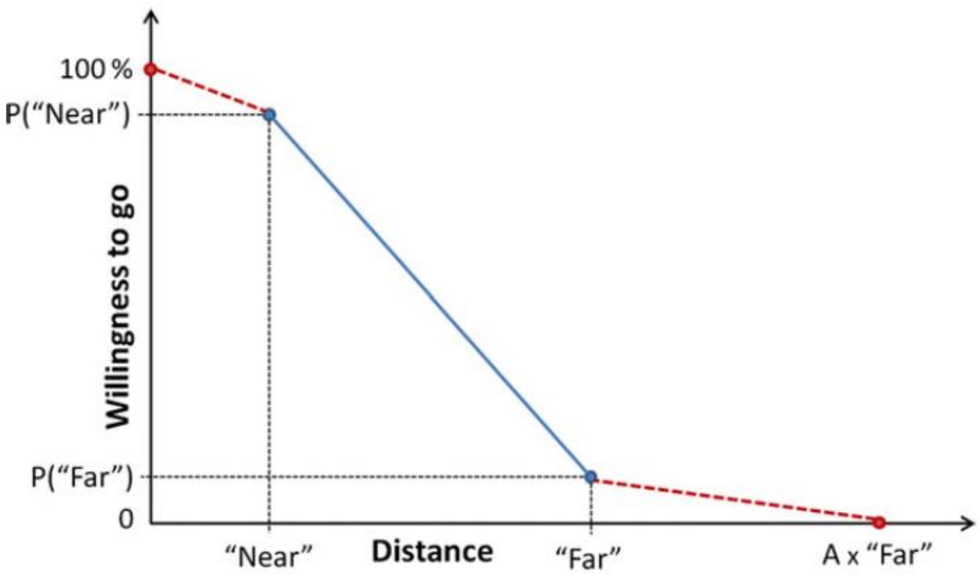
There have also been modifications of the gravity measure that consider the effect of competition for opportunities. A version of the gravity model was formulated by Huff (1963) to originally analyse market areas for retail outlets. The approach developed by Huff (1963) has been adopted by researchers (van Wee et al. 2001; Ritsema van Eck & de Jong 1999) to model the impact of competition for resources or opportunities in potential accessibility models. It is based on the notion that the degree of competition for a facility or activities can have a key effect on its accessibility, especially for those kinds of opportunities (such as jobs) where one person can 'occupy one unit of such opportunity at a given time' (Jones 1981, p. 16), and where such occupation automatically reduces the amount available. An accessibility measure that incorporates the effect of competition can be written in general form as:

$$\mathrm{A}_i = \frac{\sum_{j=1} O_j f(c_{ij})}{\sum_{k=1} P_k f(c_{ik})} \tag{3-9}$$

The numerator in Equation (3-9) is a Hansen potential accessibility measure, while the denominator is a measure of the effective competition for these opportunities (Jones, 1981). It discounts the competition due to the population P_k in the other zones according to their separation from the origin zone i. $f(c_{ij})$ remains the impedance function for travel between i and j.

In all the existing variants of the gravity measures, a common feature is the determination of the deterrence (impedance) behaviour represented by $f(c_{ij})$. Most gravity-based models differ in the approach adopted for the impedance function calibration as well as for calculating the attractiveness of opportunities (Malekzadeh 2015; Dong et al. 2006; Iacono et al. 2008). The accuracy of accessibility computed by the gravity model is highly dependent on the impedance function selected, and the parameters applied. It is therefore, important to estimate the parameters of the selected function such that it reflects the actual behaviour of trip makers in the area of interest (Geurs and van Wee, 2004). The work of Fotheringham (1981) provides a solid background and some empirical evidence of the relationship of spatial structure with decay parameter estimates.

Various approaches have been employed by researchers in the estimation of decay functions and parameters of the gravity model. Most of the traditional approaches are based on statistical techniques such as the Maximum Likelihood Estimation (for example Flowerdew & Aitkin 1982) and the Ordinary least squares regression (Taylor, 1975). A different approach to modelling of distance-decay has also been suggested by Martinez & Viegas (2013), using data on individuals' psychological perceptions of distance in relation to activities locations, rather than the conventional empirical measure of actual distance travelled. Their formulation is grounded on the psychological value of the perception of stating a distance (in terms of displacement time) as 'close' or 'far', and how this can be translated to an individual's 'willingness to go' or level of interaction between two locations separated by a distance in space or in time (Martinez and Viegas, 2013). Their specification of distance decay is shown in Figure 3-3 below, where spatial interaction is a probabilistic measure of willingness to go based on individual's perception of distance as revealed from survey.



Source: Martinez & Viegas (2013)

Figure 3-3: Specification of individual distance-decay

In Martinez & Viegas (2013) approach, the distance-decay function is estimated at the level of the individual and aggregated up for the entire population. The aggregated distance-decay reflects the 'average value of the probability of every individual to interact for each distance band considered' (Martinez & Viegas 2013, p.98). While most of the decay functions used in the majority of studies have been of either the Exponential, Power, Tanner, or Box-Cox function, the distance decay function that was proposed by Martinez & Viegas (2013) is of the logistic form (also known as the Richards function) and is given by:

$$f(x) = C + \frac{K - C}{(1 + Qe^{-B(x-M)})^{\frac{1}{v}}} \quad (3\text{-}10)$$

where;

> x is the distance (or time);
>
> C represents the minimum function value;
>
> K is the upper limit.;
>
> B, v, Q and M are the four calibration parameters. B is the growth rate, which in spatial interaction terms, is similar to the parameter β of the exponential function, and represents the average elasticity of spatial interaction relative to the travel time or cost variation. v affects near which asymptote growth occurs, Q depends on the value $f(0)$, and M is the x value of the maximum growth if $Q = v$.

Although the approach to modelling interaction decay suggested by Martinez & Viegas (2013) has the capacity to reasonably capture individuals' perceptions, which could further enable disaggregated analysis of accessibility at the person or household level, there are nevertheless, some limitations in its capability to deal with population dynamics and changing preferences among individuals. Also, it can be argued that perceptions at any given point in time can be very subjective and influenced by numerous factors, most of which are not static but change with time. Individual characteristics (for example, income level, age), as well as built environment factors (for example, neighbourhood safety), could all influence perceptions of nearness or farness. Accounting for all these factors in establishing interaction potential would lead to further questions of its usefulness in terms of applicability to planning. There also has to be some balance between effort expended in a detailed survey and the actual benefit of such an approach to estimation, as it applies to final decision making.

Some studies have compared the gravity and cumulative opportunity measures. El-Geneidy & Levinson (2006), in their evaluation of various location-based measures, found that the cumulative opportunity and the gravity-based measures tend to be similar for travel time that is within 30 minutes. Although the cumulative opportunity measure is relatively easier to understand and interpret by planners, the gravity measure is still widely utilised. Despite the popularity of the gravity measure, there have also been some criticisms raised concerning these measures. These are well documented in several review papers on accessibility measures (for example, Pirie 1979; Jones 1981; Geurs & Ritsema van Eck 2001; Geurs & Van Wee 2004; Halden et al. 2005). One of the commonly mentioned shortcomings of the gravity measure is their inability to capture actual utility of opportunities for various individuals, and the consideration of all opportunities within reach as potential opportunities. These shortcomings have led to the suggestion of using utility-based measures instead, which is further discussed in Section 3.4.4.

Place-Rank Measure

The study by El-Geneidy & Levinson (2006) for the Minnesota Department of Transportation evaluated most of the available accessibility measures in terms of three key attributes; (1) ease of understanding (2) accuracy and (3) complexity, with a view to developing a metric that is easy to comprehend and implement in terms of practical decision making. The authors introduced a new measure called the 'Place Rank' as a measure of accessibility that 'can take advantage of the vast amount of information on origin and destination, which is commonly now available for transport and land use planners' (El-Geneidy & Levinson 2006, p. 12). A key feature of the 'Place-Rank' measure is that point-to-point travel time information is not required, as accessibility level of a zone is measured based on the number of persons coming into the zone to reach an opportunity. The 'Place-Rank' measure is also able to account for the number of opportunities an individual pass over in other zones to reach an opportunity in a particular zone. In this case, the destinations that are able to attract more workers from zones that already have a high number of jobs is ranked higher and considered as zones with high job accessibility (El-Geneidy and Levinson, 2006). The Place Rank measure is also regarded as adaptable to various regions and study contexts.

3.4.2 Infrastructure-based measures

Infrastructure-based measures analyse the observed or simulated performance of transport infrastructure and are usually given in terms of the length of the infrastructure network, network density, congestion travel time on links and average travel speed on the network (van Wee et al. 2001; Van Wee et al. 2013). These measures are typically useful in describing the characteristics of the infrastructure supply, although they provide no information on possibilities for opportunities reachability (van Wee *et al.*, 2001). Geurs & Ritsema van Eck (2001) state that infrastructure-based measures may result in different conclusions regarding accessibility, compared to the activity or location-based measures which incorporate both the transport and land-use components of accessibility. A case cited by the authors in this regard is Linneker & Spence (1992), who demonstrated how accessibility within inner London varies by the type of measure used between infrastructure-based measure and potential accessibility measure.

3.4.3 Person-based measure (Space-Time Framework)

These measures analyse accessibility at the individual level, say the activities that an individual can participate in at a given time (Geurs & Ritsema van Eck 2001). It is based on the concept of space-time geography in identifying the opportunities and choices offered by the physical, institutional or geographical context (Hägerstrand, 1970). In other words, it measures the limitations on an individual's freedom of action in the environment, that is, the location and duration of mandatory activities, the time budgets for flexible activities and travel speed allowed by the transport system (Van Wee et al. 2013; Kwan & Weber 2008). The development and application of space-time mapping (Timmermans et al. 2002; Miller 1999) as a tool to understand the impact of transport in distorting the geographical space remains a contemporary research topic since the 1960s (Martinez and Viegas, 2013). Several authors (for example, Miller 1999; Miller 1991; Miller & Wu 2000; Wu & Miller 2001) have explored this concept of functional space and time geography as a powerful analytical tool to explain both human behaviour and the effect of transport networks over space on human interactions with activities.

According to Miller (1991), the application of the space-time framework is based on the assumption that;

> *(1) Events that are undertaken by an individual have both a spatial and a temporal dimension, and*
>
> *(2) Individuals can only partake in activities at a single location in space, and at a single point in time.*

From these assumptions, it can be said that accessibility measures that are based on the time-geographic formulation of individual movement can be derived through the identification of those areas which the individual can reach during the day and the opportunities within those areas (Kwan & Weber 2008; Kwan 1998). Data utilised for the space-time framework include; the time available for activities; the distance between relevant locations; and the velocities of travel between locations (Miller

1991). Data representing constraints of space and time on people can also be used to determine the availability of activities to people (Jones, 1981). Jones (1981) further described two approaches for determining space-time prisms as (1) the sequential and (2) non-sequential approach. Both approaches consider the spatial and temporal options available to a person. The sequential approach considers activities sequentially whereas the non-sequential approach only partially considers activities sequentially. The non-sequential approach also does not take into account that participation in one activity may prevent participation in another (Jones, 1981).

The space-time approach to accessibility measurement is based on a large range of factors which can influence a person's ability to take part in desired activities (Geurs & Ritsema van Eck 2001). These factors range from transport, land use, individual to organisational factors. Although space-time measures are able to capture accessibility at a person level, one of the major disadvantages lies in its reliance on a large amount of data at the person level, which in most cases are not readily available. Geurs & Ritsema van Eck (2001) also pointed out the problem of aggregating the space-time accessibility outcome at a person level, to inform infrastructure or land use planning decisions at a macro level.

3.4.4 Utility-based measures

Utility-based measures (also known as logsum or revealed value measures) analyse the benefits that people derive from access to spatially distributed activities (Jones 1981; Geurs & Ritsema van Eck 2001; Geurs & Van Wee 2004). These measures are founded on the random utility theory and are increasingly receiving attention in accessibility investigations (Geurs et al. 2010). Utility or revealed value is described by how much people are willing to pay for something. In terms of land use and transport, the utility is hinged on the notion that people seek to maximise net benefit or consumer surplus obtainable from transport and land-use system (Jones, 1981).

Random utility models assume that an individual's preferences (and therefore choices) can be measured only up to a random or error term, with the random term resulting from 'unmeasurable psychological factors or changes in the individual's state of mind over time' (Miller & Shaw 2001, p.256). In other words, these models assume that the decision-maker has a perfect discrimination capability among a set of choices, and the analysts are assumed to have incomplete information, therefore uncertainty must be accounted for (Ben-akiva and Bierlaire, 2003). The uncertainties are captured as the random components of the model. The specification of different distributions for the random components yields different kinds of random utility models. The most common of these classes of models is the multinomial logit model (MNL), which assumes that the unmeasured components of each destination are unrelated (Miller & Shaw 2001).

In the utility-based measures, the probability of an individual making a particular choice depends on the utility of that choice relative to the utility of all other choices. That is, if it is assumed that an individual assigns a utility to each destination or mode choice in some specified choice set, and then selects the alternative which maximises his or her utility, accessibility can then be defined as the denominator of the multinomial logit model (Handy & Niemeier 1997; Ben-Akiva & Lerman 1979).

Utility-based accessibility is formulated as:

$$\mathrm{A}_n = \ln\{\sum_{\forall \in C_n} \exp(V_{n(c)})\} \qquad (3\text{-}11)$$

where;

A_n is accessibility for an individual n;

$V_{n(c)}$ is the observable temporal and spatial transportation components of the indirect utility choice c for person n;

C_n is the choice set for person n;.

Since utility-based measures analyse accessibility at the level of the individual (just as space-time measures), aggregating at the zonal level would theoretically be a total or average of the indicators at the person level. One significant advantage that has been associated with utility-based measures is that they enable the testing of alternative formulations of the utility function in the search for one that best matches actual travel behaviour. However, the calibration determines the relative importance of various factors and need not be pre-specified as in some cases of the gravity-type measures (Makrí and Folkesson, 2000). Despite the associated advantages, questions have also been raised concerning utility-based measures. Geurs & Ritsema van Eck (2001) point to the weakness of empirical evidence for the link between infrastructure provision and economic activity, and the relative inability of utility-based measures to capture feedback effects between transport patterns land-use changes over time. Bhat, Handy, Kockelman, Mahmassani, Chen, *et al.*, (2002) further point out the bias in defining choice set for activities and opportunities to be included in the utility function of utility-based measures. Also, considering that individuals' choices do change with time, there is a failure of this measure to predict or account for changes in choice set and their resultant effect on travel behaviour.

For each of the traditional measures discussed in Section (3.4), there is one or more combination of associated components described in Section (3.3.2). Geurs & Ritsema van Eck (2001) presented a matrix relating the component areas and the associated attributes to each of the measure. This is shown in Table 3-2:

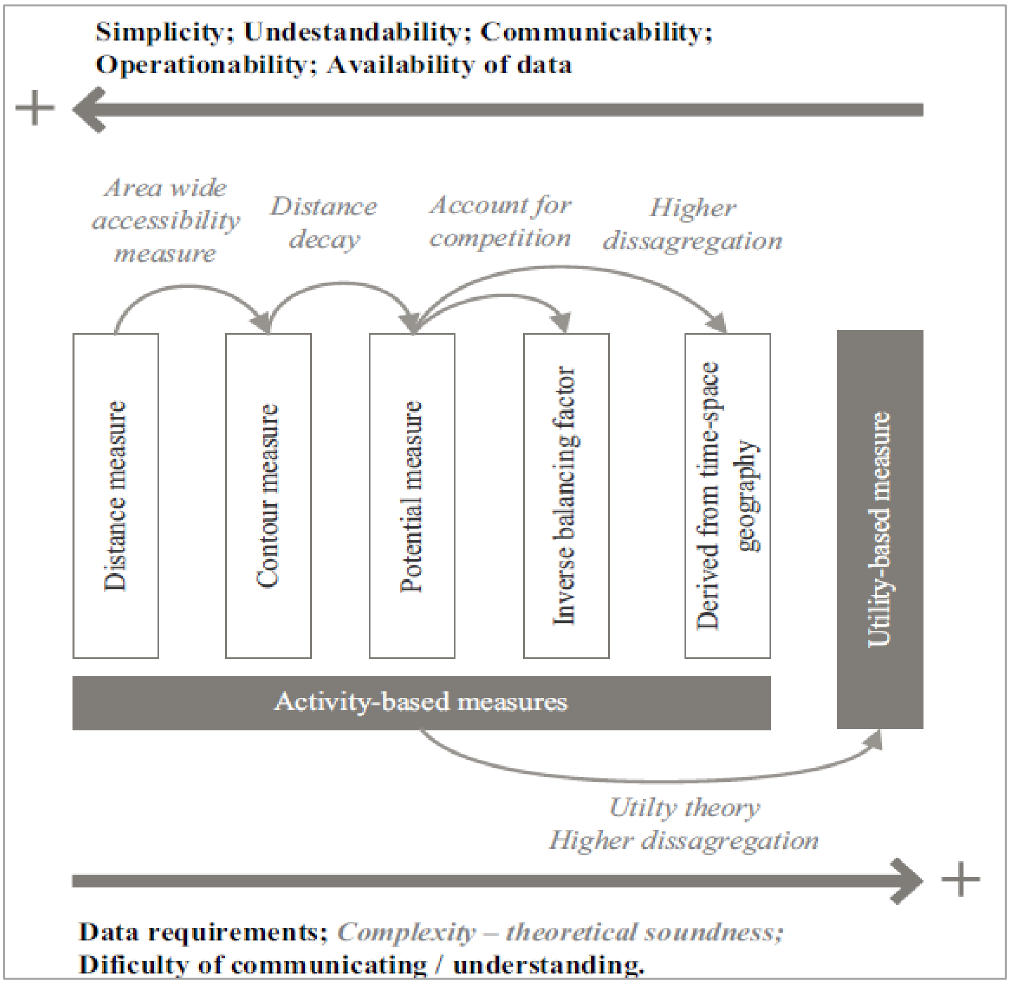
Table 3-2: Accessibility measures and components

	Transport component	Land-use component	Temporal component	Individual component
Infrastructure based measures	Travel time; Travelling speed; Vehicle hours lost in congestion.		Peak-hour period; 24-hr period	Trip-based stratification (e.g. home-work, business trips
Location-based measures	Travel time and/or travel costs between locations of activities	Amount and spatial distribution of the demand for and/or supply of opportunities in space (e.g. number of workers; number of jobs)	Travel time and costs may differ between hours of the day, between days of the week or seasons	Stratification of the population (e.g. by income, educational level)
Person-based measures	Travel time between location of activities	Amount and spatial distribution of supplied opportunities	Temporal constraints for activities and time available for activity participation are accounted for	Accessibility analysed at individual or household level
Utility-based measures	Travel costs between locations of activities, using a distance decay function	Amount and spatial distribution of supplied opportunities	Travel time and costs may differ, between hours of the day, between days of the week or seasons	Utility estimated for population groups or at the individual level

Source: Geurs & Ritsema van Eck (2001)

From Table 3-2 above, it is seen that some attributes of specific component areas are common among most of the measures. For example, travel-time as an attribute of the transport component is typical among all measures of accessibility. Also, most of the accessibility measures (other than the infrastructure-based measures), do consider the land-use opportunity as a critical component in the measures.

Silva (2013) gave a comparison of the various accessibility measures in terms of their level of complexity, data requirements, communicability and ease of understanding. The illustration given by the author is shown in Figure 3-4:



Source: Silva (2013)

Figure 3-4: Comparison of various accessibility measures

From Silva (2013) illustration shown above, utility-based measures are theoretically more complex, require more data, and are more challenging to communicate, compared to the other kinds of measures. The major advantage of the utility measures, however, lies in their ability to capture behaviour and presents analyses of accessibility at a more robust and disaggregated level. Although, as pointed out by Silva (2013), with 'increase in complexity and theoretical soundness, other vital aspects relating to the operationalisation of the measures are often lost' (Silva 2013, p. 18). Therefore, a balance must be achieved between theoretical soundness and ease of applicability for planning and decision making.

The various traditional measures of accessibility have been applied in developing several accessibility instruments (Karou & Hull 2012; Hull et al. 2012; Te Brömmelstroet, Silva and Bertolini, 2014; Te Brömmelstroet *et al.*, 2014). Hull et al. (2012) present a summary of these instruments that have been developed in different countries and the various measures on which these instruments are based. This is presented in Table 3-3 below.

Table 3-3: Accessibility instruments and associated measures

Accessibility Instruments		Accessibility measure traditions								
Acronym	Country	Spatial separation	Contour	Gravity	Network	Time-space	Information	Utility	Competition	Other
SNAPTA	UK	■	■	■				■		
SNAMUTS	AU	■	■	■	■					
TRACE	BE	■	■			■				
IMaFa	ES	■	■		■					
ASAMeD	UK;NL;SE;BRA;CHI;SA;JA	■	■		■					
ATI	SL	■						■		
SOTO	NO	■	■							
SAL	PT	■	■							
MSC	USA	■			■		■			
GDATI	PO	■			■					
PST	SW				■					
PlaSynt	SW				■					
RIN	DE				■					
MRSC	NO			■		■			■	
EMM	DE		■	■						
HIMMELI	FI			■	■					
JAD	NL		■	■						
ABICA	DK			■		■				
GraBAM	IT			■						
UrbCA	PT, ES			■						
INVITO	IT					■				
SoSINeTi	SW					■				
ACCALC	UK /EC/ Global									■

Spatial separation/ contour measures

Network measures

Gravity-based measures

Source: Hull et al. (2012)

Details on each of the instruments in Table 3-3 above are well covered in Hull et al. (2012); Hull, Silva, et al. (2012) and Te Brömmelstroet *et al.* (2014). SNAPTA – Spatial Network Analysis for Public Transport Accessibility, for example, is an accessibility tool that was developed in the UK to analyse accessibility by public transport at the census tract level. It employs measures such as the contour, gravity and utility measures. SNAMUTS[2] – Spatial Network Analysis for Multimodal Urban Transport Systems, is a decision tool developed by researchers in Australia, which incorporates measures such as contour, gravity and network measures.

Apart from the traditional measures of accessibility presented in Table 3-2, other unconventional approaches have also been developed to investigate accessibility. The work of Thériault et al. (2005), for example, looked at the mobility behaviour of households and their perception of accessibility to urban amenities in relation to house price dynamics, as captured through hedonic modelling. Their approach involved developing and comparing what they referred to as the 'objective' and 'subjective' indicators of accessibility, with the former based on observed travel time and the latter based on Fuzzy Logic theory. Their findings suggested that statistically significant differences occur in the way accessibility is structured, depending on the trip purpose and household profiles. The authors also suggest that while the objective measure of accessibility tends to yield satisfactory results, resorting to the subjective accessibility indices derived from fuzzy logic, 'provides greater insight into the understanding of commuting patterns and travel behaviour of people (Thériault et al. 2005, p.22). The fuzzy approach was initially propagated in the field of science and mathematics to understand uncertain phenomena, based on the recognition that the traditional view of science which strives for certainty, specificity and precision, often fail to capture physical processes and systems that are characterised by uncertainties, non-specificity and inconsistencies (Klir, Yuan and Klir, George J., Yuan, 1995).

Páez et al. (2012) described accessibility measurement as comprising two aspects (1) the normative (or prescriptive) aspect and (2) the positive (or descriptive) aspect. The normative or prescriptive aspect of accessibility is seen in terms of the expectations on the part of the policymaker or analyst, while positive or descriptive accessibility aspect is based on actual experiences of travellers (Páez et al. 2012). A normative measure can be defined, for example, in terms of how far people ought to travel or how far it is reasonable for people to travel, while the positive aspect would be in terms of how far people actually travelled. In other words, for the positive aspect of accessibility measurement, travel cost will vary from one individual to another, while for the normative aspect, there is an assumed uniform 'reasonable' cost across all individuals. The setting of travel cost threshold in terms of time or distance can be considered as the normative aspect of accessibility analyses.

[2] http://www.snamuts.com/indicators.html

While various measures of accessibility have been developed over the years, many issues have also been raised concerning these measures. Among these issues, as identified by Handy & Niemeier (1997) is the gap between the measure development and the practical application to planning and decision making. With this in mind, this study aims to develop indicators of accessibility that is both context-sensitive and easily interpretable. Context-sensitive implies that the measures are developed in line with the current level of detail of available data, and also take into account, the socioeconomic reality and unique spatial features of the study area as highlighted in the introductory chapter.

3.5 Mode Dimension – Public Transport Accessibility

There is also a mode dimension to accessibility. It can be measured for both motorised and non-motorised modes of travel. For this research, accessibility by motorised modes, especially by public transport is of key consideration. Public transport (or transit) accessibility (Polzin et al. 2002; Rastogi & Krishna Rao 2003; Lee 2005; Gadzinski & Beim 2010; Tribby & Zandbergen 2012; Stewart 2017; Manout et al. 2018; Liu et al. 2018) reflects the relative convenience of public transport/transit as a mode choice. It can be represented in terms of distance/time to transit stops or travel time on the transit system. Measures of transit accessibility emphasize the availability of transit where people live, where people work, and on routes that connect the two (US Environmental Protection Agency, 2011). Spatial planning of public transport infrastructure and services, therefore, require the identification of suitable locations for a given number of facilities such as transit route, stops or intermodal transfer facilities, in such a way that the transport needs of the population who have no access to car are met sufficiently. Hence, measures of transit accessibility can help in evaluating the performance of the transit system (Foth, Manaugh and El-geneidy, 2013) in relation to the land use, which ultimately serves as means of easily identifying transport-disadvantaged locations.

Several aspects relating to public transport accessibility have been discussed by various researchers. Hillman & Pool (1997), for example, made a distinction between 'network' and 'local' aspects of public transport accessibility. Local accessibility is seen as the accessibility of a given location (say residential) to public transport while network accessibility is described as the accessibility of specific locations to destinations using public transport. In other words, the overall public transport accessibility can be said to comprise two distinct aspects; access to the public transport service point (say bus stop or rail stations) and access to destinations by the public transport service.

Polzin et al. (2002) emphasized the importance of considering the spatial and temporal dimensions of demand and supply when carrying out transit accessibility analysis. Their transit accessibility measurement tool considered two facets of the temporal dimension. The first is the supply side of the time dimension which considered the span and headway of the transit service as well as the willingness to wait to determine the actual time duration that a service is available to potential users. The other involves the demand side of the time dimension which considered the time-of-day variability in travel demand to determine the relative value of transit service at any time period of the day. This approach to measuring transit accessibility will, however, rely on the availability of comprehensive data on the public transport service. A related work by Xu et al. (2015) also emphasised the temporal dimension of transit accessibility with focus on consideration of schedules/ timetables at transit stations. Their findings showed that fluctuations in travel demand and the passenger-carrying capacity of bus stations in different time periods make bus accessibility significantly different throughout the city.

Woldeamanuel & Cyganski (2011) discussed measures of the subjective aspect (satisfaction) of accessibility to public transportation. Their methodology involved the application of a panel-based binomial probit model to describe the level of travellers' satisfaction with the accessibility to public transport service. The work of Karner (2018) focus on equity assessment in public transit service using route-level accessibility measures computed from publicly available General Transit Feed Specification data. Other notable works that have focused on transit accessibility include O'Sullivan et al. (2000); Murray et al. (1998); Murray (2001); Lei & Church (2010); Langford et al. (2012) and Gulhan et al. (2014).

Although several methodologies have been developed over the years in measuring public transport accessibility, one common component in most of these methods involves the computation of travel cost (in either distance or time) from an origin to destinations. O'Sullivan et al. (2000) developed and used the shortest path algorithm that identifies the least cost path in terms of travel time from an origin to destination. Considering that transit trips begins and ends with pedestrian travel, Foda & Osman (2010) estimated transit stop access using the actual pedestrian road network around a stop. They developed indices which measure the accessibility of a bus stop through the surrounding road network in addition to the ratio of actual access coverage to the ideal access coverage of a stop. Another dimension to estimating access is by comparing the distance (normally Euclidean distance) from the centroid of a spatial block to its nearest bus stop. If this distance is within the threshold distance, then it is taken that the stop is within coverage or accessible (Foda & Osman 2010; Murray et al 1998). One of the shortcomings with this approach despite its advantage of been easy to implement is that measured distance is not always accurate, as it does not consider the geography of the route nor account for physical barriers to access.

The approach employed by Hillman & Pool (1997) as well as Tribby & Zandbergen (2012) in measuring transit accessibility involves consideration of various time components such as access time to stops, waiting time, boarding time, transfer time and in-vehicle travel time. This approach relies on the availability of highly detailed data and information regarding the public transport network and service. This study adopts similar approach described by Hillman & Pool (1997), Lei & Church (2010) and Mavoa et al. (2012), which all consider measures of time to access transit stations and time to access destinations using transit.

While most of the existing literature on accessibility have focussed on conventional modes such as public transport, car or walking, emerging research has also begun to investigate the potential implications of unconventional modes such as Autonomous Vehicles (AVs) on accessibility in cities, and to provide some insights on the shape of future AVs-dominated cities. In the study by Meyer et al. (2017), for example, the impact of Autonomous Vehicles on the accessibility of the Swiss municipalities was simulated using the Swiss National Transport Model. Their results showed that autonomous vehicles can cause a 'quantum leap in accessibility' (Meyer et al. 2017, p.80). By examining the spatial distribution of the accessibility impacts, the authors had concluded that Autonomous Vehicles could favour urban sprawl and make public transport redundant especially in the less dense areas. Papa & Ferreira (2018) also explored the likely consequences of Autonomous Vehicles on accessibility by using a scenario-based approach that allows identifying the critical decisions that could emerge from automated travelling. Based on their approach, the authors opined that the impact of Autonomous Vehicles on accessibility could go in two different directions; either 'seriously aggravate' or 'seriously alleviate' accessibility problems (Papa & Ferreira 2018, p.1).

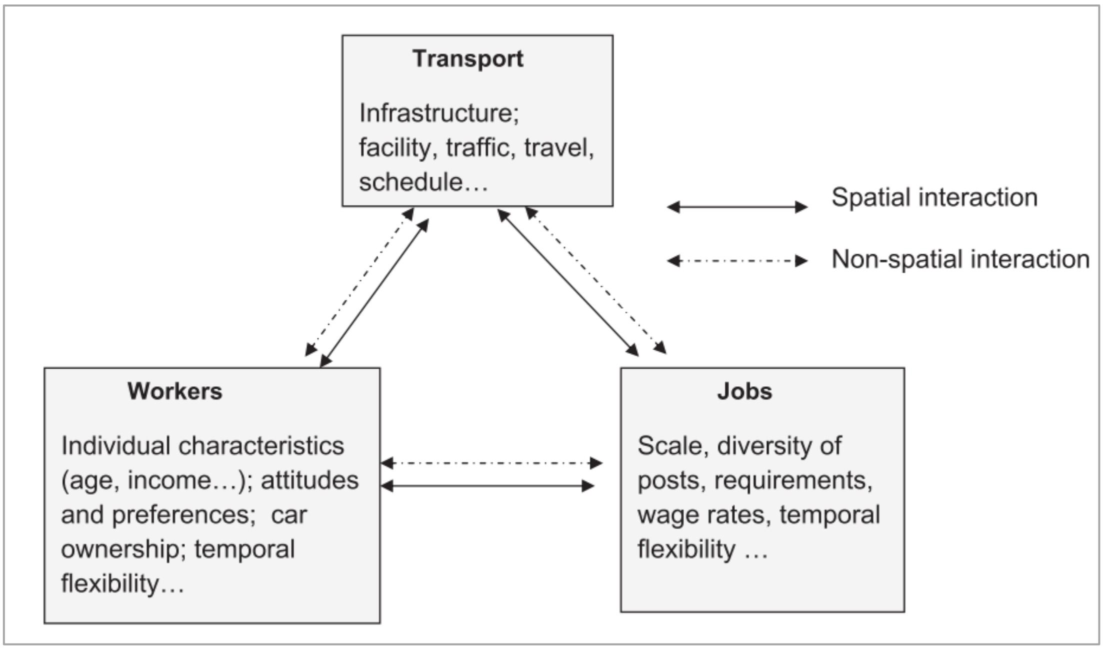
The next section looks at, yet, another dimension of accessibility; the opportunities dimension. It specifically discusses some case studies that have focussed on the kinds of opportunities considered in this research, which include; jobs, healthcare and education. Of note are the frameworks and methods employed in measuring accessibility to these opportunities.

3.6 Opportunities/Activities Dimension of Accessibility

Accessibility can be measured for numerous kinds of opportunities or activities, for example, jobs, shopping, leisure parks, healthcare, education, among. The kind of opportunity considered also guides the type of measure to be employed. For example, as pointed out in Jones (1981), the Hansen's potential measure, which considers all relevant opportunities in an area may be suitable for opportunities such as jobs, but less satisfactory for other kinds of activities such as hospital or post office, where the one of interest is usually the nearest; or for shops where the relevant ones are usually the nearest few ones (Jones 1981). The next sub-sections discuss some literature on accessibility for the case of jobs, healthcare and education.

3.6.1 Job Accessibility

One of the most important functions of a transport system is to connect workers to jobs (Grengs 2010). In the conceptual framework for job accessibility measurement described by Cheng & Bertolini (2013), as shown in Figure 3-5 below, job accessibility is considered to comprise three sub-systems; transport, workers (or places of residence) and the jobs (or places of work).



Source: Cheng & Bertolini (2013)

Figure 3-5: Conceptual framework for job accessibility

Each of the sub-system represented in Figure 3-5, comprises various elements which Cheng & Bertolini (2013) categorised as spatial and non-spatial. For the transport sub-system, the spatial elements include the distribution of the infrastructure, such as roads and other public transport facilities that enable connectivity of workers and jobs. The non-spatial elements of the transport system include aspects such as service frequencies, operational policies, pricing and traffic management, which also contribute to the mobility provision. Both the spatial and non-spatial elements of the transport system determine the spatial location of workers and jobs, and the concentration of workers and jobs across space further determines the intensity of transport service and mobility. The non-spatial elements of workers include various person attributes, such as age, income, qualification, personal preferences. These individuals' attributes also influence the kinds of jobs sought by the individuals. The non-spatial elements of the jobs, such as the scale of employer and the diversity of positions, further impact the demand of workers and the transport services to places of work (Cheng & Bertolini 2013). Thus, a feedback of interaction is created among the three subsystems, defining a framework for job accessibility analyses. Most of the studies on job accessibility utilise a methodology that aligns with the framework described in Figure 3-5 above.

Grengs (2010) investigated the issue of spatial mismatch using a gravity-based model of job accessibility to test differences in access to jobs among places and people in the Detroit metropolitan region of the United States, for travel by automobile and public transit. In their findings, the transit system offered poor accessibility to jobs for those residing in the inner-city neighbourhood. Interestingly, additional investment in transit was not seen as a viable option that could alleviate the problem of joblessness and poverty. The authors also suggest that subsiding the automobile for the poor might be one of the options that could improve the accessibility to jobs, considering that public transport was already enjoying so much subsidy but not necessarily providing good access to jobs. The car's advantage in job accessibility was considered extreme in comparison with public transit, which made the authors suggest that the real issue was not a 'spatial mismatch' but rather, a 'modal mismatch'. The suggestion of subsidizing car ownership for the poor as a viable option to further investment on public transport has however ignored economic efficiency, wider environmental implications and the sustainability of such proposition.

The effect of spatial competition has also been recognised by some authors (Eck & Jong 1999; Cheng & Bertolini 2013b; van Wee et al. 2001) in constructing measures of job accessibility. The basis of such inclusion stems from the notion that competition is bound to occur when dealing with any situation that involves allocation or utilisation of resources especially when such resources are limited in nature. Such competition could be either from the demand side of the resource or from the supply side.

According to Cheng & Bertolini (2013), when dealing with job access, where supply side of the jobs are the employers and demand side are the workers, competition could exist either between the employers or among the workers, depending on which side of the resource is scarce and where. As pointed out by van Wee et al. (2001), if there are many competitors for jobs within a given area, the chances of getting the desired job are lower than in a situation where there are few or no competitors. The authors proposed a potential accessibility measure that is corrected for competition in the job market and applied the measure to a case study of Netherland. The issue of competition is, however, much less important for certain activities such as shopping or leisure, where consumption does not necessarily result in a diminishing of potential or a reduction in available resource (Jones, 1981).

3.6.2 Healthcare Accessibility

When healthcare facilities are distributed across space, it creates an opportunity for healthcare services to be accessed by the population (Mokgalaka, 2015). Healthcare accessibility analysis, therefore, helps in interpreting the performance of healthcare systems in a region (Kanuganti et al. 2016).

Khan (1992) classified healthcare accessibility along two dimensions (1) potential versus revealed, and (2) spatial versus aspatial. While potential access has to do with what is being offered to potential users, revealed access involves the actual utilisation of the services. As noted by Khan (1992), revealed or realised access is only achieved when the barriers to entry are overcome. On the spatial versus aspatial dimension, spatial access is that which is conditioned by space and geographic barriers, while aspatial access is conditioned by non-geographic barriers. From these two dimensions, are four categories of access, which include; potential spatial access, potential aspatial access, revealed spatial access, and revealed aspatial access. According to the definition given by Khan (1992), the potential spatial access of an area's population to any given service refers to the availability of such service as moderated by space, or the distance of separation (Khan, 1992). This study focuses on potential spatial access.

Spatial access to healthcare have been measured using various approaches. Kanuganti et al. (2016) utilised the Two-Step Floating Catchment Area method (Luo and Wang, 2003) to quantify spatial accessibility of healthcare in the Alwar district of Rajasthan, India. The work of Rosero-bixby (2004) employed the closest facility measure and proposed an accessibility index that aggregates all health facilities weighted by their size, proximity, as well as the characteristics of the population and the facilities. Perry & Gesler (2000) utilised GIS technology to measure physical access to primary healthcare in the remote area of Andrean, Bolivia and proposed an 'alternative model of health personnel distribution that maximises physical accessibility' (Perry & Gesler 2000, p.117).

3.6.3 Education Accessibility

In the 2010 Commonwealth Education Partnership report of the Department of Basic Education South Africa, physical accessibility of schools is recognised as one of the core dimensions of access to education. It has also been recognised in the National Learners Transport Policy 2015 (Department of Transport, 2015) that most learners in South Africa have difficulty in accessing schools in both urban and rural settings.

Studies on accessibility to schools investigate the level of connectedness or association between geographical locations of schools and the residential location. The study by Talen (2001) on school accessibility employed datasets of distances between students and eighty-four elementary schools in three counties of West Virginia in the United States. In their study, the authors investigated the issue of equity in accessibility by examining 'whether or not the distribution of travel cost between residential locations and schools is equitable, on the basis of the density of residential population and the socioeconomic status of residents' (Talen 2001, p. 465). They found that spatial inequities in access to schools exist substantially and varies by county and school zone. However, relating access level to the socioeconomic status of the population showed no defined pattern of inequality.

School accessibility has also been recognised as one of the drivers of housing property prices. Using the case of Singapore, Chin & Foong (2006) investigated the relationship between accessibility to prestigious schools and the value of housing properties using a hedonic housing price model. Their findings revealed a positive relationship between accessibility and residential housing prices.

3.7 Accessibility research in South Africa

The survey of literature has revealed that only a handful of studies on accessibility with focus on South Africa have been carried out within the last decade. One of the few studies is Venter et al. (2002), who investigated access and mobility needs of people in some developing countries, including South Africa, with a view to finding the critical policy issues and opportunities for improving accessibility. Venter & Cross (2014) also developed a GIS-based accessibility measurement technique known as the "Access Envelope", to assess the impact of transport and spatial development strategies on location-specific affordability of job access for poor households in the city of Tshwane, South Africa. The approach was developed to reflect accessibility reality in South Africa, which goes beyond just physical accessibility but also incorporating public transport service and transport costs as a core component of accessibility. Their calculated access value regarded as the "Net Wage After Commute (NWAC)", reflects the potential wage earnable at specific job locations less the actual monetary cost to travel from home to those locations. Their study also showed how the Bus Rapid Transit (BRT) system only selectively enhances accessibility to jobs in certain parts of the city. The NWAC approach was also applied by Lionjanga & Venter (2017) who explore accessibility patterns over time for poor households in the city of Johannesburg, South Africa. The authors' analyses showed a yearly increase in accessibility levels as a result of increase in the potential wage earnable for the analysis period 2009-2013.

Venter and Mohammed (2013) considered indicators of job accessibility in an investigation of energy use in daily travel in the Nelson Mandela Bay region of South Africa. The study by Ziemke et al. (2017) applied two accessibility computation approaches; a household-based accessibility indicator, and an econometric accessibility indicator in a study of the Nelson Mandela Bay area of South Africa. The authors showed that both approaches provide similar insight with regards to identifying locations with low accessibility. Nevertheless, the econometric indicator was considered to have the advantage of being able to utilise only open source data as compared to the more data-intensive household-based metric.

Although studies on accessibility with focus on South Africa are still relatively few, there is a growing interest on this subject as a planning goal, both at the national and municipal levels. One of the objectives of this research, therefore, is to contribute to the body of knowledge on accessibility and equity in South Africa, by developing indicators of accessibility based on existing spatial interaction theory, but reflective of the Cape Town context or similar low-income cities.

3.8 Summary and Conclusion

There is a vast body of research on the topic of accessibility. This review chapter has focussed specifically on some of the approaches with which accessibility have been defined and measured over the years, and some of the critical issues that have been raised by various authors as regard the various measures, particularly the gravity-based measures.

While the underlying principle behind spatial interaction and the accessibility concept have remained the same, various dimensions and numerous measures have been developed over the years. A look at most of the measures earlier discussed reveals that accessibility is indeed a multidimensional concept. As Scheurer & Curtis (2007) had stated, there is not a one-size-fits-all indicator/metric for accessibility. This reinforces the initial proposition of Gould (1969) that accessibility is indeed a 'slippery notion'. Despite the multidimensionality, there is some consensus among researchers that accessibility is a measure of both the effectiveness and efficiency of an integrated land use-transport system. The approaches to accessibility from previous studies also tend to be guided by factors such as the context of investigation and the available data.

Among the measures discussed, the gravity measure is considered suitable for this research. These measures, despite their wide application, have also been criticised. One of the criticisms of the gravity measure raised in Dong et al. (2006) is that it neglects the variations across individuals in any particular location. The illustration given by the author is that of a retired grandfather and his college student grandson, who will be attributed equal level of accessibility by a gravity model if they happen to live in the same location. While this point might be considered valid to some extent, it also depends on the interpretation given to the accessibility values computed by the gravity measure. Gravity measures are ideally location-based and not necessarily behavioural. Therefore, the interpretation of the accessibility values must be about its spatial dimension.

The argument that the gravity measure fails to account for the variations in person characteristics in space does not necessarily diminish the strength of the measures when interpreted from a spatial perspective of land-use location with respect to the transport systems connecting them. The consideration of person attributes is merely another layer of analysis which can be incorporated within the gravity framework. For instance, in Dong et al. (2006) illustration of grandfather and grandson living in the same location and attributed with identical levels of accessibility, the consideration of their individual characteristics can be incorporated in the gravity model through the impedance weighting of opportunities available to each individual. In which case, the impedance function will be calibrated at the level of the individual to capture the variability in persons' perception of 'nearness' or 'farness' of opportunities'. The question then would be the feasibility of carrying out accessibility analysis with individual impedance representation at the person level, without having to do some spatial aggregation. Also, there is the need to consider the overall value of such individual-level analyses for actual decision making, considering that the ultimate goal of accessibility indicators is to inform planning and decision-making about land use and transport, which in most cases are carried out at a macro level. say, at the zonal or regional level.

Another vital point concerning gravity measure is the relative ease of computation and intuitiveness, even from a ‘common sense’ perspective, which have made the measure one of the standard operational techniques in most metropolitan area transportation studies (Jones, 1981). The gravity models are also calibrated based on observed travel data and can be made sensitive to small differences in the volumes of flows between origin and destination. They have also been found to be satisfactory especially in the context of aggregated mass movement at the intra-metropolitan level (Lowe and Moryadas, 1975). These combinations of factors have influenced the utilisation of the gravity-based approach for the indicators developed in this study.

In conclusion, based on the review of various measures, and given the study context and problems, the accessibility measures considered for this study, as will be discussed in the methodology (Chapter 5), are the location-based measures that incorporates a person component. The person component is reflected through the stratification of the population by income level. In other words, the accessibility computed for any given space (zone) is attributed to a person/household of a particular income group, living or travelling from that space. There is also a land use component, reflected through the various opportunities for which accessibility is computed (jobs, healthcare and schools). Opportunities such as jobs are also stratified by income level. In other words, a distinction is made between low-income jobs or high-income jobs. The stratification of opportunities is considered relevant for a case like Cape Town, where there is high level of inequality. The measure also considers observed travel patterns in terms of flows and travel time, which takes care of the transport component. The monetary cost of travel, as well as the affordability of fares are also considered in the measure. These components (monetary cost and affordability) were found to be lacking in most of the measures reviewed.

Chapter 4
Case Study Background

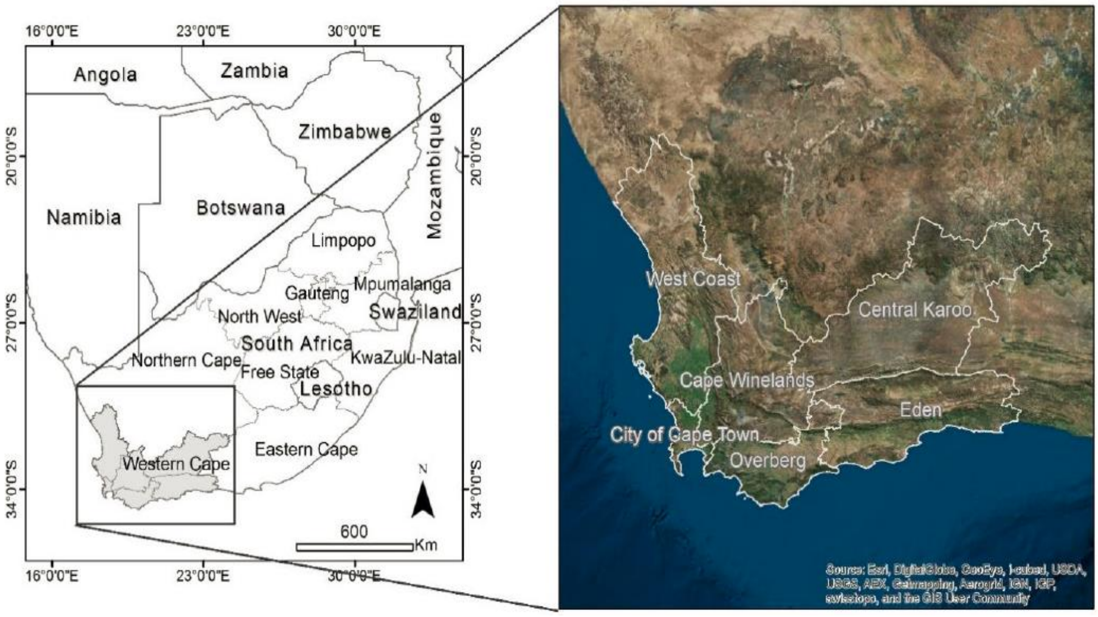
"Do not lead with a history lesson. Save it for the background."- Ann Wylie, writing coach

4.1 Introduction

The case study for this research is the city of Cape Town, South Africa. This chapter presents an overview of the socio-demographic profile of the city, its land-use, and transport system characteristics. A demographic analysis of a city or municipality allows observing, not only the simple changes in population growth but also the various developments that can influence the social life of its inhabitants. The major demographic elements presented in this chapter comprise of the estimates of population size, growth trend, and the distribution of the population by income level across zones. In line with the accessibility investigation, the land-use overview focuses on the amount, quality and spatial distribution of opportunities considered in this research, which include jobs, healthcare, and education. On the transport side, the focus is on the public transport system and its operational characteristics. A summary discussion of the household travel survey and travel expenditure by income group is presented. Also discussed are some of the existing planning policies and strategic frameworks about land use and transport planning, both at the national and municipal levels.

4.2 Demographics

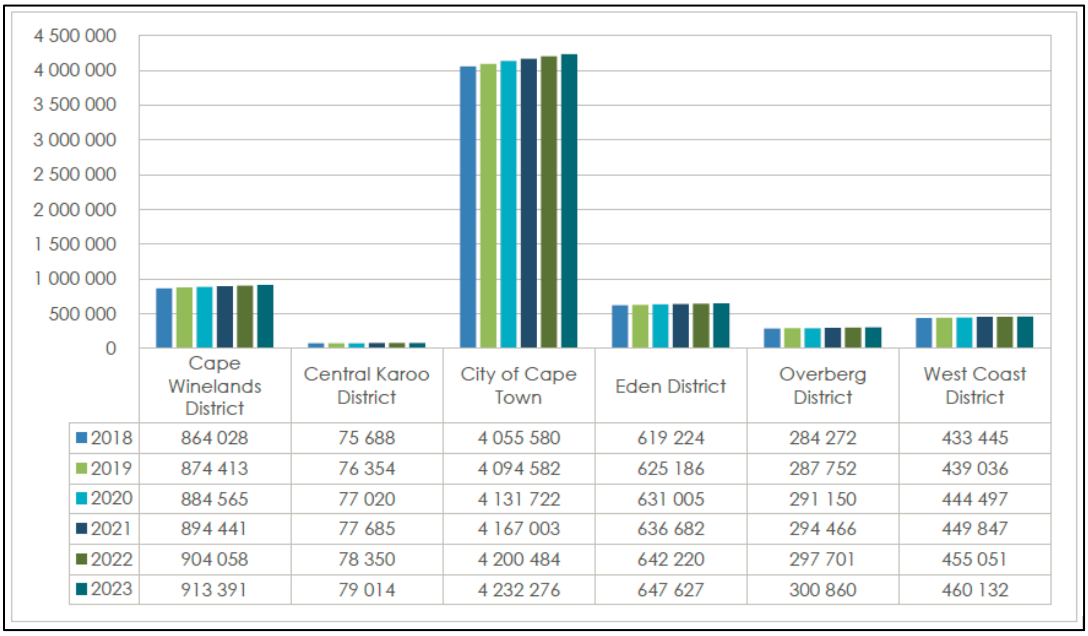
The city of Cape Town is a metropolitan municipality in the Western Cape province of South Africa, and one of the rapidly urbanising cities in Africa. The geographical location of the Western Cape Province and each of its districts within South Africa and the broader Southern Africa Development Community (SADC), is shown in Figure 4-1.



Source: Tizora et al. (2016)

Figure 4-1: Geographical location of the Western Cape Province and its five districts

Cape Town generates approximately 76% of the Western Cape Province's Gross Regional Product and 11% of the country's GDP (City of Cape Town, 2009). Within the past decade, the population of Cape Town has grown by almost 30%, from about 2.8 million in 2001 to 3.7 million in 2011, according to the 2011 census report. Current population level (for the year 2018) is estimated to be above 4 million inhabitants. The number of households has also risen significantly by about 37% from 0.78million to about 1.07 million within the same period (City of Cape Town, 2012). The population projection for the six districts that make up the Western Cape Province, of which Cape Town is the largest according to the Provincial government report of 2017, is shown in Figure 4-2.



	Cape Winelands District	Central Karoo District	City of Cape Town	Eden District	Overberg District	West Coast District
2018	864 028	75 688	4 055 580	619 224	284 272	433 445
2019	874 413	76 354	4 094 582	625 186	287 752	439 036
2020	884 565	77 020	4 131 722	631 005	291 150	444 497
2021	894 441	77 685	4 167 003	636 682	294 466	449 847
2022	904 058	78 350	4 200 484	642 220	297 701	455 051
2023	913 391	79 014	4 232 276	647 627	300 860	460 132

Source: Western Cape government (2017)

Figure 4-2: Projected population of districts in the Western Cape Province

Figure 4-2 shows the population projections from the year 2018 to 2023. The figure shows that the population of Cape Town is expected to follow on a steady growth trend within this period, with growth likely to continue into the near future. Such growth ultimately implies more significant strain on public infrastructure, social systems and delivery of essential services. In view of this, planning measures to manage growth and promote sustainable development have been top on the urban policy agenda. The 2012 Cape Town Spatial Development Framework (CTSDF) is one of such long-term initiatives that have been put in place to manage the future growth structure in the city.

4.3 Income Profile

Cape Town is predominantly a low-income to lower-middle income society, with most of its population falling within these two income categories. Table 4-1 shows the population and jobs distribution according to income level across the city.

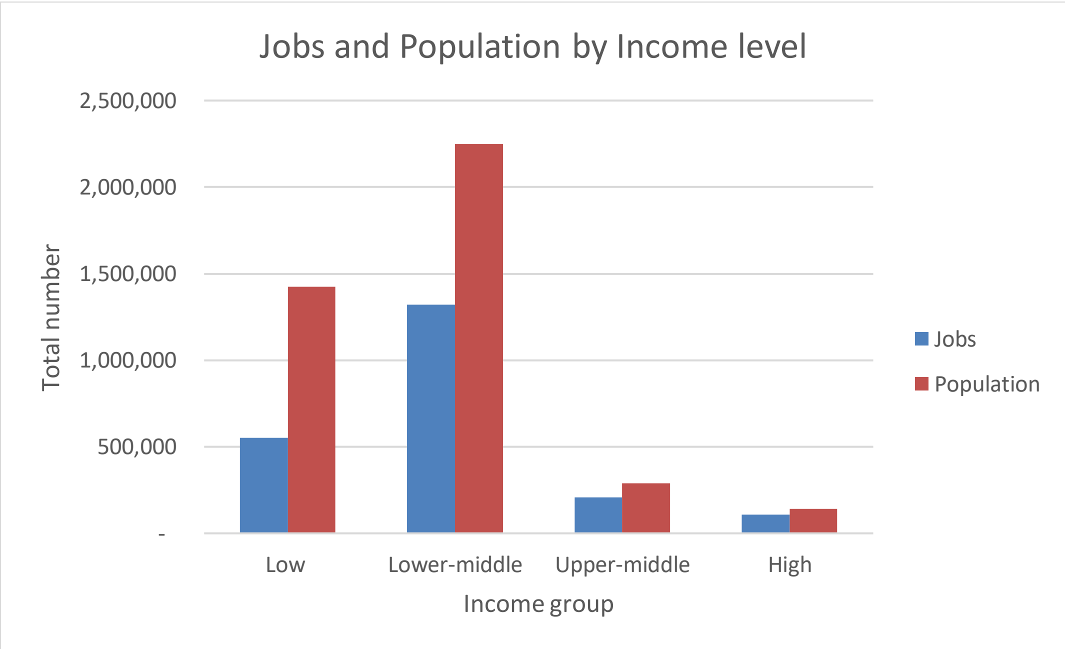
Table 4-1: Population and jobs by income group (2013 data)

Income group	Monthly Income range (ZAR)	Population ('000)	Population proportion (%)	Number of Jobs ('000)	Jobs proportion (%)
Low	0 – 3,200	1 424	34	550	25
Lower-middle	3,201 – 25,600	2 249	55	1 320	60
Higher-middle	25,601 – 51,200	290	7	207	9
High	51,201 or more	143	4	107	5
Total		4 104	100	2 186	100

Data source: City of Cape Town 2013

Table 4-1 shows that about 90% of the entire population of Cape Town is within the low and lower-middle income categories. Similarly, the number of jobs in these income categories make up about 85% of the total available jobs. The figures above are according to the data from the City of Cape Town (planning authority) as utilised in its EMME transport model of 2013.

A graphical representation of the population and jobs according to income group is further shown in Figure 4-3 below.

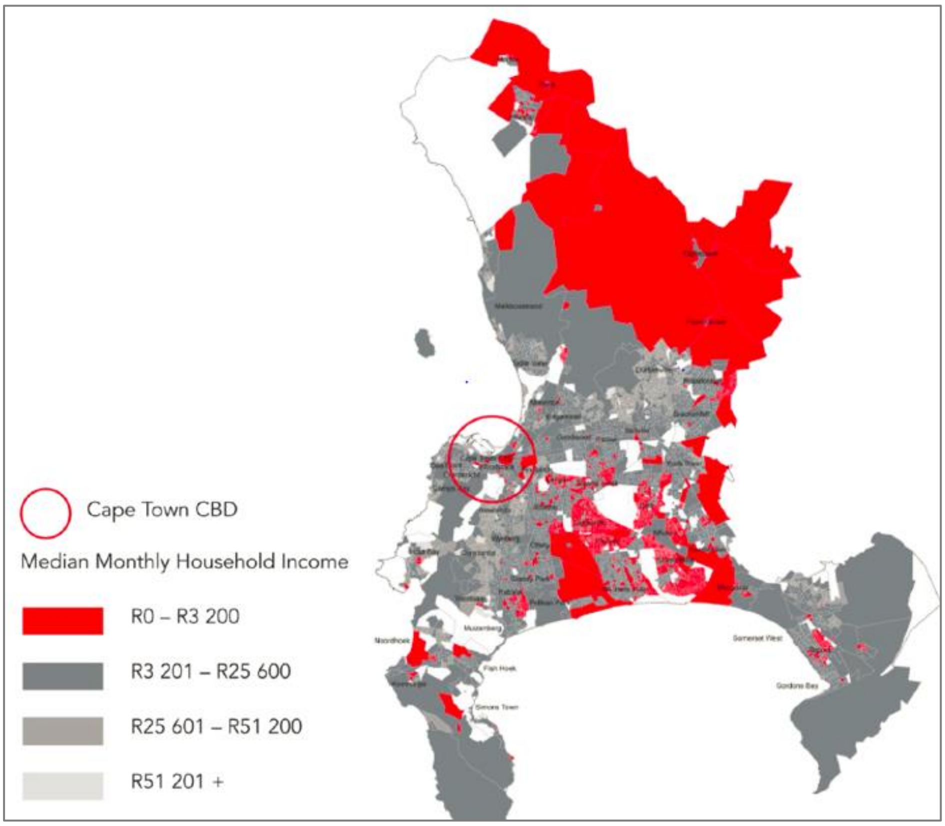


Source: Author's impression of the 2013 Data of the City of Cape Town

Figure 4-3: Comparison of jobs and population by income level

The Figure shows the difference in proportions of population and job numbers within the various income categories. It further shows that the margin between the number of persons and number of available jobs, is higher for the lower income categories, compared to the higher income categories.

The spatial concentration of the various income groups across the city, based on the 2011 census data, is further shown in Figure 4-4 below.



Source: Whitehead (2015)

Figure 4-4: Spatial concentration of the population by household income level

The Figure shows that most of the low and lower-middle income population are located in the outskirts of the city, relatively far from the Central Business District (CBD). These are distances of over 25 kilometres from the CBD (Whitehead, 2015), which ultimately has a significant implication on transport costs for low-income households.

4.4 Public Transport Systems and Regulation in Cape Town

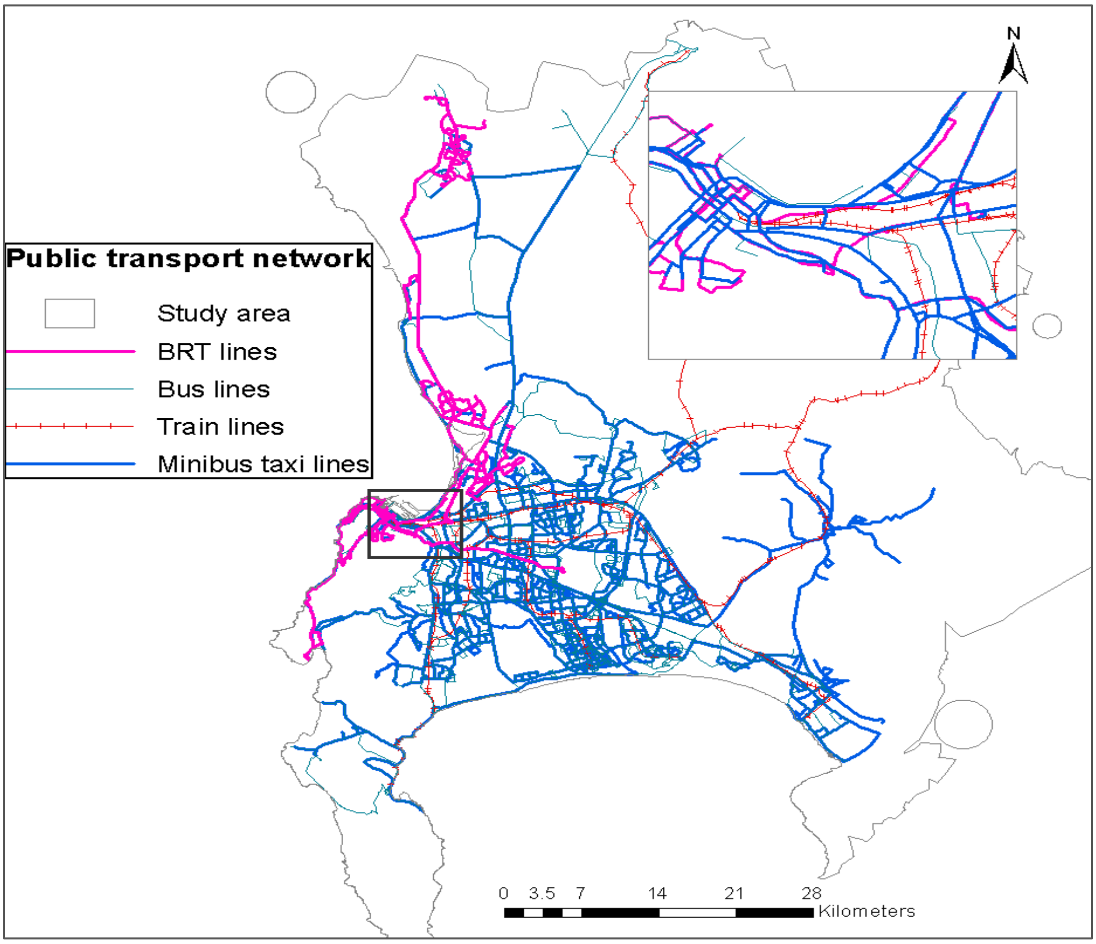
Public transport in Cape Town is regulated by the Transport and Urban Development Authority of Cape Town (TDA), formerly known as Transport for Cape Town (TCT). Through its constitution by-law, TDA[3] is responsible for planning, contracting, regulating, monitoring, evaluating, and maintaining the city's transport infrastructure, systems, operations, facilities and network (Transport and Urban Development Authority, 2017). TDA is also mandated to regulate the safety and other performance-

[3] https://www.tda.gov.za/en/transport/

oriented service delivery aspects of public transport in Cape Town. The various characteristics of the public transport system of Cape Town are described in the next section.

4.4.1 Modes and Features

The public transport system of Cape Town comprises the rail service, scheduled bus service, paratransit (minibus taxi), as well as the metered and unmetered taxi services. The scheduled bus service comprises (1) the Bus Rapid Transit (BRT), also known as the Integrated Rapid Transit (IRT) or the MyCiTi bus, and (2) regular bus, also known as the Golden Arrow Bus (GAB) and Sibanye Bus, which is operated by the Golden Arrow Bus services (GABS) and Sibanye respectively. The paratransit or minibus taxi service is an unscheduled service operated by private individuals and cooperatives. Shown in Figure 4-5 below is the map of the public transport network.



Source: Author's elaboration of the 2013 data of the city of Cape Town

Figure 4-5: Public transport network of Cape Town

The study area covers the entire Cape Town and surrounding Winelands area while the zoomed-in area is the city's Central Business District (CBD). The operational features of each mode are further discussed below.

Bus Rapid Transit (BRT)

The bus rapid transit (BRT) system of Cape Town, also popularly known as the 'MyCiti', is the most recently introduced mode among all the public transport modes in Cape Town. It is a trunk-and-feeder service operating on a regular time-table throughout the day. This mode is the result from a scoping study carried out in February 2007 by the City of Cape Town regarding the development of an Integrated Public Transport Network (IPTN) to complement the already existing rail system (Strydom 2010). The concept of this system was modelled on highly successful BRT projects in some cities across the world, including Beijing, Bogota, Curitiba, Ottawa, Paris, Los Angeles and Seoul (City of Cape Town, 2010a).

From the network map shown in Figure 4-5 above, it could be seen that the BRT only covers a limited part of the city. Most of the low-income zones (see Figure 4-4) are not covered by this mode. Figure 4-6 below shows a typical BRT vehicle in operation around the CBD of Cape Town.

Source: https://myciti.org.za/en/about/about-us/about-myciti/

Figure 4-6: BRT (MyCiTi) bus of Cape Town

The BRT system delivers relatively fast and comfortable mobility along the corridors which it operates. A key feature of this mode that differentiates it from other road-based public transport modes is the segregated right-of-way infrastructure for some of the major corridors. Additionally, the mode is considered to deliver comfort and high-frequency operations, especially during peak periods.

Regular Bus Service (GABS and Sibanye)

The Golden Arrow Bus service (GABS) and Sibanye are both contracted bus services run by private operators through a partnership agreement with the Provincial Government of the Western Cape(City of Cape Town, 2013e). GABS provides a direct metro-wide origin-destination type service, focusing on high demand routes for limited periods of the day (City of Cape Town, 2013e). GABS is considered as one of a few privately-owned companies that have provided scheduled public transport services in a South African urban environment (GABS, 2017). The operations are highly subsidized based on contractual agreement with the Provincial government of the Western Cape (City of Cape Town, 2013e). A typical Golden Arrow Bus is shown in Figure 4-7 below.

Source: https://www.vacorps.com/knowledge-base/golden-arrow-bus/

Figure 4-7: Golden Arrow Bus

The Golden Arrow Bus service is also considered as one of the most affordable mode among all the public transport modes in Cape Town. As a result, it enjoys a high level of patronage by the lower income population, especially for long-distance intra-urban commute. The bus network (see Figure 4-5) is relatively dense and has an extensive coverage of most parts of the city.

Paratransit (Minibus Taxi)

The paratransit or minibus taxi service is the informal transportation service that operates in Sub-Saharan African cities (Behrens, McCormick and Mfinanga, 2015). In Cape Town, paratransit is run by private operators who are mostly individuals or cooperatives. The services are less regulated and operates with semi-fixed routes, but without fixed schedules. Route licences are however required for operations and these are usually acquired from the city authority (Behrens *et al.*, 2015). The minibuses also commonly referred to as ‘taxis’ in local parlance, usually have fixed terminals (also known as taxi ranks) at the origin and destination end of each route. Figure 4-8 below shows an image of the main taxi terminal at the central business district (CBD) in Cape Town.

Source: EWN[4]

Figure 4-8: Minibus taxi terminal at the CBD.

For the minibuses, stop locations are usually on-demand along the routes, and mostly at road junctions. Another key feature of this mode is that passengers can board at any point along the route. In modelling the network of this mode, as will be discussed in Chapter 7, stop locations are assumed to be at road junctions along each route. This is considered to closely represent the existing operational pattern of this mode. In terms of network density (see Figure 4-5), the minibus taxi network is relatively denser than that of other modes such as the BRT and the bus. Although the network coverage follows a similar pattern to that of the bus.

A summary of the key operational features of the BRT, bus and minibus taxi services, according to a 2013 report of the City of Cape Town (City of Cape Town 2013d), is shown in Table 4-2 below.

[4] https://ewn.co.za/2018/06/03/cape-taxi-bosses-threaten-to-halt-operations

Table 4-2: Summary of operational features of the BRT, bus and paratransit

Features	Quantity		
	BRT	**Bus**	**Paratransit**
Fleet size	81	1 056	7600
Peak (buses)	60	971	7600
Departures per day	1,015	5198	30,800
Departures per week	6,805	29,337	175,000
Passengers carried per day	10,754	220,028	323,300
Passengers carried per year	3,144,361	39,635,309	90,000,000
Kilometres travelled per year	595,408	56,000,000	Unknown
Number of routes operated	7	2269	565
Average trip length (km)	16.7	30.7	Unknown
Staff employed	250 drivers 500 total	1355 drivers 2645 total staff	7,600+ drivers 5,000+ assistants

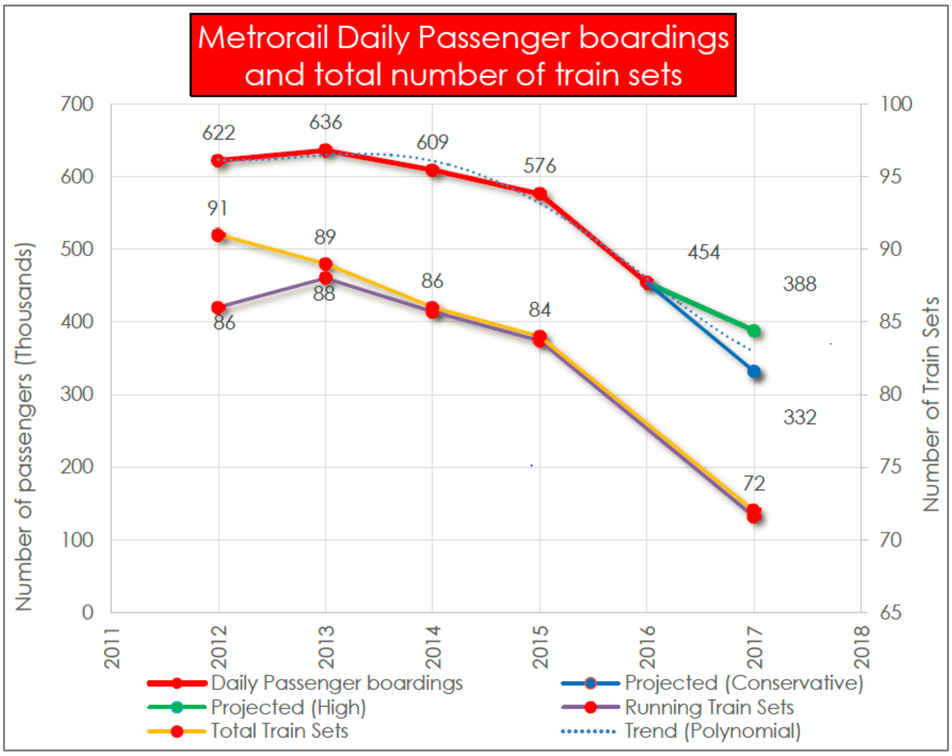
Data source: City of Cape Town (2013d)

From Table 4-2, it is seen that the paratransit services provide the highest capacity in terms of the number of passengers served per year, compared to the regular bus or the BRT. The average trip length in the Table refers to the average distance travelled per trip by each mode and not the average trip distance per passenger. There are, however, no information on the average trip length and the total kilometres travelled per year for the paratransit services.

Rail

The entire rail network in Cape Town consists of about 1,014 km of rail lines, comprising both passenger and freight rail lines (City of Cape Town 2017). The passenger rail network is owned and operated by Metrorail for the Passenger Rail Agency of South Africa (PRASA). The rail network as shown in Figure 4-5 comprises about five corridors all running from the CBD across the southern, northern and central parts of the city. In terms of operational capacity, according to PRASA, the city has 72 train sets in operation, with each train set having about 12 coaches (City of Cape Town, 2017). The reported average fleet coach capacity (crush capacity) is 401 passengers/coach. Trips per peak/train-set, based on the current (2017) infrastructure is reported to be about 2.5, while the total passenger rail capacity per hour is reported to be about 1.058 million passengers (City of Cape Town, 2017).

Shown in Figure 4-9 below, is the reported daily passenger boardings from 2012 till 2017 based on ticket sales and census within the period.



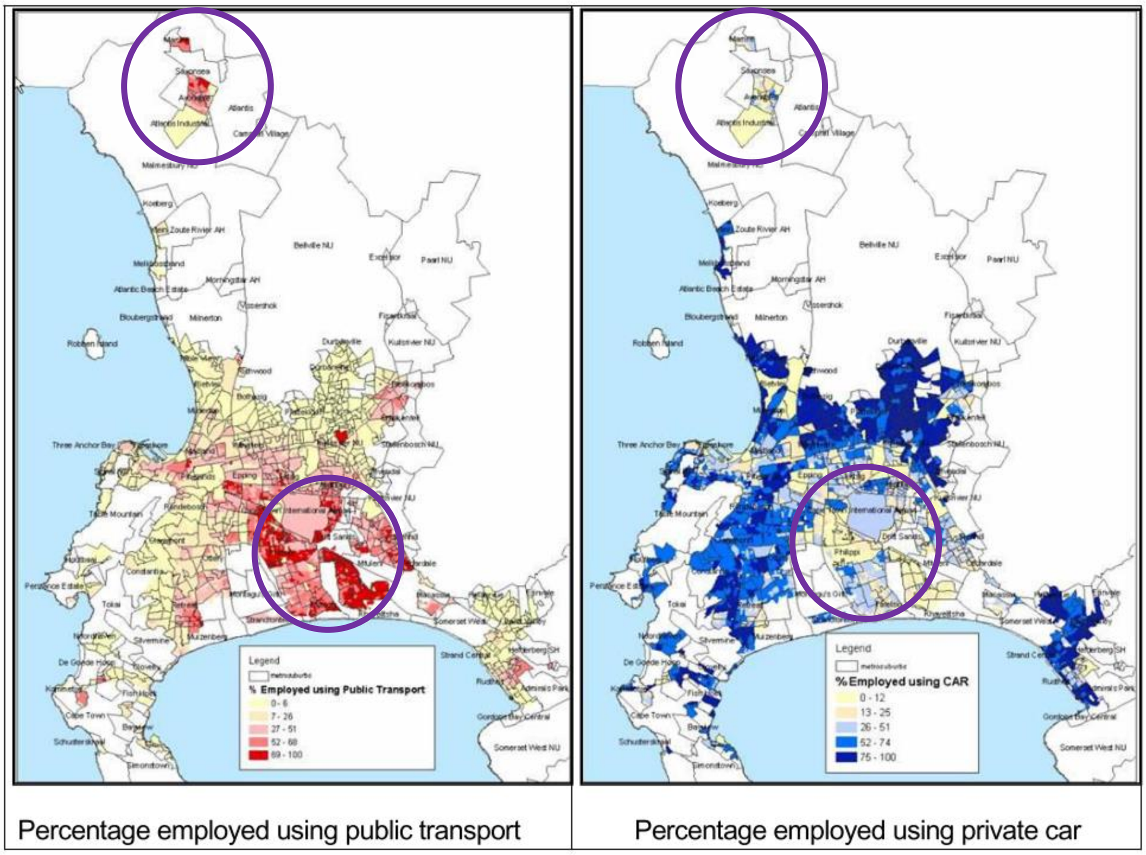
Source: City of Cape Town (2017)

Figure 4-9: Metrorail daily passenger boardings and available train sets

From Figure 4-9, the number of daily passengers boarding the Metrorail declined by 43% between 2013 and 2017, from about 636,000 passengers to about 360,000 passengers. The decline in the number of passengers is seen to correspond to a decline in the amount of running train sets (City of Cape Town, 2017) following alleged sabotage of the infrastructure within this period.

4.4.2 Public transport patronage in Cape Town

In Cape Town, public transport is mainly patronised by the low-income and lower-middle income population. A spatial visualisation of the percentage of the employed population in Cape Town using public transport in comparison to the car at the suburb level is shown in Figure 4-10.



Source: City of Cape Town (2013d)

Figure 4-10: Comparison of proportion of the employed population using public transport versus that using private car

The Figure shows that the highest percentage of employed persons patronising public transport reside predominately in the low-income zones in the city. These are the areas highlighted by the circles on the maps. These areas are also relatively farther from the CBD compared to the higher-income zones (see Figure 4-4), a result, mainly from the apartheid spatial planning enforced under the Group Areas Act of 1950 (Parliament of the Republic of South, 1950).

4.4.3 Access time of public transport

Based on the 2013 National Household Travel Survey, the average walking time to access public transport in the Western Cape region is between 10 – 30 minutes. A summary statistic from the household survey data is presented in Table 4-3.

:

Table 4-3: Summary statistics of public transport access times in Western Cape

		Time to nearest minibus taxi station	Time to nearest bus station	Time to nearest BRT/IRT station	Time to nearest train station
N (valid observations)		3232	1898	114	2098
Mean (minutes)		11.51	12.40	23.03	29.26
Median (minutes)		10.00	10.00	15.00	20.00
Std. Deviation (minutes)		12.70	12.89	21.93	21.56
Percentiles	25	5.00	5.00	5.00	15.00
	50	10.00	10.00	15.00	20.00
	75	15.00	15.00	30.00	35.00

Data Source: 2013 National Household Travel Survey, Author's elaboration

Table 4-3 above shows that the average walking time to access public transport is highest for the train compared to the other modes. The relatively high values of standard deviation, however, suggests that the records of travel time are spread out from the indicated mean values. Average travel time by these modes according to the Cape Town Household Travel survey data is further discussed in Chapter 6, which focusses on impedance function estimation.

4.5 The Cape Town Household Travel Survey 2013

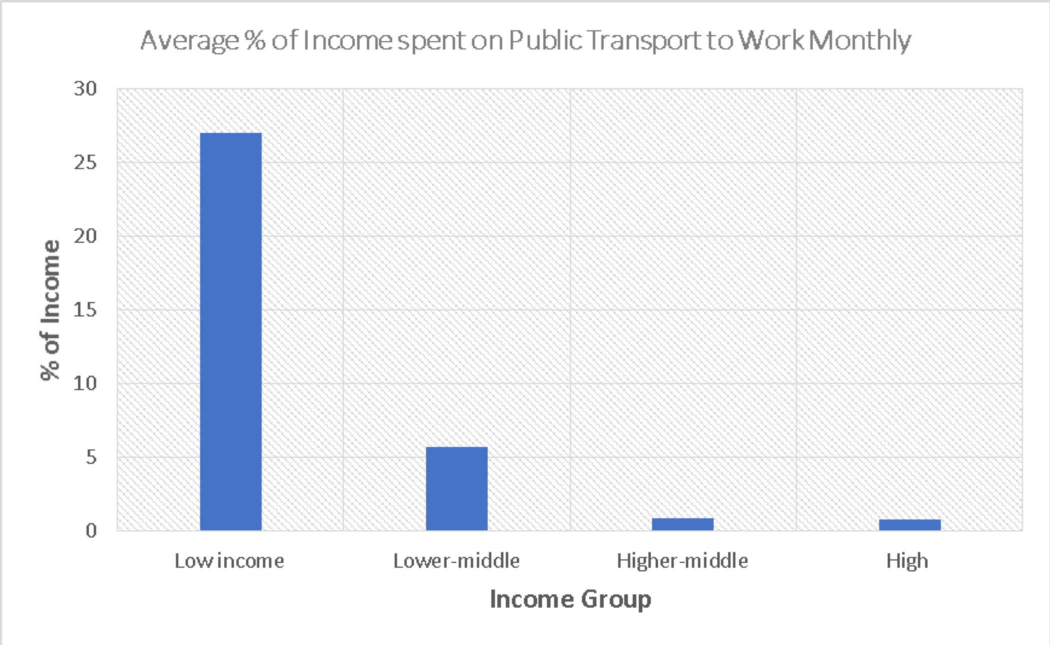
The Cape Town Household Travel Survey is a fall-out of the city's Integrated Development Plan of 2012 (City of Cape Town, 2013d), in which the authority identified eight strategic areas, among which is the development of an Integrated Public Transport Network (IPTN) to address the mobility challenges identified, and also provide adequate access for residents in various parts of the city. Towards realising the vision of the Integrated Transport Network, the citywide survey was conducted in 2013, with the goal of investigating the transport situation and travel choices of residents.

The travel survey comprises revealed and stated preference components (City of Cape Town, 2013b). The purpose of the survey was to determine; where people live and where they work; when they travel and the frequency of their travels, as well as the various modes of transport used. Trip makers' personal information such as age, income, gender, mobility impairments, as well as details on travel costs, travel time and location of service hubs and transfers were gathered. The survey involved face-to-face interviews with about 25,000 households across selected locations in Cape Town (City of Cape Town, 2013b). Three trip purposes were defined in the data; work, education and others, where ‘others’ include all trips that are neither work nor education trips. From the data collected in the survey, the income group of respondent’s households, as well as their mobility characteristics (such as the mode of transport used for different travel purposes, as well as their travel time), formed the key information utilised in the decay function estimation, which is discussed in Chapter 6. Decay functions were estimated for work and education trips and applied for the computation of potential accessibility to jobs and schools.

4.6 Analysis of Public Transport Expenditure across income groups

The framework for accessibility measurement considered in this study, as mentioned in Chapters (1) and (2) considers the affordability dimension of transport, especially for the low-income population (see Section 2.4). The affordability dimension is guided by an understanding of the prevailing situation regarding expenditure on transport across income groups in Cape Town. As such, one of the first analyses carried out in the early phase of this study was establishing the proportion of income spent on travel to work by public transport across the various population groups.

The 2013 Cape Town Household Travel Survey contains information on the monetary cost of transport to work for residents according to their regular payment method (single, return, daily, weekly or monthly pass), as well as their income level and the number of work trips they make per week. The survey did not capture the exact income of respondents but rather, their respective income groups which are categorised as low, lower-middle, upper-middle and high income. In establishing the average expenditure/income ratio, the median of the income range of each group was utilised. For every payment method or pass type and amount utilised by respondents, the monthly equivalent is calculated. Using this information and knowing the number of weekly work trips by a household, a monthly travel expenditure/income ratio is computed for households, for travel to work. The average percentage of income spent, according to income group is presented in Figure 4-11 below.



Source: Author's impression of the 2013 Cape Town Household Travel Survey data

Figure 4-11: Percentage of Income spent on public transport to work

Figure 4-11 shows that, on average, a low-income household spends about 27% of their income on travel to work alone. There is a wide disparity when compared to about 6% for the low-middle income group, and 0.9% for the upper-middle-income group. Based on these percentages, it could be argued that measuring accessibility for all the income groups without taking into consideration such expenditure/income ratio disparity, would result in an unfair evaluation of accessibility. From an equity perspective, it is therefore essential to take into account such disparity in the average proportion of income spent travelling. Further details of the proposed affordability-based measures of accessibility are discussed in Chapter 5.

4.7 Relevant Policy and Strategic Frameworks

This section provides an overview of some relevant policy and strategic frameworks for land-use and transport planning in South Africa, and Cape Town in particular. The objective of this section is to establish a link between some of the policy goals/ strategic objectives and accessibility.

4.7.1 National Land Transport Act, No. 5 of 2009

The provisions of the National Land Transport Act apply throughout the Republic of South Africa. The primary objectives of this Act are:

a) To further the process of transformation and restructuring the national land transport system initiated by the earlier Transition Act.
b) To give effect to national policy.
c) To prescribe national principles, requirements, guidelines, frameworks and national norms and standards that must be applied uniformly in the provinces and other matters contemplated in section 146 (2) of the Constitution
d) To consolidate land transport functions and locate them in the appropriate sphere of government. (The Presidency Republic of South, 2009).

The critical points of this Act with relation to this study are that it provides general principles for transport planning as well as its integration with land use development. The Act also moves to provide structure to the function of municipal planning, in line with Part B of Schedule 4 of the Constitution, which must be accommodated within Integrated Development Plans, as regards the legislation applicable to local government (Strydom, 2010).

4.7.2 Department of Transport (DoT) Revised Strategic Plan 2015 - 2020

The Revised Strategic Plan forms part of the Medium Term Strategic Framework (MTSF) of the National Department of Transport for the period 2015-2020 (Department of Transport, 2017b). The strategic plan focuses on improving mobility and access to social and economic activities, maintaining the provincial and national road networks, upgrading and maintaining rail infrastructure and improving public transport for rail and road commuters (Department of Transport, 2017b). The strategic plan was developed in line with the strategic outcome-oriented goals of the national department of transport (DoT), with a total of six goals being pursued. These goals include:

Goal 1: *To develop an efficient and integrated infrastructure network and operations that catalyse social and economic developments*

Involves developing and implementing policies that are set to drive investments for the maintenance and strategic expansion of the transport infrastructure network, while supporting the development of transportation asset management systems in rural and provincial authorities. The drive for these interventions is to improve the efficiency, capacity and competitiveness of transport operations across all modes (Department of Transport, 2017b).

Goal 2: *A transport sector that is safe and secure*

Through development and implementation of policies and strategies to reduce accidents in the road, rail, aviation and maritime environment.

***Goal 3**: Improve rural access, infrastructure and mobility*

Increasing the mobility and access in the rural environment by improving transport infrastructure and implementing integrated transport services (Department of Transport, 2017b).

***Goal 4**: Improved public transport services*

To provide integrated public transport solutions through development and implementation of legislation, policies and regulations, in other to ensure safe, secure, reliable, cost-effective and sustainable public transport services (Department of Transport, 2017b).

***Goal 5:** Increased contribution to job creation*

By creating an enabling environment for employment opportunities in the transport sector through the implementation of labour-intensive interventions.

***Goal 6:** Increased contribution of transport to environmental protection*

By developing and implementing policies that aim to mitigate climate change and adaptation responses through the reduction of greenhouse gas emission, aviation noise and sea pollution (Department of Transport, 2017b).

The goals highlighted above show that strategic plans at the National level are geared towards improving access to public transport and accessibility to economic opportunities for the betterment in the welfare of the population.

4.7.3 White Paper on National Transport Policy 1996

The White Paper on National Transport Policy sets out clear outcomes for transport in South Africa. It recognises the broad goal of transport as the smooth and efficient interaction which allows society and the economy to assume their preferred form. It further recognises that policies in the transport sector must be outward-looking, guided by the needs of society in general, of the users or customers of transport, and of the economy that the transport system has to support (Department of Transport, 1996). The White paper is a result of a broad public policy-making process involving numerous consultations with stakeholders in the transport sector. The vision for transport in South Africa, according to the White Paper is having a system which ‘provide safe, reliable, effective, efficient, and fully integrated transport operations and infrastructure which will best meet the needs of freight and passenger customers at improving levels of service and cost in a fashion which supports government strategies for economic and social development whilst being environmentally and economically sustainable' (Department of Transport 1996, p.6).

With regards to accessibility and equity in transport, the policies outlined in the White paper are also targeted towards addressing the inadequacy of transport to meet the accessibility needs of the population in rural and urban areas, especially the poorest group (Department of Transport 1996). The issue of affordability is also covered within the outlined policy goals, where it is recognised that meeting the accessibility needs will involve the provision of transport services that are affordable to users, especially those who are in most need.

4.7.4 Revised White Paper on National Transport Policy, Draft 2017

This policy framework is the most recent and expanded revision of the 1996 White Paper and was developed towards addressing the triple challenge of poverty, unemployment and inequality in South Africa (Department of Transport, 2017a). The policy formulation process is reported to have engaged all transport stakeholders in identifying issues and generating the policy options and proposals. A key addition to this revision is the implementation strategies of the already identified goals outlined in the 1996 White Paper.

The vision set for transport in South Africa under the revised policy framework is;

"A transport system that provides equitable and reliable access for all in an economically and environmentally sustainable manner to advance inclusive growth and competitiveness of the country". (Department of Transport, 2017a).

The vision above also points to an emphasis on accessibility and equity in transport as the principal planning objective in South Africa.

4.7.5 Cape Town Spatial Development Framework

At the local (municipality) level, various strategic frameworks and policy plans also exist, which are targeted at guiding land use and transport development. Land use management in Cape Town is guided by the city's Spatial Development Framework, which was created as part of its Integrated Development Plan (City of Cape Town, 2013c). There are three of such frameworks (1) the municipal spatial development framework (2) district spatial development framework and (3) the local spatial development framework. While the municipal spatial development framework oversees the entire municipality of Cape Town, the district and the local spatial development frameworks apply to specific geographical areas within the city.

The main objectives of the spatial development frameworks as specified in the municipal planning By-law include;

i. To provide a long-term spatial depiction of the desired form and structure of the geographical area to which it applies.
ii. To provide land use management guidelines regarding the appropriate nature, form, scale and location of development.
iii. To contribute to spatial co-ordination.
iv. To guide investment and planning of municipal departments and where appropriate other spheres of government.
v. To guide investment for the private sector.
vi. To reflect relevant provisions of strategies adopted by the Municipal Council.
vii. To guide decision making on applications (City of Cape Town, 2015a).

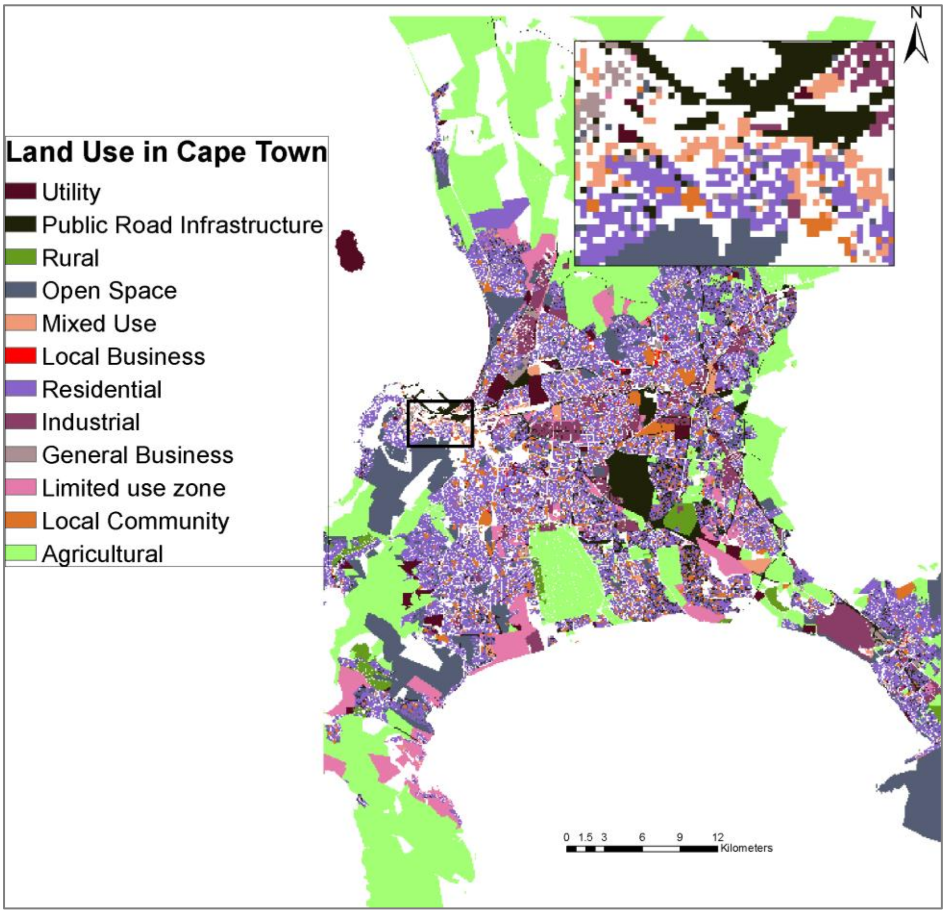
The Municipal Spatial Development Framework (MSDF) has a 10-year vision that is reviewed every five years in line with the City's new political term-of-office Integrated Development Plan (City of Cape town, 2017). The MSDF is meant to guide spatial planning towards realising the City's vision of building a more inclusive, integrated and vibrant city that redresses the legacies of the apartheid planning regime that had created a fragmented city (City of Cape town, 2017). The three vital spatial strategies highlighted in the 2017 MSDF include;

i. Building an inclusive, integrated, vibrant city while avoiding the creation of new structural imbalances in the delivery of services. Desired outcomes being; a greater mix of income groups, land uses, population density, and adequate and equitable provision of social facilities, recreational spaces and public institutions.
ii. Managing urban growth and creating a balance between urban development and environmental protection through the promotion of high-density urban development with mixed land-use patterns, supported by efficient bus rapid transit (BRT) and rail network. Desired outcomes being; more sustainable use of land and natural resources, more efficient use of infrastructure, effective and efficient public transport systems and social amenities.
iii. Planning for employment and improving access to economic opportunities while reducing accessibility costs for the urban poor.

4.8 Land Use Planning and Zoning

The land-use planning and zoning systems of Cape Town is a means of managing its land use to ensure that property development takes place in a structured manner over time(City of Cape Town, 2015b). All developments within the geographic area of the city are part of an integrated zoning scheme and are subject to land use provisions in the Development Management Scheme, which forms part of the Municipal Planning By-law (City of Cape Town, 2015b). The Municipal Planning By-law describes Cape Town's zoning categories, base zonings and the development rules that apply to each zone, including primary and consent uses. The By-law applies to all land in the city, including land owned by the state (City of Cape Town, 2015a). The By-law addresses several components of the planning system which include; spatial planning and spatial development framework, development management and the general procedures and requirements of an application for any development within the city.

The land use map of the city of Cape Town in raster format is shown in Figure 4-12 below.



Source: Author's impression of the 2012 land use data, city of Cape Town

Figure 4-12: Land use map of Cape Town

This Figure is based on the 2012 data of land use in Cape Town, drawn at the land parcel level. There is a total of about 700,000 land parcels in Cape Town and the surrounding Winelands area. The zoomed-in area of the map is the CBD which is mostly mixed-use and residential.

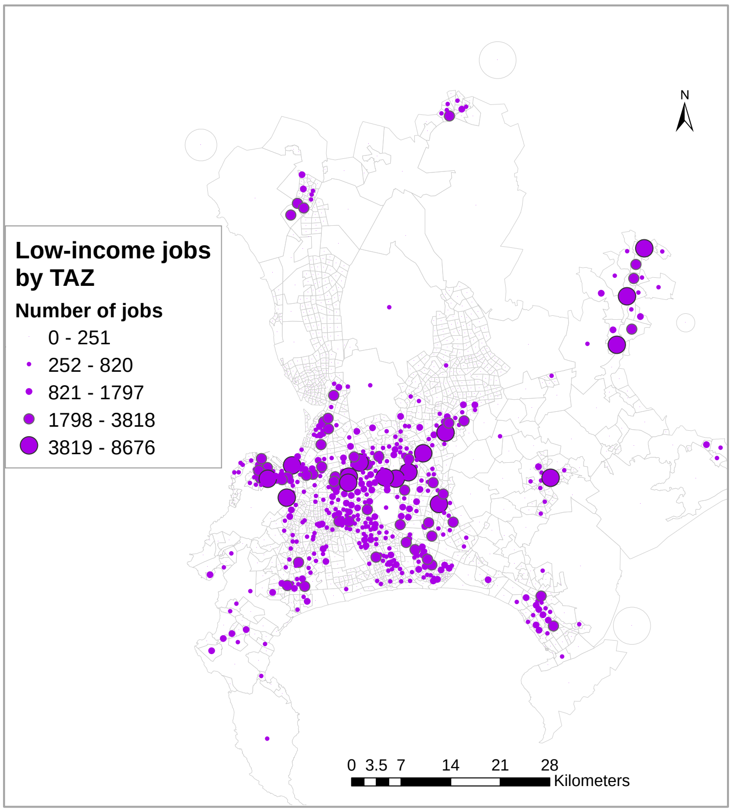
4.8.1 Distribution of opportunities: Jobs, Healthcare and Schools

This study specifically focuses on accessibility to three kinds of opportunities; jobs, healthcare facilities and schools. The next subsections discuss the distribution of these opportunities across the study area.

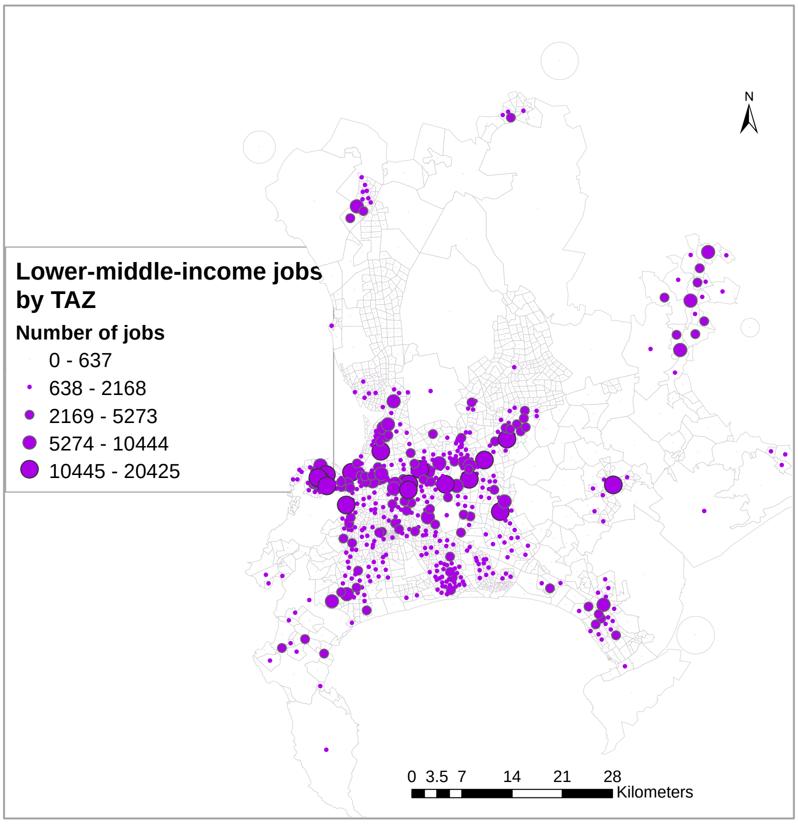
Jobs distribution

For planning purposes, jobs in Cape Town have been categorised according to the income level. Jobs in a particular zone represent the number of employment opportunities available in that location. For this study, jobs data are available at the Traffic Analysis Zone (TAZ) level and categorised by the income level of the job. As described in Section (4.3), the income levels in Cape Town are classified into four groups; low, lower-middle, upper-middle and high.

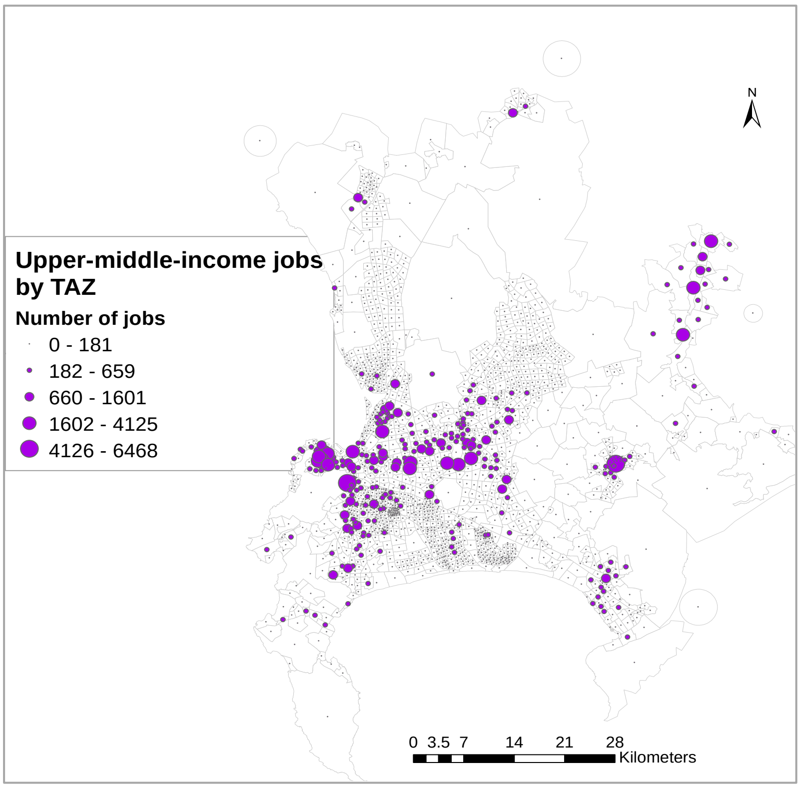
Figure 4-13 (a)-(d) shows the spatial distribution of jobs by income group at the TAZ level.



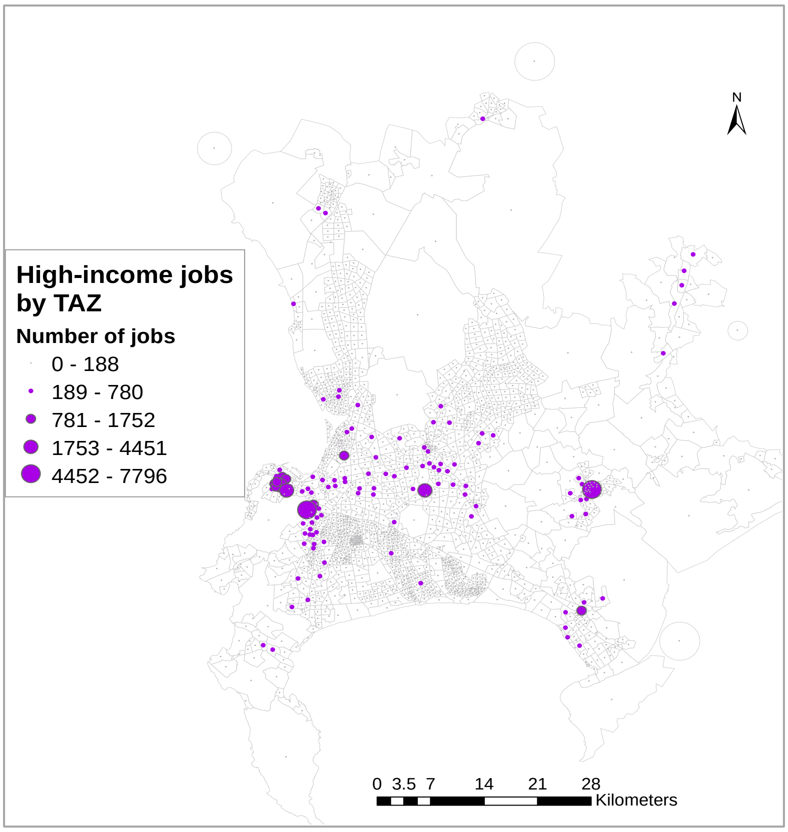
(a)


Lower-middle-income jobs by TAZ
Number of jobs
0 - 637
638 - 2168
2169 - 5273
5274 - 10444
10445 - 20425
N
0 3.5 7 14 21 28
Kilometers

(b)


Upper-middle-income jobs by TAZ
Number of jobs
0 - 181
182 - 659
660 - 1601
1602 - 4125
4126 - 6468
N
0 3.5 7 14 21 28
Kilometers

(c)



(d)

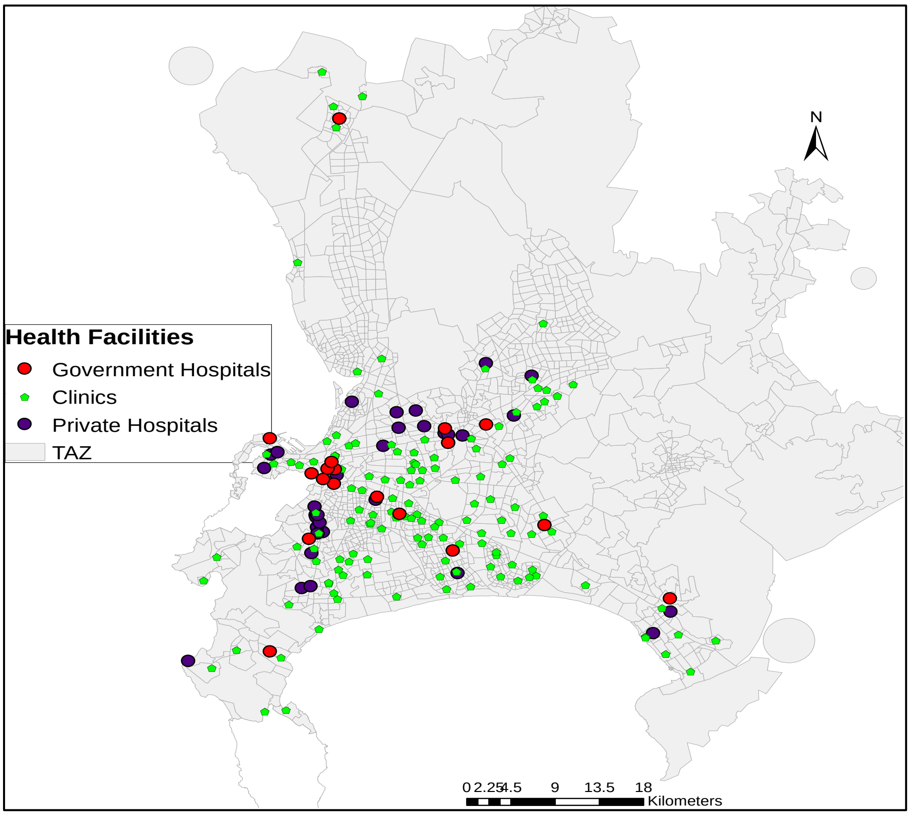
Source: Author's impression of the 2013 data of the city of Cape Town

Figure 4-13: Spatial distribution of jobs by income level (a) low (b) lower-middle (c) upper-middle and (d) high

Figure 4-13 (a) – (d) shows the total number of jobs according to income category at the TAZ level. The jobs represented in the maps are a summation of all job types. These are the jobs for which accessibility is measured, as will be discussed in subsequent chapters. Relating the distribution of jobs as shown above (Figure 4-13) to the spatial concentration of population according to income group (Figure 4-4), it can be observed that the higher income jobs are distributed at locations relatively closer to the CBD compared to the lower-income jobs.

Healthcare facilities

The healthcare facilities available in Cape Town include government and private-owned hospitals and clinics. According to the 2013 data of the City of Cape Town, there are a total of about 18 government hospitals, 35 private hospitals and 138 clinics (of both private and public owned). The spatial distribution of these facilities across Cape Town shown in Figure 4-14 below:



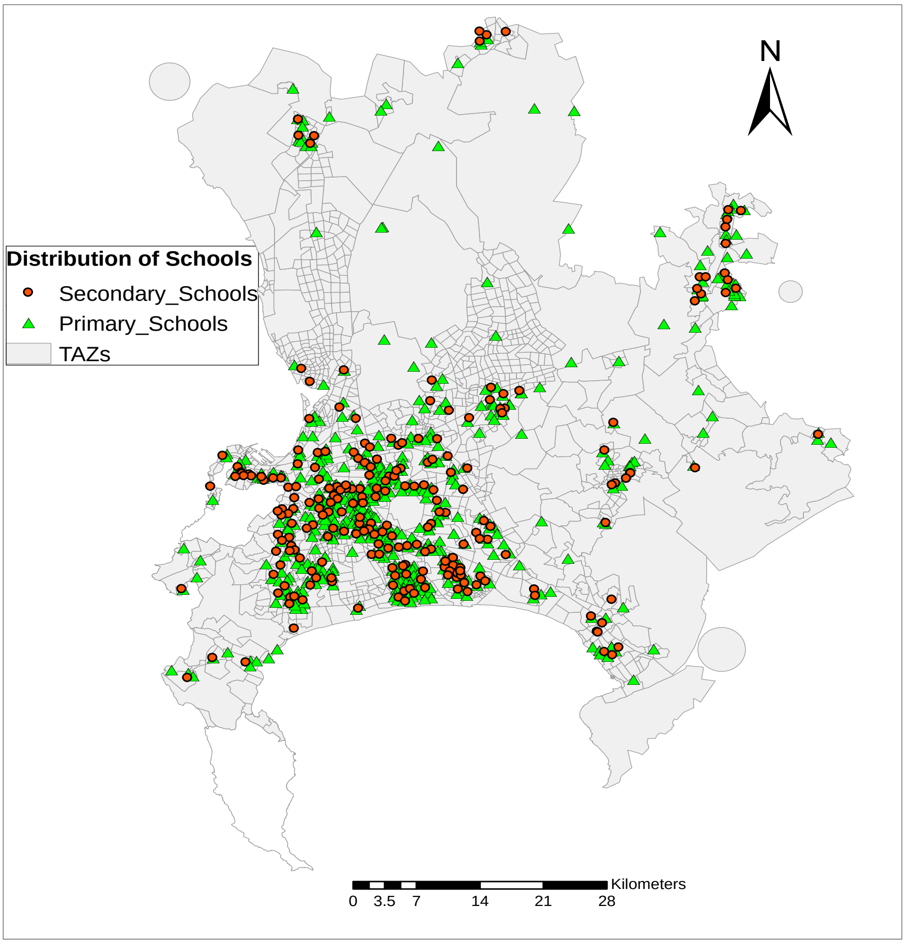
Source: Author's impression of the 2013 data of the City of Cape Town

Figure 4-14: Spatial distribution of health facilities across Cape Town

The health facilities described by Figure 4-14 comprise both public and private facilities. However, for this study, accessibility is investigated for the public healthcare facilities only, as these facilities are considered the most affordable healthcare option for the low-income population. Further discussion on measuring accessibility to these facilities is presented in Chapter 5 (Section 5.5.5).

Education facilities

The education facilities considered include the pre-primary, primary and secondary schools. According to the 2013 data, there are over 800 primary and secondary schools and about 200 pre-primary schools across the study area. Figure 4-15 below shows the spatial distribution of the primary and secondary schools across the study area.



Data Source: City of Cape Town (2013), author's elaboration

Figure 4-15: Distribution of schools across the study area

Figure 4-15 shows the spatial distribution of primary and secondary schools across Cape Town and the surrounding Winelands area. Accessibility is measured from every TAZ centroid to the schools. The indicators for accessibility are further discussed in Chapters (5) and (8).

Chapter 5

Developing the Measures of Access and Accessibility

"Essentially, all models are wrong, but some are useful" – George E.P. Box

5.1 Introduction

The research concept described in the introductory chapter of this thesis presented a research theme on accessibility, which comprises two distinct but complementary measures: (1) a measure of network access and (2) a measure of origin accessibility to opportunities. This chapter discusses the methodology applied in modelling these two aspects. While the network access measure is a measure of infrastructure or service presence of each public transport mode in an area, origin accessibility further considers opportunities or facilities that are reachable. The modelling of access and accessibility, therefore, involves combining ideas about origins and destinations, transport network, modes, cost and travel impedance to measure the relative difficulty (or ease) to reach an opportunity (Long, 2017).

The remaining parts of this chapter are organised as follows; Section 5.2 describes the data utilised for the study and the sources of these. Section 5.3 presents the various stages of model development. Section 5.4 discusses the measure of public transport network access, while Section 5.5 presents the various measures of accessibility, which include (1) job potential accessibility taking into consideration an affordability component (2) healthcare accessibility based on the 2-Step Floating Catchment Area method, and (3) school potential accessibility. Section 5.6 discusses the approach adopted for measuring travel impedance in terms of distance, time and monetary costs. The entire modelling workflow for job accessibility within GIS is also presented in this section. The concluding part of the chapter reflects on some of the modelling challenges and assumptions made in line with the quality of data and the level of aggregation of the analysis unit.

5.2 Data Description

Data utilised for parts of this study include (1) line shapefiles of road network and public transport routes for all four modes in Cape Town; BRT, regular bus, minibus & rail; (2) point shapefiles of stops/stations for each mode; (3) a polygon shapefile of Traffic Analysis Zones (TAZs) of Cape Town; (4) population and jobs data according to TAZ; (5) point shapefiles of schools and public healthcare facilities, which include government hospitals and clinics; and (6) Cape Town household travel survey data of 2013.

Table 5-1 below present the data, source and the pre-processing carried out on the data.

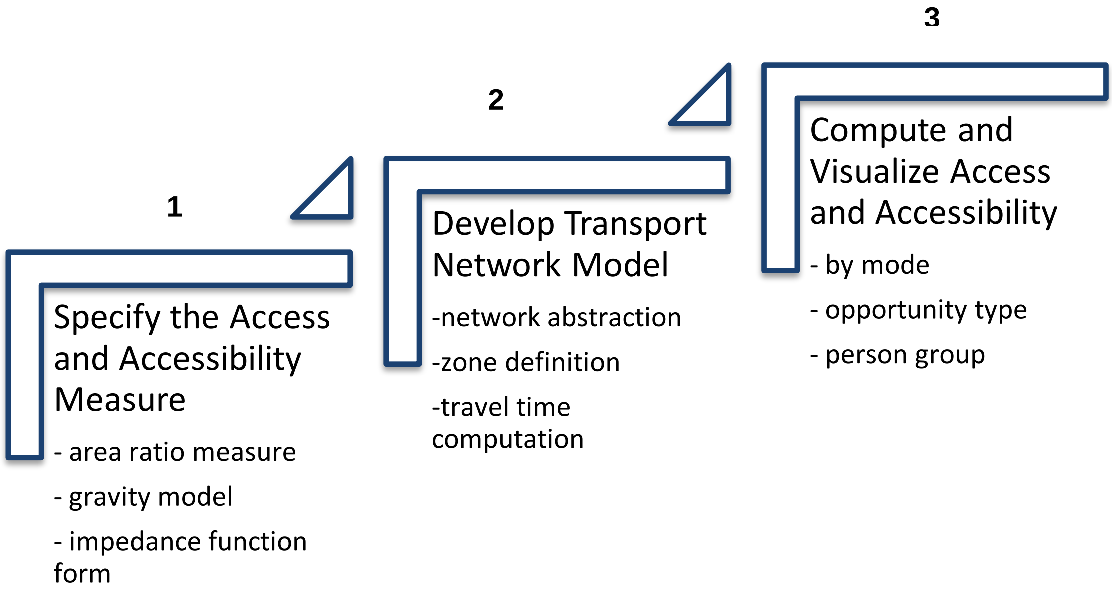
Table 5-1: Data, description and source

Data	Source	Description	Pre-Processing
Cape Town road network.	City of Cape Town	Shapefiles of the entire road network comprising all classes of roads with the various attributes.	Check for model required network attributes e.g. travel speed. Create a pedestrian network and add walking speed to the links.
Public transport routes and stops	City of Cape Town	Shapefiles of the BRT, regular bus, minibus and rail network with stop locations.	Visual checks on GIS of distribution of stop locations along the routes for each PT mode, to ensure stops are realistically spaced.
Trip fares-distance data	City of Cape Town	A spreadsheet containing fares/distance survey data across major corridors by mode	
Traffic Analysis Zones (TAZ)	City of Cape Town	TAZ system currently utilised in the EMME transport model of the city of Cape Town used as the unit of analyses in this research.	Add other model required attributes such as population and job distribution from other data sources.
Jobs distribution	City of Cape Town	Spreadsheet of the number of formal and informal jobs by TAZ.	Spatial join of data to TAZ shapefiles.
2013 Cape Town Household Travel Survey data	City of Cape Town	Raw survey data of travel behaviour of about 30,000 households.	Extract model required data such as travel expenditure by income group and trip purpose.
Health care and Education	City of Cape Town	Point shapefiles of health facilities and schools in Cape Town.	

As described in the Table above, the data utilised for this research were obtained from the city of Cape Town. The TAZ is adopted as the unit of analyses as opportunities, such as jobs were also available at the TAZ level.

5.3 Modelling Access and Accessibility

As mentioned in the introductory chapter (Section 1.5), the measures of accessibility considered in this study comprise (1) Public Transport Network Access Index and (2) Origin Accessibility Index to opportunities (jobs, healthcare facilities and schools). The model development process is depicted as a 3-stage process as shown in Figure 5-1 below.



Source: Author

Figure 5-1: Three major stages of accessibility model development

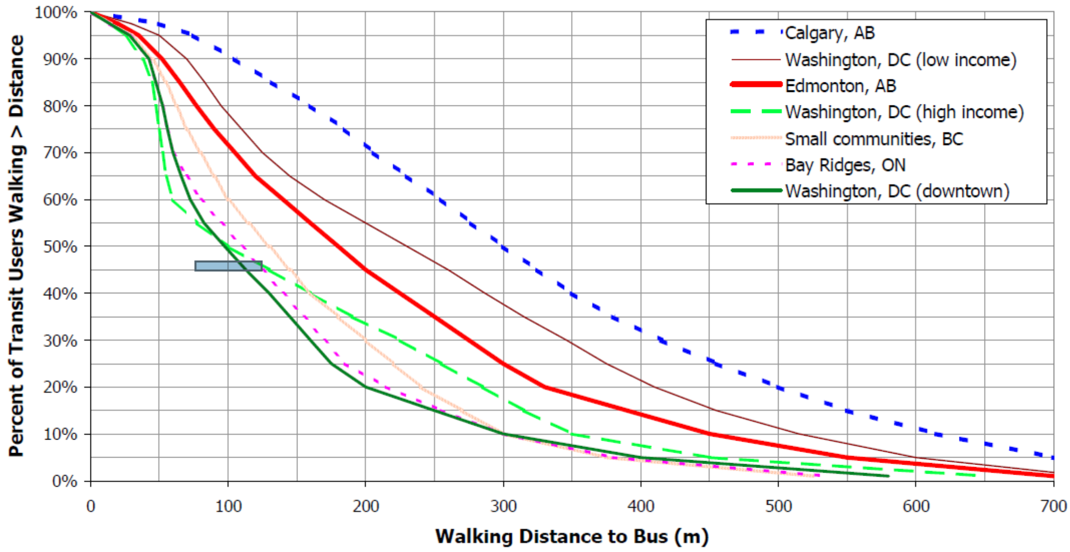
The process of accessibility model development depicted in Figure 5-1 above comprises three key stages, which include (1) formulating the measure, including the impedance function form, (2) developing a model of the transport system, that is, abstraction of the systems network and operational features to compute origin-destination travel cost, and (3) computation and visualisation of accessibility values based on a specified measure. This chapter focuses on the first stage, which is, the formulation of the measures of access and accessibility. The calibration of impedance functions is presented in Chapter 6, while the development of the transport network model is discussed in Chapter 7. Mapping and visualisation of the computed indicators of accessibility are presented in the results chapter (Chapter 8). The next sections discuss the measures of access and accessibility.

5.4 Public Transport Network Access Index (PTNAI)

The Public Transport Network Access Index (PTNAI) developed in this study is based on the Spatial Coverage Index proposed by Mamun et al. (2013). The Index gives a measure of the proportion of the population within acceptable walking distance to a public transport system in a given zone. Considering that network access forms a key part of destination reachability, this measure can inform strategies targeted at ensuring equitable distribution of public transportation services within an area.

The access indicator is measured using a walkability buffer area technique (Foda and Osman, 2010) for both the scheduled and unscheduled public transport services. The scheduled services are those with designated stop locations, fixed routes and timetables. For Cape Town, this comprises the regular bus, BRT and train system. The unscheduled minibus taxi (paratransit) service operates on routes based on demand, without designated stop locations or a timetable. The key features of the scheduled and unscheduled services in terms of developing the indicator of network access is that, for scheduled services, a walkability buffer area is generated around each stop location (considering that access to the network is only through the stop locations). For the unscheduled paratransit service, on the other hand, a walkability buffer area is generated around the route. Using a route buffer gives a close representation of the operational features of the paratransit system whereby passenger pickups can be made at any point along the route. It must, however, be emphasized that the operational features of the paratransit system of Cape Town are quite complex, and therefore problematic to model accurately. A typical example of the complexity (based on the author's knowledge of the system) is in the pattern of passenger pickups and drop-offs, which can vary by route and also dependent on the individual operator (driver). While passenger pickups can usually happen at any point along a route (, however, major highways), drop-offs are usually allowed to happen at intersections along the route. As such, the route buffer technique for modelling access for the paratransit is considered as a close approximation to reality.

The walkability buffer is informed by the distance people are most likely to walk to a transit stop or access point. The question of walkable distance is still debatable as there seems to be no definite value. Studies such as Annis et al. (2012) have shown that walkable distance is context-dependent and could vary widely among a given population. A number of factors including geographic terrain and socioeconomic status have been known to influence how much, people are willing to walk. Figure 5-2 below, from the Transit Capacity and Quality of Service Manual, shows the distribution of walking distances to access bus stops in different cities in North America.

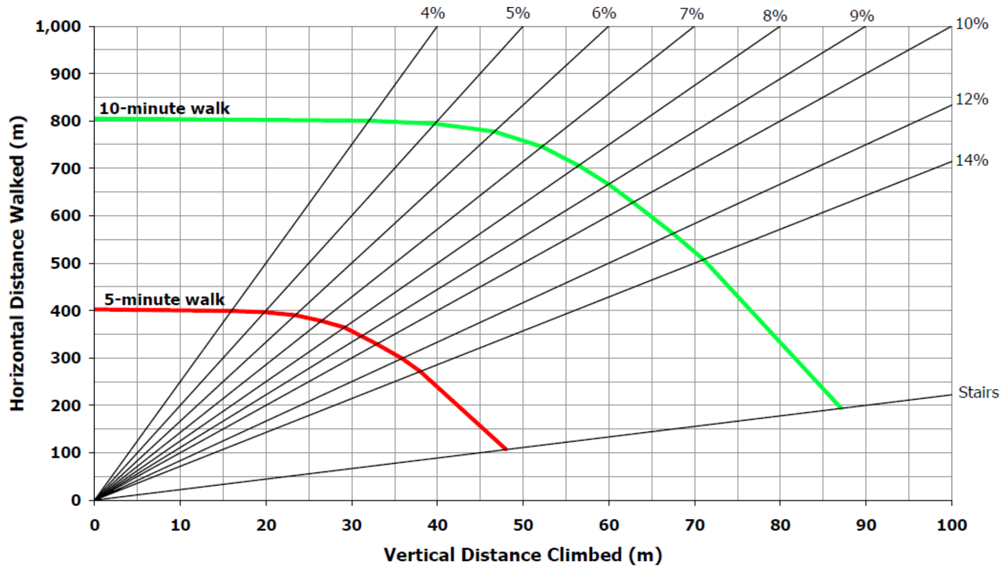


Source: Kittelson & Associates et al. (2003)

Figure 5-2: Willingness to Walk to Bus stop

The graphs in Figure 5-2 also show how willingness to walk is dependent on social class (income level) of individuals. The graphs show the proportion of persons who are willing to walk beyond certain distance thresholds. As shown for the case of Washington DC, USA, while about 20% of the low-income users are willing to walk beyond 400m to a bus stop, only about 5% of the high-income users are willing to walk beyond that same distance.

The effect of geographic terrain on walking distance (Kittelson & Associates et al. 2003) is shown in Figure 5-3. As seen from the graphs, walking distances reduce considerably at steeper grades.

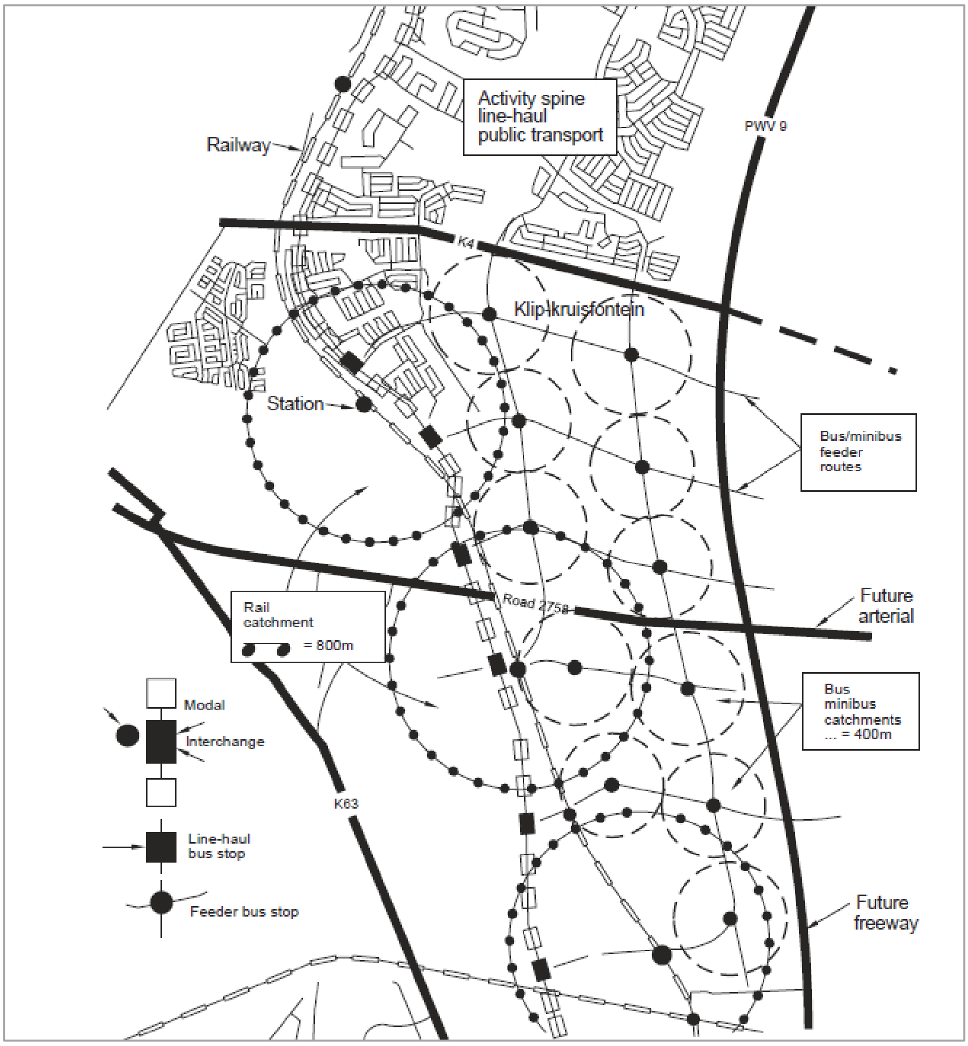


Source: Kittelson & Associates et al. (2003)

Figure 5-3: Effect of grade on walking distance

While walkability studies such as these exist for most developed societies, the literature survey in this research revealed very few studies currently exist in the context of most African cities including those in South Africa. The work of Behrens (2005), who investigated walking trips also noted that, prior to their study, very little was understood of non-motorised trips in the South Africa context, as these kinds of trips have often been ignored in past travel analysis. A distinction must be made here, however, about walking as a complete journey mode, which is the subject of Behrens study and walking as a public transport access/egress mode. Although very little is also known about the latter, reports of the most recent (2013) National Household Travel Survey of South Africa (Statistics South Africa, 2014), have helped in throwing some light towards understanding the walking behaviour of residents in South Africa. Based on the survey report (see Section 4.4.3), average walking time to public transport access points vary between 11 and 30 minutes across the various modes (Statistics South Africa, 2014), which translates to distances of between 550m – 2500m, assuming an average walking distance of 5km/hr.

Among planners and researchers (for example, Murray 2001; Murray et al. 1998; Bhat et al. 2005; Gutiérrez et al. 2011; Mamun et al. 2013), it is commonly agreed that the average walkability distance to public transport service points is around ¼ mile or 400m for bus stops and ½ mile or 800m for a busway or rail station. This is also in accordance with the service coverage estimation methodology specified in the Transit Capacity and Quality of Service Manual from Kittelson & Associates et al. (2003). These walkability distance values have also been adopted for public transport planning purpose in South Africa as specified in its Guidelines for Human Settlement Planning and Design (CSIR 2000). This is depicted in Figure 5-4.



Source: CSIR (2000)

Figure 5-4: Planning guide for public transport services

The Public Transport Network Access Index (PTNAI) in this study has adopted these prescribed values of walking distances, where buffers for bus stops are generated at 400m radius while this is 800m for train stations.

The index is formulated as a ratio of the buffer area around access point (bus stops or train stations) falling within a zone, to the overall area of the zone. It is represented as:

$$A_{mi} = \frac{\sum_{k=1}^{K} b_{mi}^{k}}{y_i} \tag{5-1}$$

where:

A_{mi} = public transit access index of mode m for zone i;

b_{mi}^{k} = the k^{th} walkability buffer or catchment area around a network access point (e.g. bus stop, station) of mode m in zone i;

K = number of non-overlapping buffer areas within zone i;

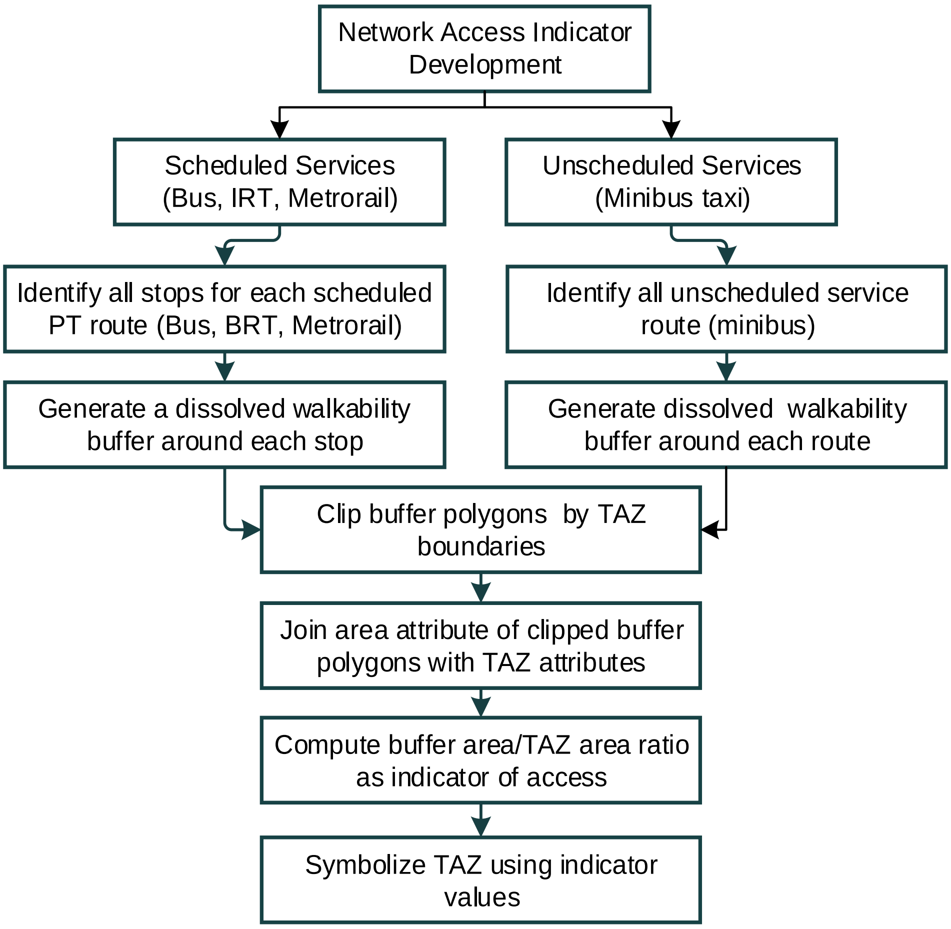
y_i = area of zone i.

Buffers that overlap are dissolved into a single polygon. If, for example, two bus stops exist within a zone, and the walkability buffers around each stop do not intersect, then K takes a value of 2. If buffers intersect, they are dissolved into 1, and K takes a value of 1.

As mentioned at the beginning of this Section (5.4), for modes operating scheduled services at designated stops (for example, bus, BRT and train), the walkability buffer is generated around each stop. For the unscheduled minibus service, on the other hand, the buffer is generated around the route, based on the logical assumption that access can be made at any point along a given route.

The access coverage area can be generated using the circular or network buffers. Although the circular buffers have been widely applied, some researchers (for example, Foda & Osman 2010) have suggested that circular buffers often lead to overestimation of the access level. In this study, however, a circular buffer was chosen for point access coverage estimation, for computational ease, given the extensive network size.

The GIS process flow for the computation of the Network Access Indicator is as shown in Figure 5-5.



Source: Author

Figure 5-5: GIS Workflow for Computing Network Access Indicator

Using the workflow described in Figure 5-5, four indicators of Network Access are developed, covering the four modes of public transport (bus, BRT, minibus and train). The computed indicators are presented in the results chapter (Chapter 8). Indicators are developed separately for the modes due to their different operational characteristics, and for comparative analysis of the access levels provided by each mode.

5.5 Origin Accessibility Indicators

In this study, the Origin Accessibility Index for a zone i is defined as the aggregate sum of impedance-weighted opportunities at potentially reachable destinations j within a specified 'reasonable' travel time for any given mode or combination of modes of travel. In other words, this index references the collective potential opportunities at destinations to the origin locations. Origin and destination are defined by the 1787 Traffic Analysis Zones (TAZs) in the City of Cape Town transport model. The TAZ is adopted as the spatial unit of analysis considering that data on population and jobs are also available at the TAZ level. The frequency distribution of the TAZ area is shown in Figure 5-6 below.

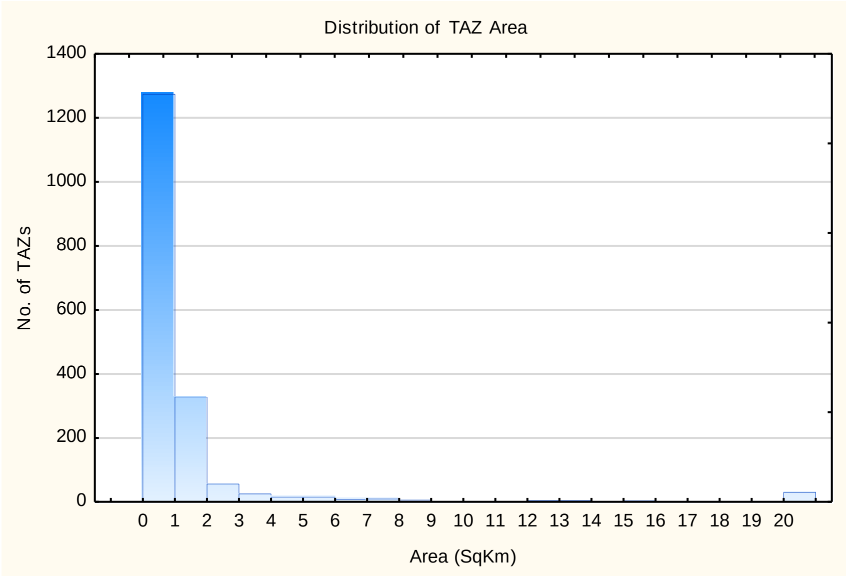


Figure 5-6: Distribution of TAZ Area

This distribution shows that about 70% of the TAZs have areas between 0 – 1 km^2. While a finer level of analysis can be achieved through tessellation of the zones to regular cells (say, for example, 250m by 250m cells), there are also inherent issues with disaggregating the opportunities to align with the cell level resolution, as such disaggregation introduce errors across boundaries of cells. There is also the issue of the limited computing capacity of the available *Windows* machine to handle origin-destination travel time calculation for very large number of zones. For example, a tessellation of the study area into a 250m by 250m cells would yield a total of about 16,400 origin cells, which is beyond the computing power of the dual-core 8GB RAM *Microsoft Windows* computer available for this study. The adoption of the TAZ level resolution also provides room for future interoperability of calculated accessibility indicators within the existing EMME transport model being utilised by the city of Cape Town, which is also built using the same TAZ resolution.

The origin accessibility indicators are being developed for three kinds of opportunities; jobs, education and healthcare facilities. For jobs, three indicators are presented (1) Potential Accessibility indicator (2) Affordable Potential Accessibility indicator and (3) Potential Accessibility loss indicator. The following subsections discuss each of these indicators and their computational procedures.

5.5.1 Potential Accessibility to jobs

The proposed potential accessibility index for jobs is based on the Hansen (1959) measure, and is formulated, both as an absolute index and as a proportional/relative index. The absolute index is represented as:

$$ACC_{ik}^{m,t_{max}} = \sum_{j=1}^{n} O_{jk} . f\left(C_{ij}\right)^{m} \tag{5-2}$$

while the relative index is written as:

$$ACC_{ik}^{m,t_{max}} = \frac{\sum_{j=1}^{n} O_{jk} . f\left(C_{ij}\right)^{m}}{\sum_{j=1}^{n} O_{jk}} \tag{5-3}$$

where $ACC_{ik}^{m,t_{max}}$ is potential accessibility to jobs (of income category k), from origin zone i, within maximum travel time t_{max} by mode m with respect to every destination zone j considered; O_{jk} is the number of jobs (of income category k) at destination zone j; C_{ij} is travel time between origin i and destination j; $f(C_{ij})^{m}$ is the impedance (cost) decay function for mode m which describes the spatial interaction effect of travel time between zones; n is the number of destination zones considered. The income categories k are; low, lower-middle, upper-middle, and high income.

While Equation (5-2) is interpreted as the absolute number of jobs potentially reachable from zone i, Equation (5-3) reads as the proportion of total available jobs in the study area that is potentially reachable from any zone i. Both indicators are applied to measure accessibility for travel by car and public transport.

5.5.2 Affordable Potential Accessibility to jobs

A modification of Equation (5-2) above, for public transport accessibility incorporating an affordability component α_{ij} is given in absolute term as:

$$ACC_{A(ik)}^{m,t_{max}} = \sum_{j=1}^{n} O_{jk} . f\left(C_{ij}\right)^{m} . \alpha_{ij} \tag{5-4}$$

which translates to Equation (5-5) as a proportional index:

$$ACC_{A(ik)}^{m,t_{max}} = \frac{\sum_{j=1}^{n} O_{jk}.f\left(C_{ij}\right)^{m}.\alpha_{ij}}{\sum_{j=1}^{n} O_{jk}} \tag{5-5}$$

with:

$$\alpha_{ij} = \begin{cases} 1 & \text{if } p_{ij}^{m} \leq x \cdot y_{ik} \\ 0 & \text{otherwise} \end{cases} \tag{5-6}$$

where $ACC_{A(ik)}^{m,t_{max}}$ is the Affordable Potential Accessibility index for individual/group k in zone i, for a maximum travel time t_{max} by mode m; α_{ij} is an additional binary parameter that reflects the affordability of travel between origin i and destination j; p_{ij}^{m} is the average monthly monetary cost of travelling between origin i and destination j for mode m; x the pre-defined travel affordability index benchmark given as a percentage of income; and y_{ik} the average household income for household of income group k in zone i; $x \cdot y_{ik}$ can be considered the 'reasonable travel cost' or 'affordable travel budget'.

The impedance function $f(C_{ij})^{m}$ allocates weights to the jobs at the destinations based on the travel time by mode m from the zone of origin i . The implication is that accessibility increases with decreasing time cost and vice versa (Ford *et al.*, 2015). The function is estimated across modes using the observed travel time data from the 2013 Cape Town Household Travel Survey. Details of the estimation procedures and output are presented in Chapter 6.

The further multiplication of the impedance expression by the binary parameter α_{ij} in Equations (5-4) and (5-5) implies that destinations that cannot be reached within predefined 'reasonable' monetary cost of travel are considered inaccessible and hence, those origin-destination pairs are excluded while aggregating accessibility for that particular origin, in which case, α_{ij} takes a value of 0. For destinations reachable within such 'reasonable' cost, α_{ij} takes a value of 1, as shown in Equation (5-4).

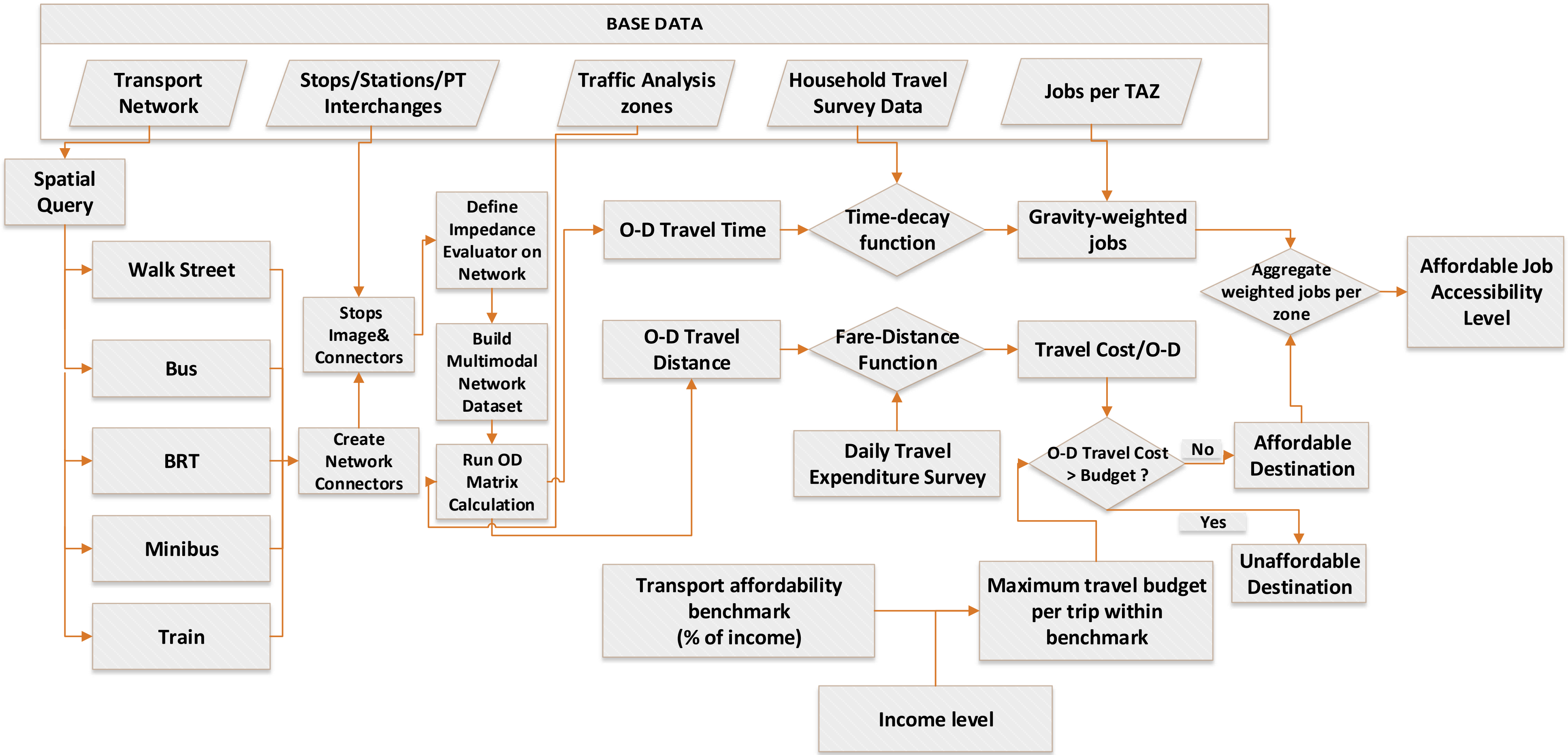
Equations (5-4) and (5-5) can be considered as 'Affordable Potential Accessibility indicators', considering that it aggregates only the opportunities that can be reached within a 'reasonable monetary cost' of travel. It must, however, be emphasized that what can be considered 'reasonable cost' is not definitive in any way, due to inherent heterogeneity in trip-making behaviour and varying willingness to pay among different individuals, irrespective of their income levels. In other words, reasonable cost or willingness to pay would normally vary from person to person. While there are numerous factors that could influence one's willingness to pay, the income level is considered as one of the key factors that could most likely influence such trip decision, especially in the context of low-income societies. The relationship between income and trip demand have been discussed in Chapter 2 of this thesis.

The affordable cost benchmark is established using the upper limit of the low-income wage range, and accessibility is computed for each income group within the zone for travel costs within the affordable benchmark. With the consideration of affordability, accessibility of a zone to opportunities is not only given in terms of the amount of opportunities available and the transport supply connecting it but also regarding the impedance in terms of its spatial orientation with respect to the transport system, but also focuses on the subjects (person and household) that make up the zone.

For a zone-based measure to take into consideration, person characteristics, it is necessary to aggregate such characteristics of the population by income level, as it becomes impractical to measure zonal accessibility taking into account the exact income of every household within a zone. The approach that is being utilized in this study is to select the upper limit of the low-income wage range to reflect an aggregated best-case income situation for low-income households. Since this income assumption is made for the purpose of a zone-based analysis, it must be emphasized that household earnings less than the upper limit value would invariably translate to less travel resources.

A key attribute of the measure represented by Equation (5-4) is that it can be applied to evaluate accessibility for an individual/household or for a group of individuals of the same income class. When applied for an individual, y_{ik} becomes the monthly income of the individual/household, and the term, $x \cdot y_{ik}$ will be the actual monthly travel budget for that individual or household. When the measure is attributed to a group of individuals (say, the low-income persons/households a zone), then y_{ik} will be the average monthly income across the group, while x will be a pre-established benchmark percentage of income applied in defining affordability. The World Bank, for example, defined public transport affordability with a maximum of 10% of monthly income as travel expenditure (Armstrong-Wright and Thiriez, 1987). This benchmark has also been adopted for planning purpose in South Africa as reflected in its 1996 White Paper on National Transport Policy (Department of Transport, 1996) which is being revised in 2017 (Department of Transport, 2017a). An intuitive way to operationalise this benchmark of affordability is through an evaluation of its implication on accessibility especially for the poorest population group, using the proposed measure in Equation (5-4). As will be shown later in the results chapter (8), for the case of Cape Town, affordable potential accessibility when restricted to a travel budget of 10% of average low-income wage, amounts to only 20% of the maximum potential accessibility achievable within a 120 minutes travel time threshold by public transport without budget restriction. In other words, potential accessibility drops by 80%.

The overall workflow for computing the indicator of accessibility described by Equation (5-4) is presented in Figure (5-7). The workflow described is executed using a combination of ArcGIS and Microsoft Excel.



Source: Author

Figure 5-7: Affordable Potential Accessibility modelling workflow

In the workflow described in Figure 5-7, the base transport network and stops data are utilised to develop a multimodal network dataset. This process starts with a spatial query of the base network shapefile to generate an individual network of each mode. Other network elements such as connectors and images of stops are further created to enable connectivity. The preparation of the network elements and building of multimodal public transport network dataset to enable computation of origin-destination travel time are described in detail in Chapter 7, which focusses on the methodology of network model development in GIS. The estimation of decay functions and parameters utilise observed travel time data from the Cape Town Household Travel Survey. The procedure of estimation, as well as the parameter outputs, are discussed in detail in Chapter 6. The impedance evaluators defined for the network elements are travel time and distance. Thus, the multimodal network model is utilised to compute origin-destination travel time and distance. Using linear fare-distance functions estimated from daily travel expenditure survey data, the monetary cost associated with every origin-destination pair is computed. The estimated impedance function is utilised to compute time-weighted opportunities associated with every origin-destination pair. In other words, for every origin-destination pair, there is the weighted opportunity reachable from an origin, and there is an associated monetary cost of travel. Every weighted opportunity associated with an origin is considered an affordable opportunity (in terms of travel cost) if the monetary cost of reaching that opportunity is within the pre-established affordability threshold as defined by percentage of income. All the weighted opportunities within reach of the affordability threshold of monetary cost, are then aggregated for each zone and considered as the affordable potential accessibility indicator of the zone.

5.5.3 Potential Accessibility Loss Index

The Potential Accessibility Loss Index is a measure of the percentage difference between Potential Accessibility (Section 5.5.1) and Affordable Potential Accessibility (Section 5.5.2). Derived from Equations (5-2) and (5-4), the index can be written as

$$ACC_{L(ik)}^{m,t_{max}} = \frac{\left[\sum_{j=1}^{n} O_{jk}.f\left(C_{ij}\right)^{m}\right] - \left[\sum_{j=1}^{n} O_{jk}.f\left(C_{ij}\right)^{m}.\alpha_{ij}\right]}{\left[\sum_{j=1}^{n} O_{jk}.f\left(C_{ij}\right)^{m}\right]} \tag{5-7}$$

where $ACC_{L(ik)}^{m,t_{max}}$ is the Potential Accessibility Loss Index. Other variables are as defined in Sections (5.5.1) and (5.5.2)

Since Potential Accessibility Loss of Equation (5-7) is a function of income level and travel affordability, this index is considered as a measure of vertical equity in accessibility. More details of this index are discussed in Chapter 10 of this thesis, which focuses on the evaluation of equity in measured accessibility.

5.5.4 Potential Accessibility to Schools

For schools, the Potential Accessibility index is given as:

$$ACC_{Si}^{m,t_{\max}} = \sum_{j=1}^{n} S_j . f\left(c_{ij}\right)^m \tag{5-8}$$

with:

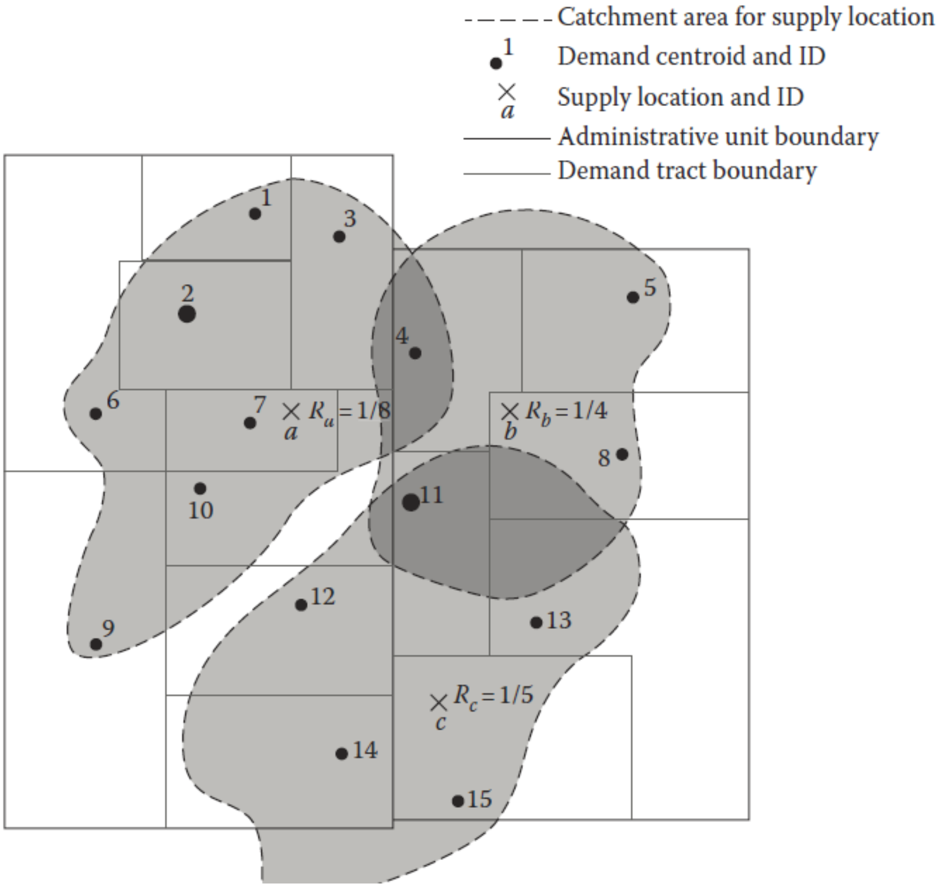
$$s_j = \begin{cases} 1 & \text{if } t_{ij} \leq t_{max} \\ 0 & \text{otherwise} \end{cases} \tag{5-9}$$

where $ACC_{Si}^{m,t_{\max}}$ is the potential accessibility to schools from zone i, under a maximum travel time, $t_{\max}$ by mode m; $f\left(c_{ij}\right)^m$ is the impedance function associated with mode m ; C_{ij} is the travel time from the centroid of zone i to school location j; S_j is a binary variable indicating whether the school location j is reachable within the travel time threshold t_{max}. The negative exponential function is selected for $f\left(C_{ij}\right)$ with parameters estimated using data of observed travel time to schools. Calibration of decay functions is further discussed in Chapter 6 of this thesis.

In this study, accessibility to school is measured separately for each mode of public transport (bus, BRT, minibus, train), as well as for car and walking. This utilised six network datasets developed for each mode. Walking is considered as a crucial mode for school accessibility analysis, considering that a high proportion (up to 50%) of education trips (according to the Cape Town household travel survey) are walking trips. The computed indicators of accessibility for each of these modes are presented in Chapter 8, Section 8.5.

5.5.5 Healthcare Accessibility Indicator (Two-Step Floating Catchment Area Method)

While accessibility to jobs and schools, as discussed in the previous sections, have been based on the gravity potential accessibility model, healthcare accessibility in this study is based on the Two-Step Floating Catchment Area (2SFCA) method. Developed initially by Luo & Wang (2003), it is one of the widely applied methods of measuring spatial accessibility of health care facilities. It is based on the premise that healthcare access comprises mobility in two directions. Supply towards demand and from demand towards supply locations. The 2SFCA method, as the name implies, comprises of two steps. Each step creates an area of coverage or catchment, both from the supply locations (health facilities) and from the demand points (zone centroids), with both areas overlaid on one another (floating) to create the spatial accessibility output. This is depicted in Figure 5-8 below.



Source: Wang (2015)

Figure 5-8: Two-step floating catchment area method

Figure 5-8 shows the 2SFCA method where catchments are generated around three facilities (supply location). Based on Luo & Wang (2003) illustration, the healthcare accessibility index using the 2SFCA method is derived as follows:

For every supply (healthcare facility) location j, search for all the demand points k that are within a threshold travel time (t_{max}) from location j (that is, catchment area of j) and compute the supply-to-demand ratio R_j within the catchment area, as given by:

$$R_j = \frac{S_j}{\sum_{k \in [t_{kj} \le t_{max}]} D_k} \tag{5-10}$$

where t_{kj} is the travel time between k and j; D_k is the demand (number of persons) at location k that falls within the catchment (i.e., $t_{kj} \le t_{max}$); S_j is the capacity of supply at location j, represented as the bed capacity of each facility.

Then, for each demand location i, search all supply locations j that are within the threshold travel time t_{max} from location i (i.e., catchment area i), and sum up the supply-to-demand ratios R_j at those locations, to obtain the accessibility index ACC_i^H, at demand location i. This is represented by:

$$ACC_i^H = \sum_{j \in (t_{ij} \le t_{max})} R_j = \sum_{j \in (t_{ij} \le t_{max})} \left[\frac{S_j}{\sum_{j \in (t_{ij} \le t_{max})} D_k} \right] \tag{5-11}$$

where t_{ij} is the travel time between i and j; R_j is the supply-to-demand ratio at supply location j that falls within the catchment, centred at i (i.e., $t_{ij} \le t_{max}$).

The first step of the measure above assigns an initial ratio to each service area of the healthcare facility location, as a measure of facility availability. The second step then sums up these ratios in the overlapped service areas to measure accessibility for a demand point (zones) where residents can 'possibly' have access to multiple supply locations.

The accessibility index ACC_i^H is given as the number of hospital beds per thousand population. Higher values for a zone indicate higher accessibility.

The procedure developed in this study for implementing the 2-Step Floating Catchment Area method within GIS is described below:

STEP 1:

I. Create car-based network dataset in ArcGIS Network Analyst, using the street network, with the distance and travel time impedance evaluators defined on the network.
II. Open the 'Create New Service Area' and load hospitals point file as the facility supply locations.
III. Set up other required parameters in Network Analyst and do service area calculation for 30minutes travel time breaks from all facility points.
IV. Save service area output in step III above as separate polygon shapefile.

V. Join attributes of the hospitals point shapefile (containing the bed capacity of each facility) to the attributes table of the service area polygon shapefile.

VI. Do spatial join of the service area polygon in step V with the TAZ centroid point file containing population of residents. Using the 'SUM' merge rule, all residents' population from TAZ centroids falling within each service area is summed up and added to the attributes of the corresponding service area.

VII. Do hospital bed per thousand population ratio computation: Add new attribute field to the attribute table of the service area polygon output from step VI above, and using field calculator, compute the bed/thousand population on the new field.

VIII. Join the resulting attribute table of the service area polygon output in step VII above back to the hospitals point shapefile, such that the 'bed-per thousand population' is populated as a new field to the hospitals attribute.

STEP 2:

In step 2 of the Two-step floating catchment method, similar procedures in step 1 are repeated, but around the demand points. In other words, this step creates a population catchment while the first step creates a hospital catchment. The algorithm for step 2 within GIS is described in the following steps:

I. Using the same network dataset as in step 1, create new service area

II. Load the TAZs centroids point shapefile as the new facility locations and set up all other required parameters in network analyst.

III. Do service area calculation (population catchment) with travel time of 30minutes around the TAZs and export the output as separate polygon shapefiles.

IV. Do spatial join of the service area with the point shapefile of the hospitals from step III. Using the 'Sum' merge rule on the attribute, 'bed-per-thousand population', all values of this field for all hospitals falling within each TAZ service area, are summed up and added to the attributes of the TAZ service areas. The output of this step is a TAZ service area containing among its attributes, 'bed per thousand population'.

V. Join the output of step IV with the TAZ polygon shapefile using the join tool. The output is a TAZ shapefile with the attribute 'bed per thousand population'. This attribute is the spatial accessibility index for healthcare facilities.

VI. Create visual maps of the accessibility values using layer symbology.

This method is accordingly applied to measure accessibility to public healthcare facilities in Cape Town. Healthcare facilities in Cape Town are either public or private facilities, which both comprises hospitals and clinics. For this study, only the public facilities are considered, due to lack of data on private hospitals and clinics. The computed and mapped indicators of accessibility are presented in Chapter 8 (Section 8.6)

5.6 Chapter Conclusion

This chapter presented the first part of the research methodology which discussed the various indicators of access and accessibility developed in this study. The measures of Access and Accessibility presented are two separate indicators which are meant to inform or guide different planning decisions. The Network Access indicator is developed for each of the public transport modes, and specifically show the extent of infrastructure coverage across the study area, while the accessibility indicators show the land use opportunities potentially accessible, given the available transport options. The Access measure is therefore only a ‘potential access’, based on the availability of public transport routes and stops in an area, and can only guide decisions regarding infrastructure network expansion or stops spacing. It is recognised, however, that ‘potential access’ can differ from ‘revealed’ or ‘perceived’ access, as the latter is usually measured at the person level, and informed through empirical observation of users or potential users of public transport facilities. Such empirical investigation of ‘revealed’ or ‘perceived’ access can, however, serve as a means of validating the ‘potential’ network access indicator presented in this study.

Regarding accessibility, different indicators are proposed for the various opportunities. The proposed job accessibility index incorporates an affordability dimension. While most accessibility measures described in the literature have only utilised the network and service component in deriving accessibility, affordability has been identified as a key aspect that should be considered within accessibility measures. A user’s ability to pay for transport services (affordability) plays a role in determining whether potential opportunities can be reached, and the number of trips that can be made. Therefore, if affordability is regarded as a constraint to trip making, a measure that quantifies such affordability should be recognised within accessibility measures. This would especially be significant when quantifying accessibility in low-income cities. A high affordability level should have an increasing effect on potential accessibility while low affordability should have decreasing effect.

The remaining parts of the research methodology, which involves the calibration of impedance functions from observed data, computation of travel cost, and the development of network data models within GIS, are presented in the next two chapters (6 and 7). This is followed by the results presented in Chapter 8, showing the computed and mapped indicator values.

Chapter 6

Impedance Functions and Travel Cost Estimation

"Each of us has been doing statistics all his life, in the sense that each of us has been busily reaching conclusions based on empirical observations ever since birth" - William Kruskal

6.1 Introduction

A critical component in gravity-based accessibility measurement is the definition of suitable impedance functions that describe the effect of spatial separation for whatever cost element (distance, time, or generalised cost) being considered. As stated in Ha et al. (2011), an impedance function represents the degree to which a given zone i is attracted to other zones based on travel time and/or travel costs. Although the traditional name of 'distance-decay', which came from earlier developed models, signifies the effect of spatial separation by distance on the potential for interaction, most researches (de Vries et al. 2009; Skov-Petersen 2001; Iacono, K. Krizek, et al. 2008) have modelled separation in terms of travel time or generalised cost of travel.

In the literature, spatial interaction is usually modelled using an assumed negative exponential, power or Tanner functions (Martinez & Viegas, 2013; Skov-Petersen 2001; Cheng & Bertolini, 2013). The choice of function should ideally depend on the data and its distribution. While the assumption of certain kinds of distribution such as the negative exponential distribution or the power distribution is a relatively straightforward way to model spatial interaction, there are usually concerns about the reliability of model, as to whether the assumed distribution describes the observed data. Therefore, selecting an appropriate decay curve is critical to achieving a more realistic accessibility estimate.

The accessibility measures for jobs and schools presented in Chapter 5 are based on the Hansen's model, with an impedance function $f(C_{ij})$. The impedance function weighs the opportunities based on the probabilities of trips happening within a certain travel time threshold. In other words, the impedance function in terms of travel from origin to destination tends to answer the questions, *'how close is close enough?'* or *'how far is too far'* (Iacono *et al.*, 2008). The calibration of impedance functions, therefore, involves establishing the shape or form the decrease in the interaction intensity assumes, as travel time increases, based on observed data.

This chapter discusses both the method and output in the calibration of the decay functions of the potential accessibility measures discussed in Chapter 5. Decay functions are estimated separately for private car and travel by the various modes of public transport. Also presented in the chapter is the approach adopted for measuring travel cost in terms of time and out-of-pocket cost of overcoming distance. Other aspects of the chapter discuss the survey data, the limitations in its application, and the assumptions made with regards to estimating decay parameters.

6.2 Density Estimation as the Basis for Decay function estimation

The estimation of decay functions from empirical data through statistical fitting of the data can be hinged on one of the most fundamental problems in statistics, which is density estimation or simply put, the estimation of data frequencies or concentrations. As stated in Silverman (1986), one of the primary uses of density estimates is in the investigation of the properties of any given dataset. The mathematical formulation of a simple density problem as described in Simonoff (1996) and Silverman (1986) can be represented as:

$$P(a < X < b) = \int_a^b f(X)\mathrm{dx} \ \ \forall\, a < b \qquad (6\text{-}1)$$

where X is a random quantity that has a probability density function $f(X)$ which describes the distribution of X, and allows the probability P, associated with X within interval a and b to be established. With regards to this study, the decay function is a statistical transformation of the probability density function formed by the observed travel time data. The transformation is such that the probability density takes a maximum value of 1 and a minimum value of 0. While the first part of decay estimation is specifying the function, the second part deals with estimating parameters for the chosen function, based on observed travel time data.

Taylor (1975) discussed some general approaches that can be employed in the estimation of decay parameters. For non-linear data, three strategies that can be employed are (1) breaking up the data into parts and fitting several linear equations within those parts (2) fitting a smooth polynomial curve or (3) transforming the data to make it linear. The first approach, which is also the simplest, involves fitting several straight lines to separate parts of the data. It usually results in some function that applies from zero distance to some threshold and another function that applies from this threshold onwards. The third approach is to transform the data such that it has a linear pattern, and a simple linear regression line is then fitted to the transformed data.

This function gives a smooth curve when transformed back into the original data. This study adopts the third approach in estimating the parameters of decay functions, whereby data is transformed into linear patterns, and regression is applied to the transformed variables.

The data utilised for estimating the decay functions are the travel time records from the Cape Town Household Travel survey. Details of the survey have been discussed in Chapter 4 (Section 4.5). The next section discusses the key assumptions made in line with the limitations of the survey data.

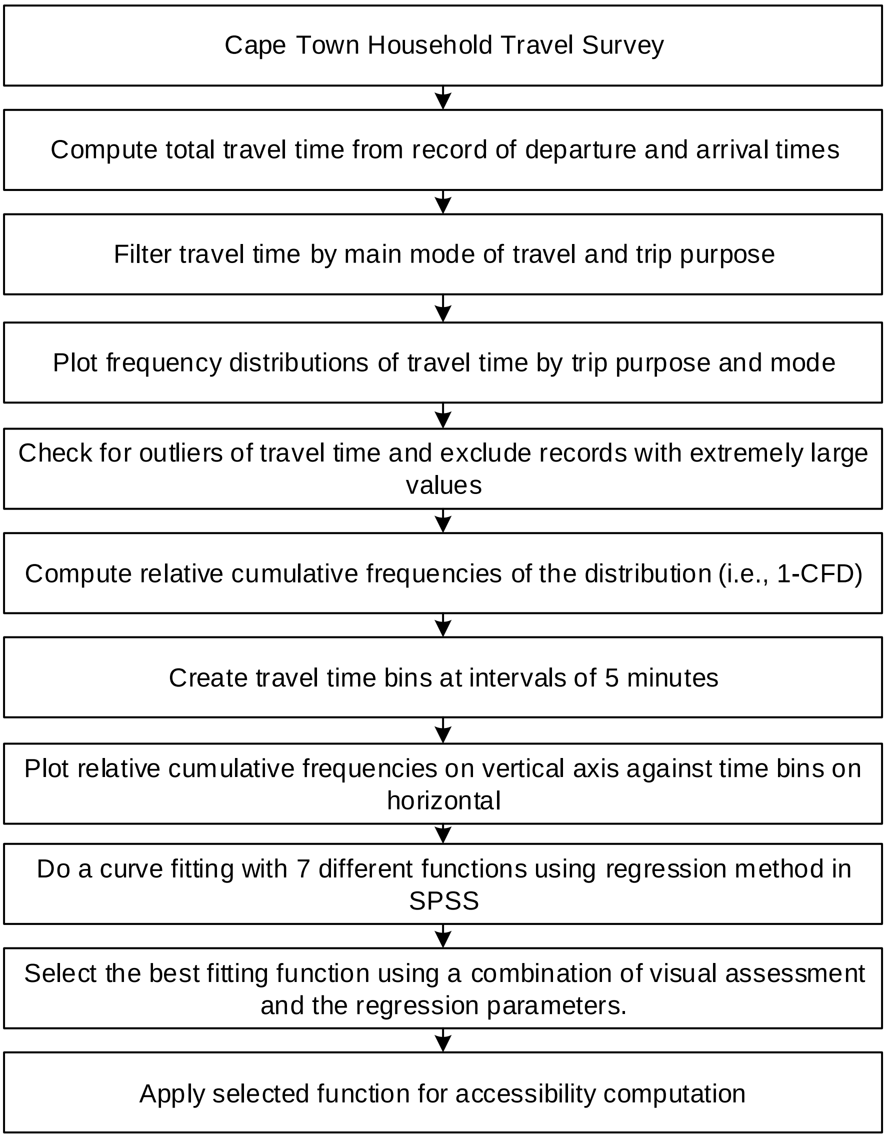
6.3 Assumptions & Limitation of the Household Travel Survey Data

Certain assumptions have been made with regards to the application of the survey data for estimating decay functions. In the survey, information on travel time by mode was collected by asking residents when they normally leave their home and what time they get to their destination using a particular mode or combination of modes. The limitation in this data is that the trip length from origin to destination by any mode or combination of modes do not specify the walking access and egress time component of the journey. In an ideal situation, the estimation of trip length by any given mode should be based on data of travel time between access and egress points of the journey. For a bus trip, for example, it would be the time from the first bus stop from which the trip maker embarks on a journey and the last bust stop where s/he disembarks before walking to the final destination. Depending on the proximity of the trip maker's origin point (residence) to a public transport access point, walking time spent on access could create a measurement bias on the estimate of average time spent on travel by that mode, which would therefore affect the estimation of how far an individual would likely travel for a specific trip purpose and specific mode of travel.

Based on the limitations of the available travel survey data, the analysis of travel time spent travelling a given mode is assumed to be a summation of waiting time, boarding time, in-vehicle travel time as well as access and egress times. Since the travel time information in the survey is only based on departure time at the origin and arrival time at the destination, the estimated impedance function is therefore reflective of the entire journey, and not just for the main mode of travel utilised.

6.4 Estimating Impedance Functions based on Travel Survey Data

As mentioned in the Section (6.2), impedance estimation is based on fitting a probability density function to the observed travel time from a survey. The travel survey data captured departure and arrival times, as well as the travel mode/combination of modes used for the journeys. Other information on the respondents includes; income level, age, gender, education level, employment status, trip purpose, travel frequency, departure zone, arrival zone, amount spent per mode, number of transfers made, mode of payment and ticket type. The workflow developed for estimating the decay function is shown in Figure 6-1 below.



Source: Author

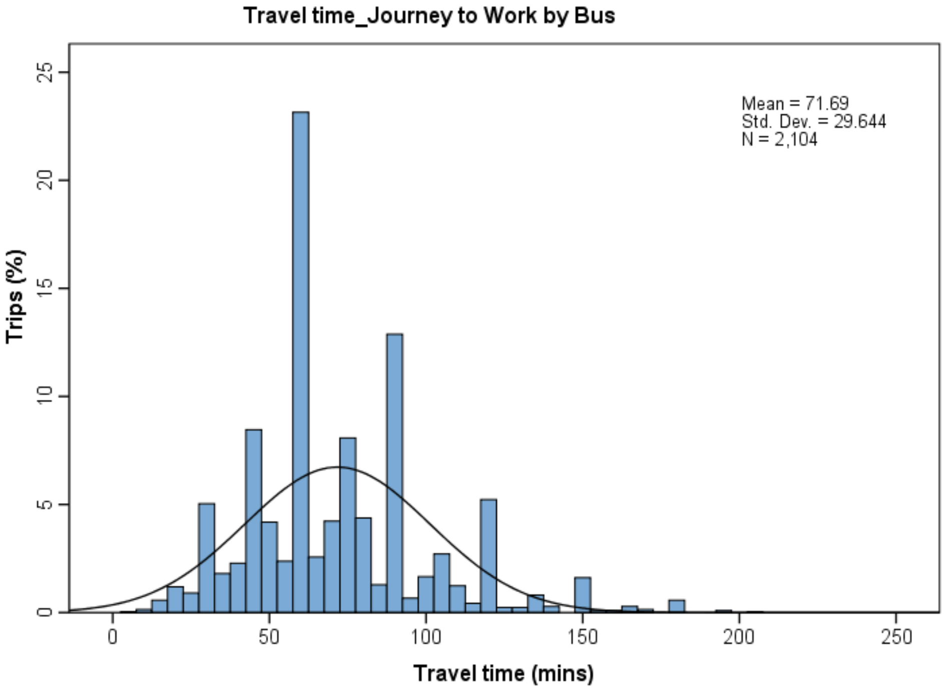
Figure 6-1: Workflow for estimation of decay parameters

The travel times extracted from the recorded departure and arrival times are first scrutinised for any irregularities and outliers. From an observation of the data, it was seen that a few of the responses on travel time by various modes are, in fact, not realistic. In the data cleansing process, entries of travel time of 0 minutes by car or any public transport mode are considered not logical. Similarly, entries of unreasonably high values of travel time (of say above 300 minutes) were considered as non-valid observations for the purpose of estimating the decay function. The establishment of the applicable range of travel time to be considered was based on an initial frequency distribution of the data, where it was observed that most of the surveyed trips fall within a travel time boundary of 0 - 180 minutes, with a few cases of zero travel time and extremely high travel time of over 3 hours. These extreme values were considered as outliers and attributed to either data capturing error from the interviewer or poor judgement/lack of knowledge of actual travel time on the part of the respondents.

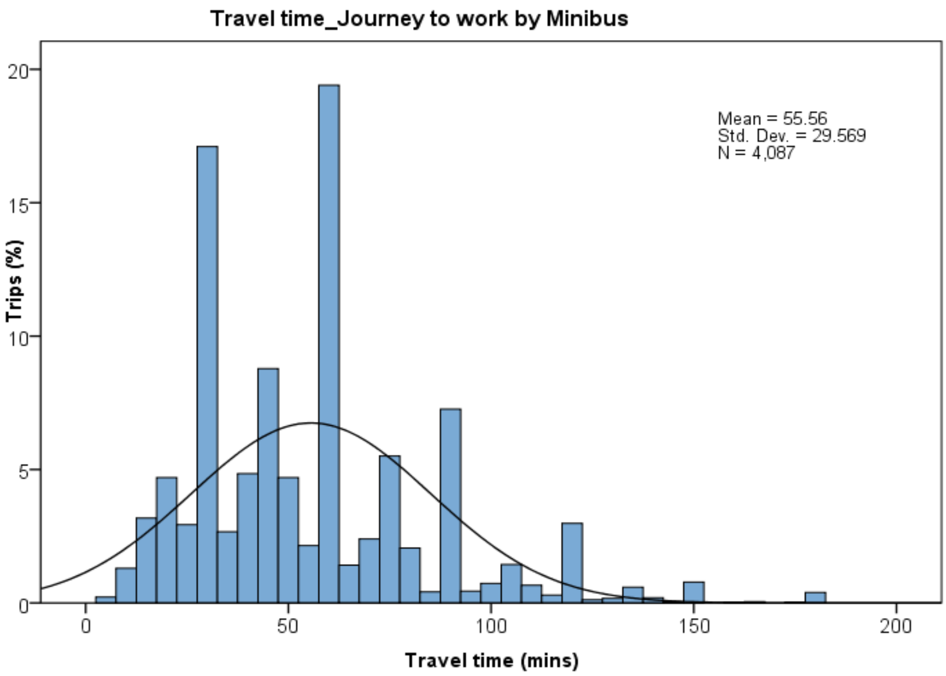
To minimise the estimation bias that could be created from the inclusion of such extremely low or extremely high travel time entries, a benchmark of travel times ranging from 2 - 250 minutes was considered for all main modes of travel other than walking. Hence, only survey entries with reported travel time that falls within that range were considered for the estimation of decay function. The decay curves are established from the frequency distribution of travel time, otherwise regarded as trip length frequency distributions (TLFDs). The various TLFDs for the various modes of travel are presented in the next section.

6.4.1 Observed Trip Length Frequency Distributions

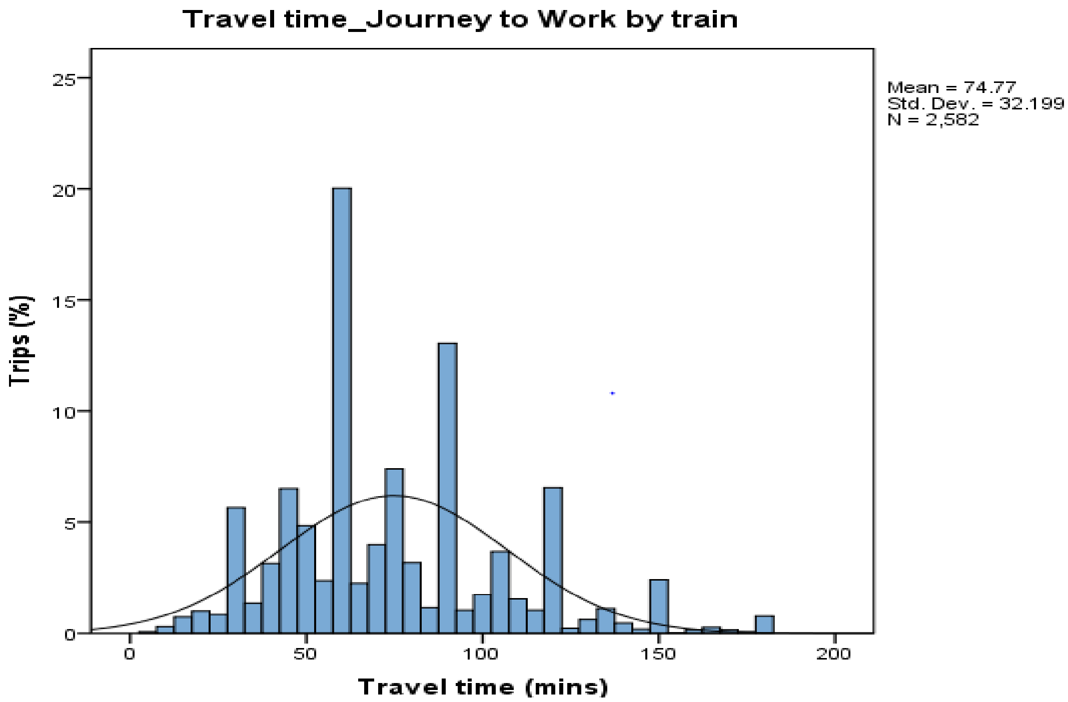
The trip length frequency distribution (TLFD) is a histogram of travel time in bins, with the frequency of trips associated with each bin. The trip frequency is plotted as percentage of total trips on the vertical axis, with travel time in the horizontal axis. The trip length frequency distributions for the public transport modes (regular bus, minibus taxi and train) are as shown in Figures 6-2 (a) –(c) below.


Travel time_Journey to Work by Bus
Mean = 71.69
Std. Dev. = 29.644
N = 2,104
Trips (%)
Travel time (mins)
0
5
10
15
20
25
0
50
100
150
200
250

(a)


Travel time_Journey to work by Minibus
Mean = 55.56
Std. Dev. = 29.569
N = 4,087
Trips (%)
Travel time (mins)
0
5
10
15
20
0
50
100
150
200

(b)



(c)

Source: Author's impression of the 2013 Cape Town Household Travel Survey data

Figure 6-2: Trip length frequency distribution for travel to work by (a) bus (b) minibus taxi and (c) train

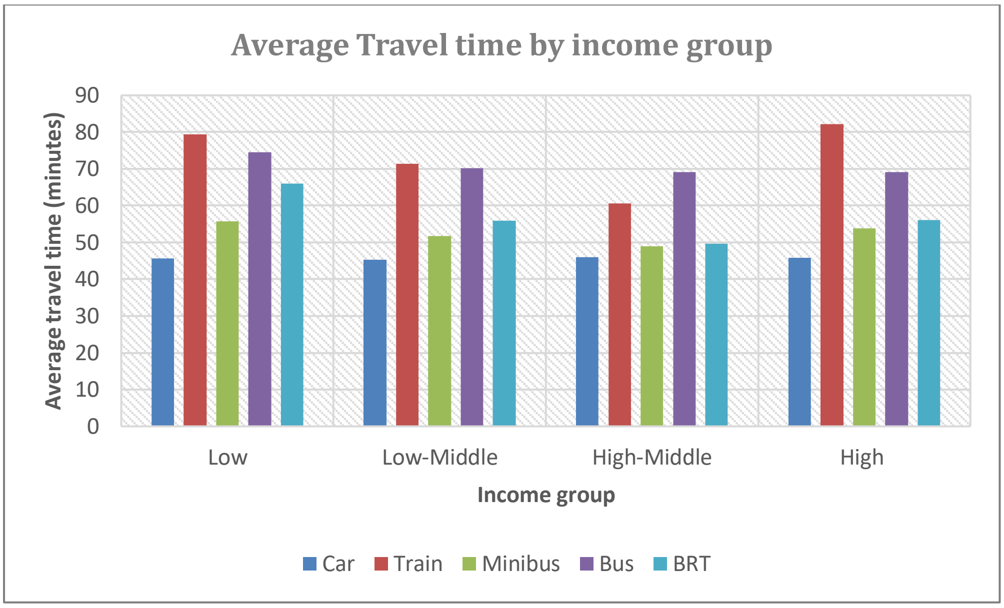
The trip length frequency distributions above are for all users of these modes, irrespective of their income group. Also shown in the figures are the mean travel time and standard deviation in minutes. The observed distribution in the figures tends to follow a random pattern, with several spikes. The histograms show peak concentration of trips around the 55-60 minutes bin for all the modes of public transport. For bus, about 24% of the trips take about 60 minutes, while for minibus taxi and train, the proportion of trips is about 20%. A summary statistic of the travel times by income group of travellers, for all public transport modes and car, is further shown in Table 6-1 below.

Table 6-1: Summary statistics of travel time to work by income group

Income Group	Mode	No. of valid observations	Mean total travel time (min)	Std. dev (min)
Low Income	Car	691	45.57	25.12
	Train	430	79.45	34.70
	MBT	818	55.68	30.46
	Bus	405	74.58	31.81
	BRT	5	66.42	27.34
Lower-Middle Income	Car	5038	45.32	25.63
	Train	748	71.34	31.17
	MBT	1877	51.74	28.75
	Bus	1082	70.24	27.87
	BRT	30	55.93	29.79
Upper-Middle Income	Car	1582	45.97	26.19
	Train	36	60.69	32.01
	MBT	46	48.96	28.73
	Bus	47	69.04	29.43
	BRT	16	49.69	17.93
High Income	Car	755	45.75	37.65
	Train	9	82.22	75.50
	MBT	17	53.82	45.45
	Bus	11	69.09	60.00
	BRT	5	56	60.01

Source: Author's elaboration of the 2013 Cape Town Household Travel Survey data

The Table shows the average travel time and standard deviation for journeys to work by public transport and car, for respondents of the various income categories. The travel times are based on survey records of respondents' departure time from home and arrival time at work, using these modes as the main mode of travel. Therefore, the travel times indicated for the public transport modes are considered to include the walking access and egress times components of the journey, as well as the boarding and alighting delays. The relatively high values of standard deviation show that the surveyed travel times are quite dispersed or spread out from the mean, across all modes. The average travel times from Table 6-1 is further visualised in Figure 6-3.



Source: Author's impression of the 2013 Cape Town Household Travel Survey data

Figure 6-3: Average travel time to work by mode and income group of travellers

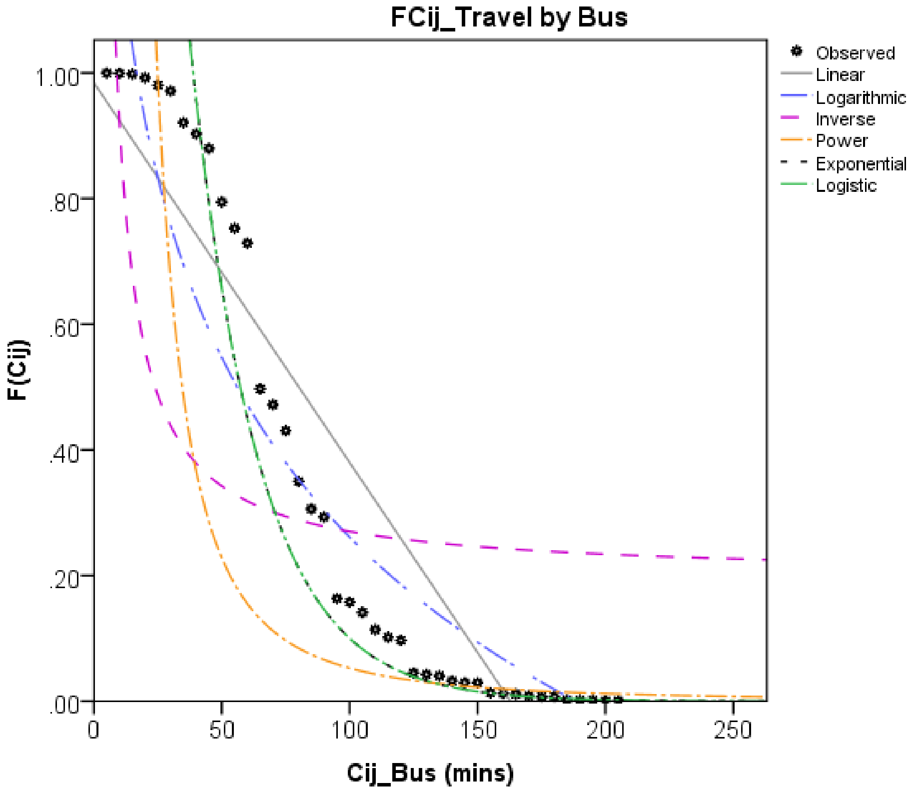
The Figure shows that for commute to work, the use of the train as the main mode takes the longest time on average among all the public transport modes, while the minibus taxi takes the shortest time. As expected, travel by car takes the shortest time when compared to public transport. Although, it is not apparent from the survey data, what factors might be contributing to the noticeable variation in travel time by public transport among travellers of the various income groups, one reasonable explanation would be to attribute it to land-use factors, such as the spatial separation of places of residence and workplaces for the various population groups. For travel by car, there is no much variation in travel time, as the average travel time is seen to be about 45 minutes across all income groups. Although not obvious from the survey, one explanation for this would be that the low-income travellers who reportedly use car as mode of travel to work might be travelling similar distances to work as the higher income travellers, or rather, experiencing similar mobility conditions as the higher income car travellers.

The analysis of surveyed travel times across modes, as shown in Table 6-1 and Figure 6-3 above, informs the selection of appropriate travel time thresholds for calculation or evaluation of accessibility. Furthermore, the distribution of travel time enables the estimation of interaction decay parameter for accessibility computation. The next section presents the decay curves estimated for public transport.

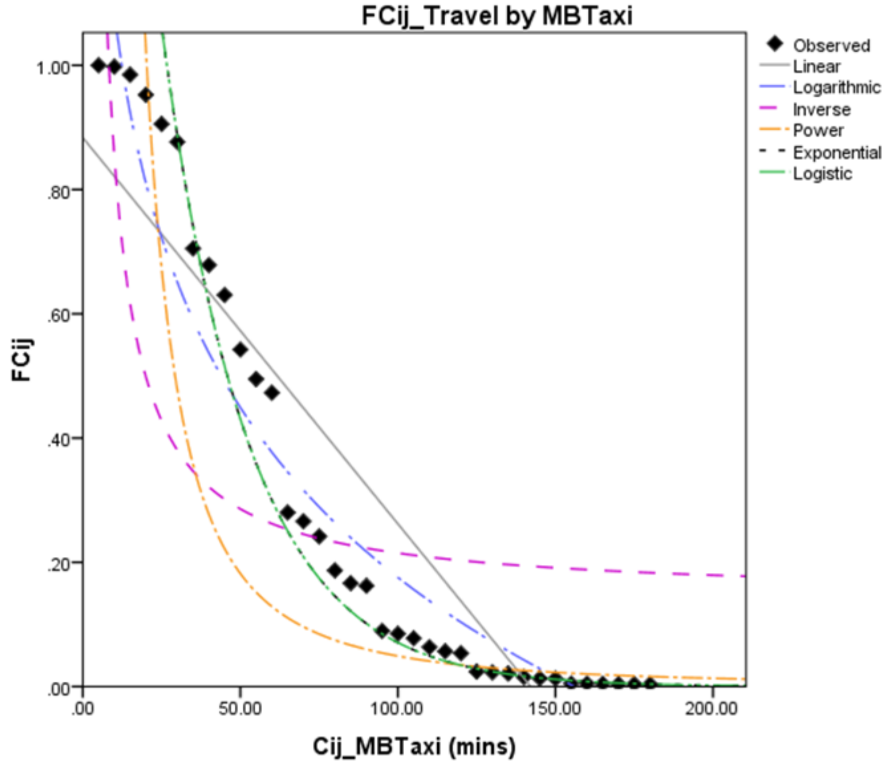
6.4.2 Decay Curves for Travel to Work by Public Transport

A transformation of the Trip Length Frequency Distributions (Figure 6-2) into relative cumulative frequencies yields a range of values from 0 to 1 (see Appendix 1A), forming a decay pattern which is read as the probabilities associated with trips within the respective time bins. These probabilities are the impedance weights applied in the gravity measures discussed in Chapter 5. The pattern of decay was fitted with seven different functions including the negative exponential and the power functions. Similar approach to estimating decay weights has been discussed in Skov-Petersen (2001).

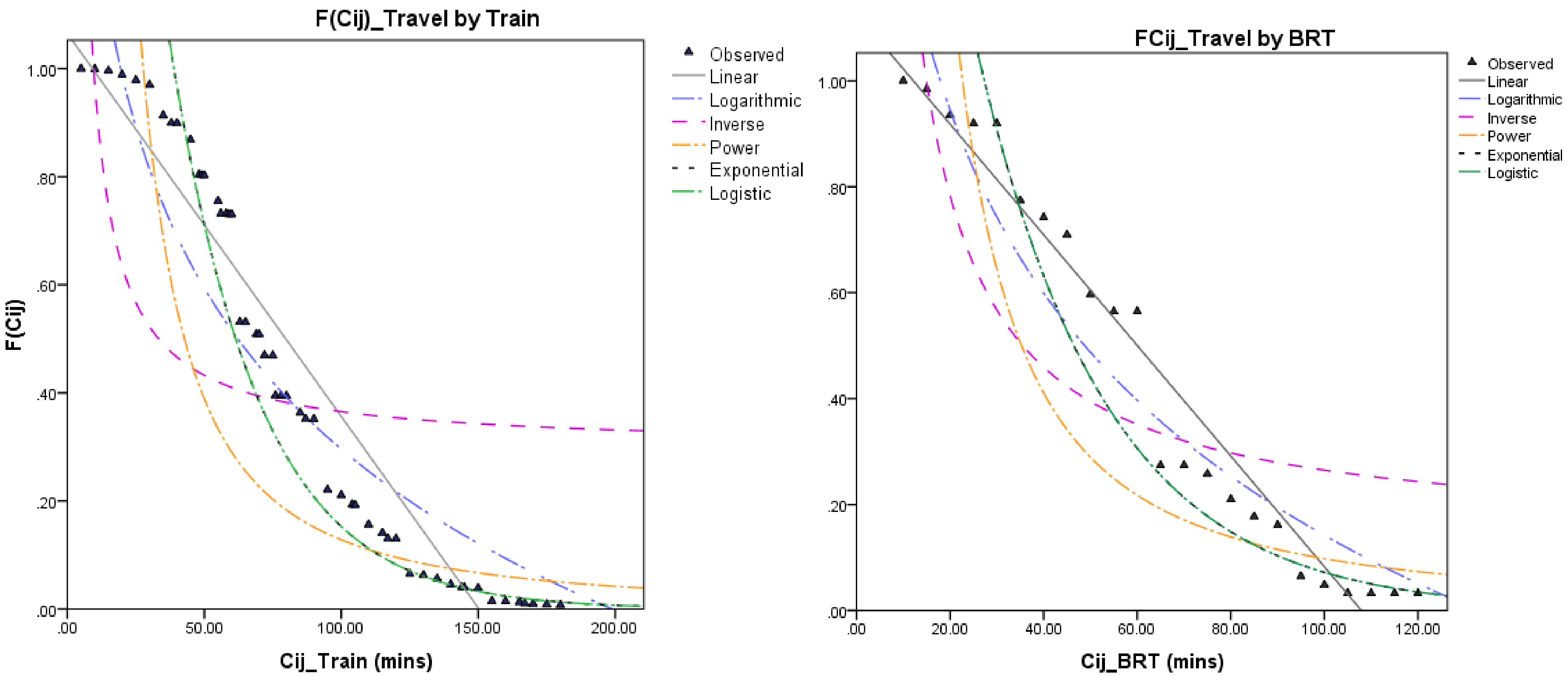
The decay curves estimated for travel to work for the public transport modes (bus, minibus, train and BRT) are shown in Figures 6-4 (a)-(d).


FCij_Travel by Bus
Observed
Linear
Logarithmic
Inverse
Power
Exponential
Logistic
F(Cij)
1.00
.80
.60
.40
.20
.00
0
50
100
150
200
250
Cij_Bus (mins)

(a)


FCij_Travel by MBTaxi
Observed
Linear
Logarithmic
Inverse
Power
Exponential
Logistic
FCij
1.00
.80
.60
.40
.20
.00
.00
50.00
100.00
150.00
200.00
Cij_MBTaxi (mins)

(b)



(c) (d)

Figure 6-4: Decay curve fitting for travel by (a) Bus (b) Minibus taxi (c) Train (d) BRT

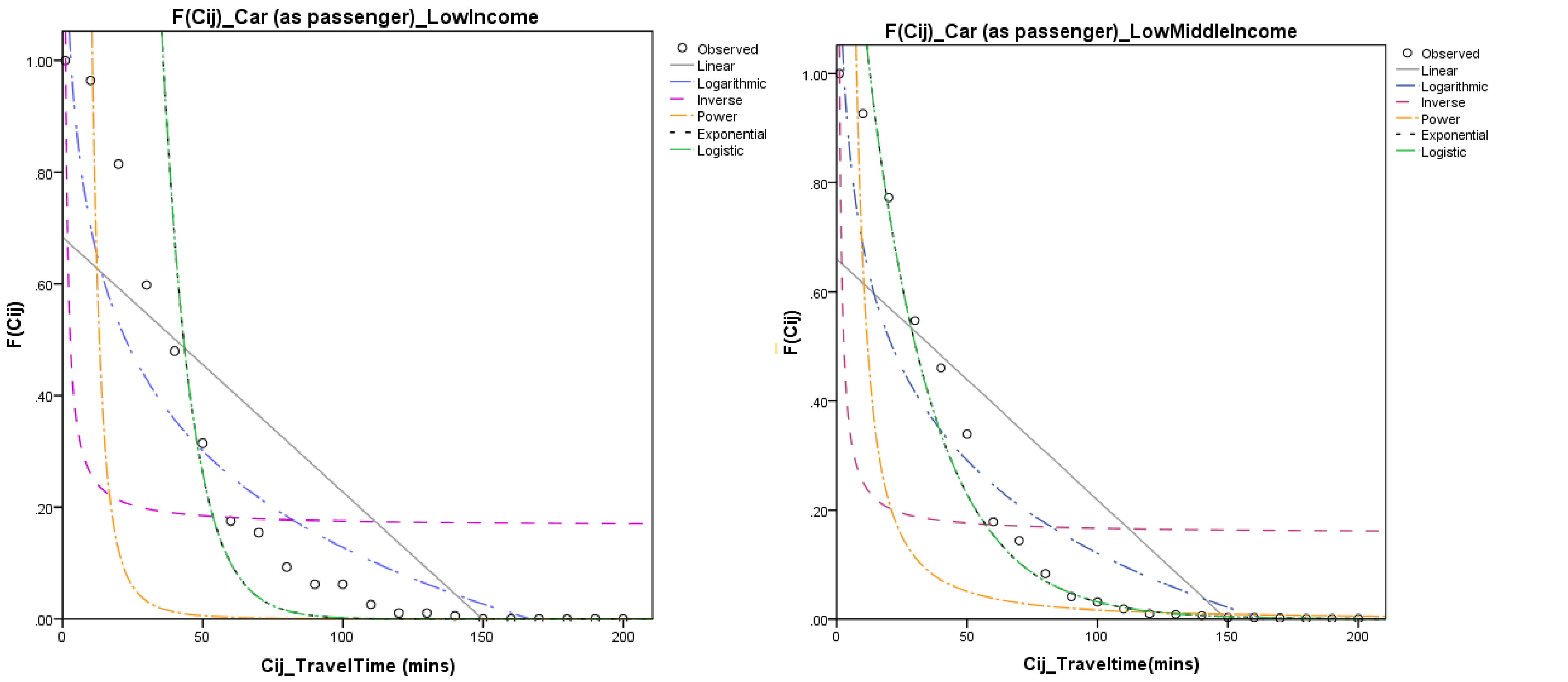
Figures 6-4 (a)–(d) show the decay curves, with travel time, C_{ij} in minutes on the horizontal axes, and $f(c_{ij})$, the decay weight associated with travel time, on the vertical axes. The estimated parameters associated with the curves, are presented in Appendix 1B.

6.4.3 Decay Curves for Travel to Work by Car

Although the focus of this study is on accessibility by public transport, it was considered vital to also carry out analysis of accessibility by car, to create some basis for comparison of accessibility between these two modes of travel. This could further indicate the level at which public transport users are disadvantaged when compared to car users, in terms of the potential accessibility to opportunities.

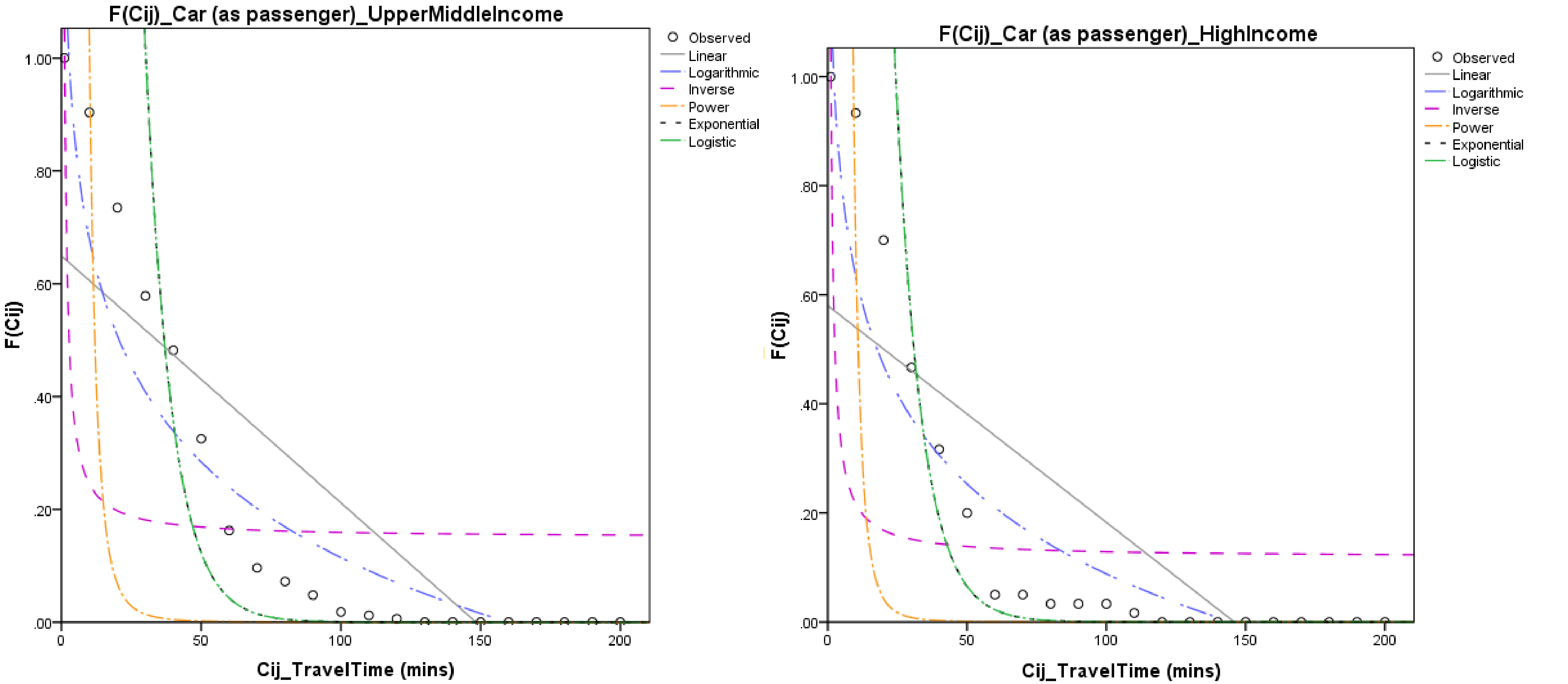
In the household travel survey data, car travel is further differentiated either as the driver or as a passenger. Car travel as passenger is taken to include services such as car-pooling or ride-sharing. Using a similar approach as for public transport (Section 6.4.2), decay curves are estimated for travel by car as (1) passenger and (2) as driver. The curves were also estimated by income group of users to further assess variability in the pattern of decay across income groups.

Figures 6-5 (a) – (d) show the decay curves for car travel as a passenger by income group, while Figures 6-6 (a) – (d) shows the curves for car travel as a driver. The associated parameters are as shown in Appendix 1C.


F(Cij)_Car (as passenger)_LowIncome
F(Cij)
1.00
.80
.60
.40
.20
.00
0
50
100
150
200
Cij_TravelTime (mins)
Observed
Linear
Logarithmic
Inverse
Power
Exponential
Logistic
F(Cij)_Car (as passenger)_LowMiddleIncome
F(Cij)
Cij_Traveltime(mins)

(a)

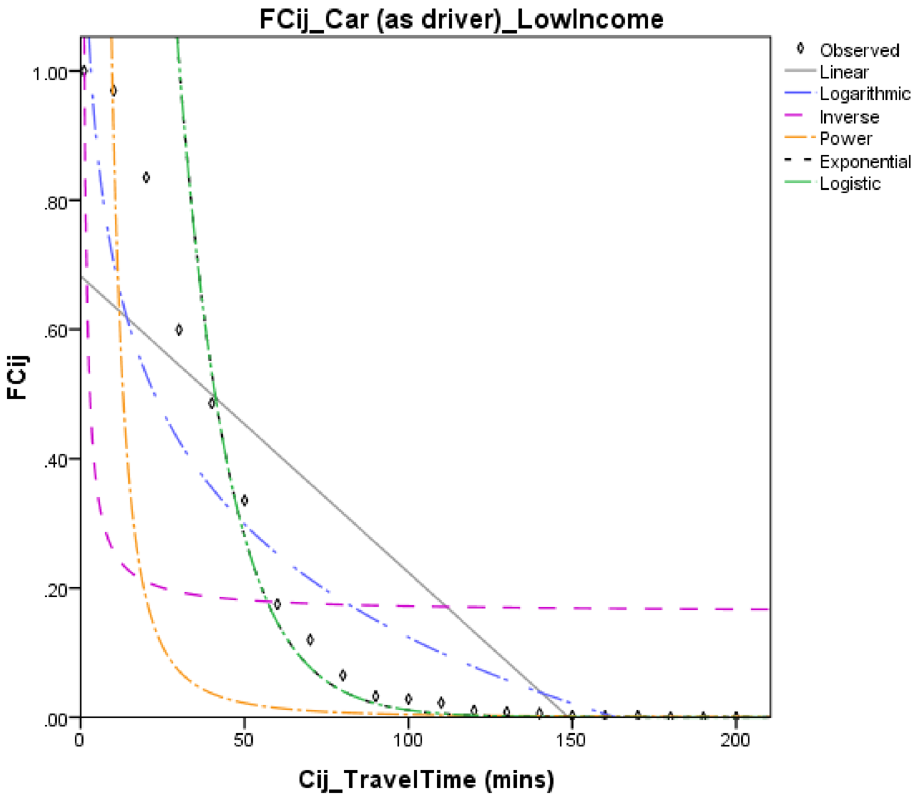
(b)



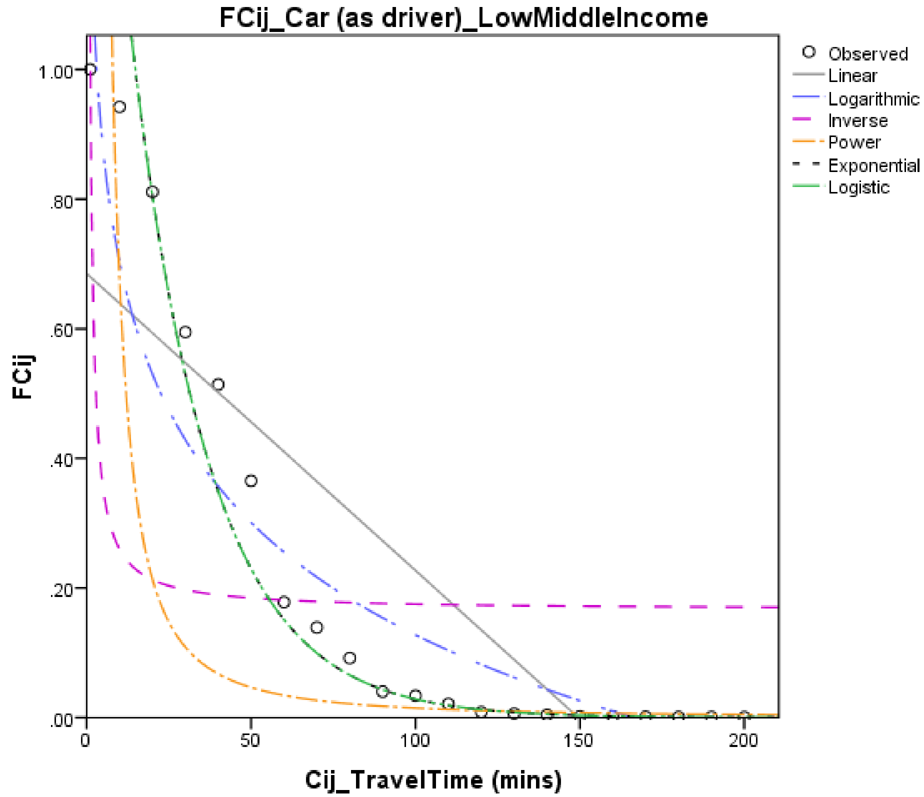
(c)

(d)

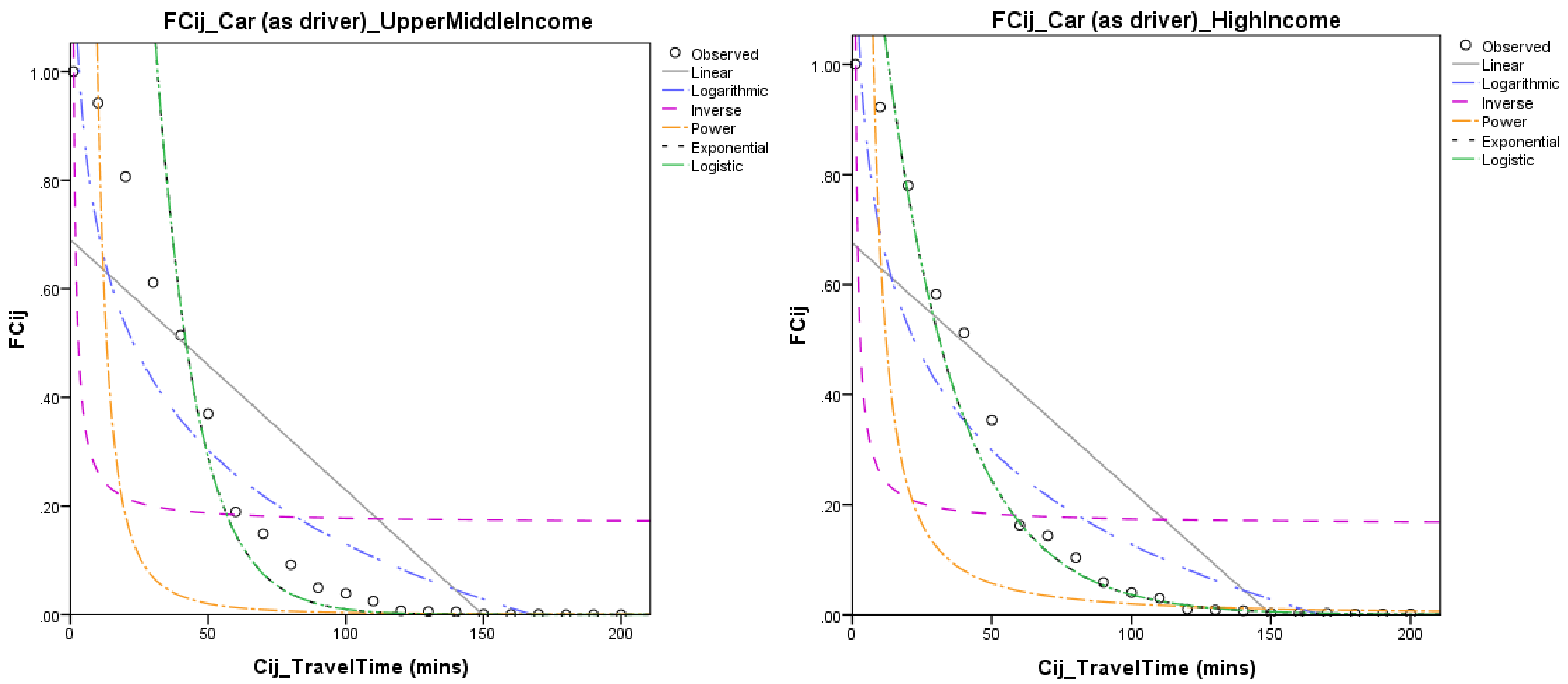
Figure 6-5: Decay curves for car travel as passenger for (a) low income (b) lower-middle income (c) upper-middle income and (d) high income travellers


FCij_Car (as driver)_LowIncome
Observed
Linear
Logarithmic
Inverse
Power
Exponential
Logistic
FCij
1.00
.80
.60
.40
.20
.00
0
50
100
150
200
Cij_TravelTime (mins)

(a)


FCij_Car (as driver)_LowMiddleIncome
Observed
Linear
Logarithmic
Inverse
Power
Exponential
Logistic
FCij
1.00
.80
.60
.40
.20
.00
0
50
100
150
200
Cij_TravelTime (mins)

(b)



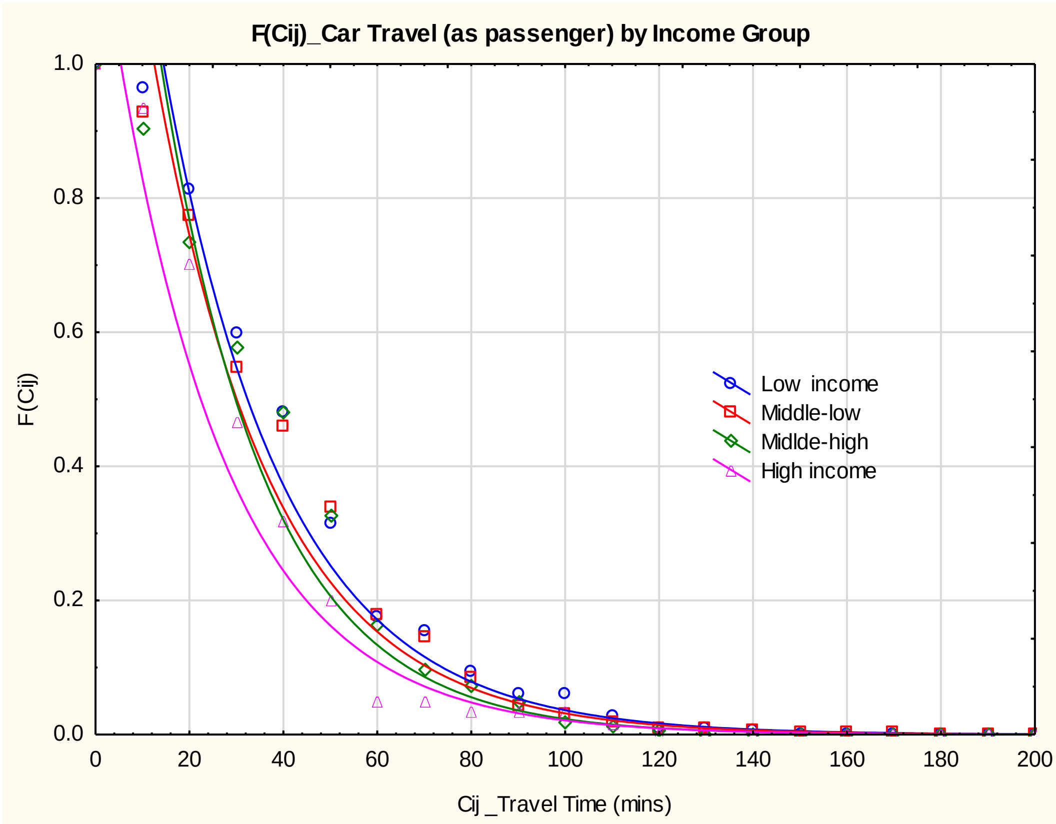
(c) (d)

Figure 6-6: Decay curves for car travel as driver for (a) low income (b) lower-middle income (c) upper-middle income and (d) high income population

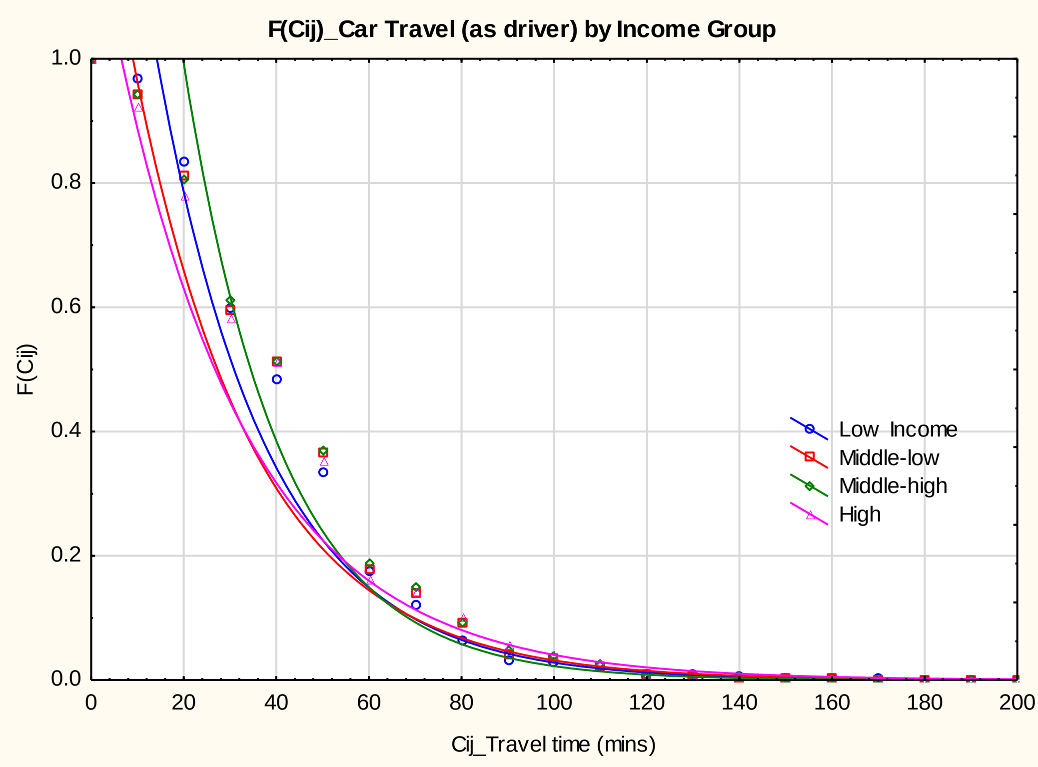
From the curves in Figures (6-5) and (6-6) above, and the associated regression parameters presented in Appendix 1C, it can be observed that the negative exponential function provides the best fit for the data. This is also the case for public transport (Figure 6-4). As such, the exponential decay functions and estimated parameters were applied in the final accessibility computation. This also conforms with some literature on gravity-based accessibility analysis (for example, Ha et al. 2011; Teunissen et al. 2015) where the exponential function has been utilised to model decay effect of distance or time.

From Appendices 1B and 1C, it is also seen that the exponential function parameters vary considerably between car travel and public transport journeys.

To further assess if any variability exists in decay behaviour across income groups, the data points for the respective income groups for car travel shown in Figures 6-5 (a)-(d) and Figures 6-6(a)-(d) above, were fitted with only the exponential function, to create two summary charts as shown below.



(a)



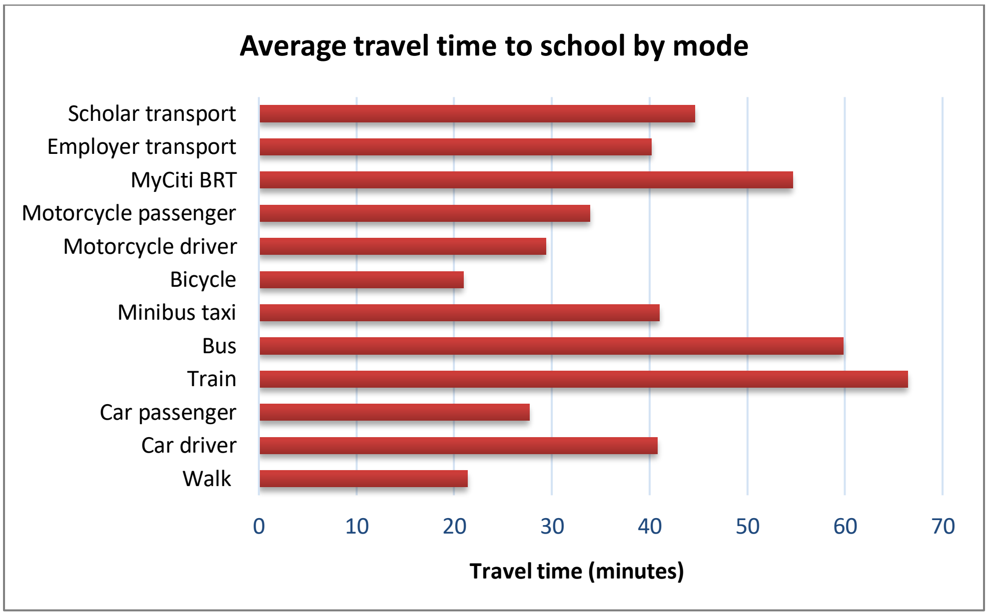
(b)

Figure 6-7: Exponential decay curves for travel to work by car as (a) passenger (b) driver

Figures 6-7 (a) and (b) show the summary of the exponential decay curves by income group for travel to work by car as (a) passenger and (b) driver. The decay curves reveal no considerable variation in decay pattern across income groups, whether travelling by car as a passenger or a driver. From Appendix 1C, the estimated parameter, β, is seen to vary closely between -0.0388 and -0.0437. This suggests that the extent to which car travel influences individuals' interaction with space does not necessarily depend on the individual's socioeconomic characteristics like the income level.

6.4.4 Decay Curves for Journey to School

While the decay curves for journey to work (as discussed in Sections 6.5.2 and 6.5.3) are applied in computing potential accessibility to jobs, accessibility to schools employs decay curves for journey to school. By filtering education trips from the household travel survey data and using similar decay estimation procedures as for travel to work, decay patterns and parameters are estimated for travel to school by car, public transport and for walking. The relatively high proportion of walk trips to school warrants the inclusion of walking in the accessibility analysis for schools. The average travel time to school across the various modes of travel, based on the Cape Town Household Travel survey is shown in Figure 6-8 below.



Source: Author's impression of the 2013 Cape Town Household Travel Survey

Figure 6-8: Average travel time to school across various modes

The Figure shows that travel to school by train and by bus takes the longest time of about 65 minutes and 60 minutes respectively. As the case for travel to work, these values are also considered to include access and egress time, to and from the entry and exit points of the public transport system. Walk trips to school take an average of about 20 minutes.

The decay function selected for travel to school is the exponential function. Similar procedures as discussed in Sections 6.4.2 and 6.4.3, were employed in estimating the curve parameters. Public transport, in this case, is taken as the combination of all modes of public transport. Thus, travel times recorded for school trips by all four modes of public transport were considered in the curve estimation. The exponential decay curves for travel to school by car, public transport, and walking are shown in Figure 6-9.

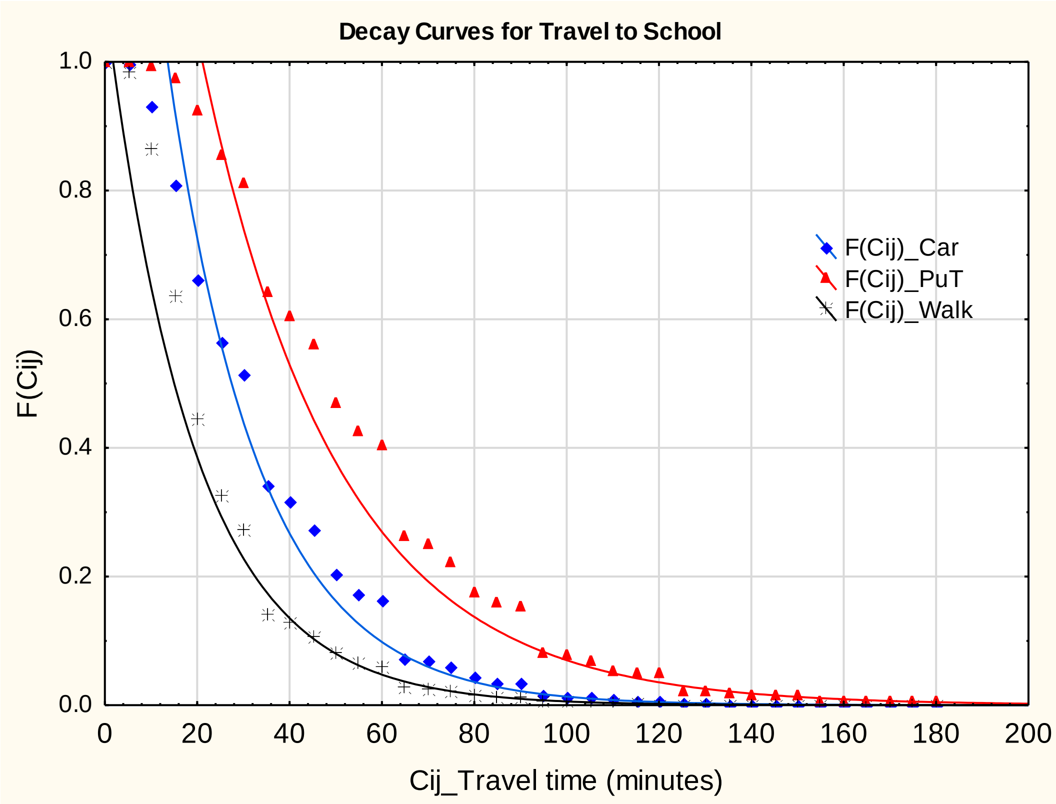


Figure 6-9: Exponential decay curves for travel to school by car, public transport and walking

The decay curves in Figure 6-9 above are given by Equations (6-2) – (6-4) below:

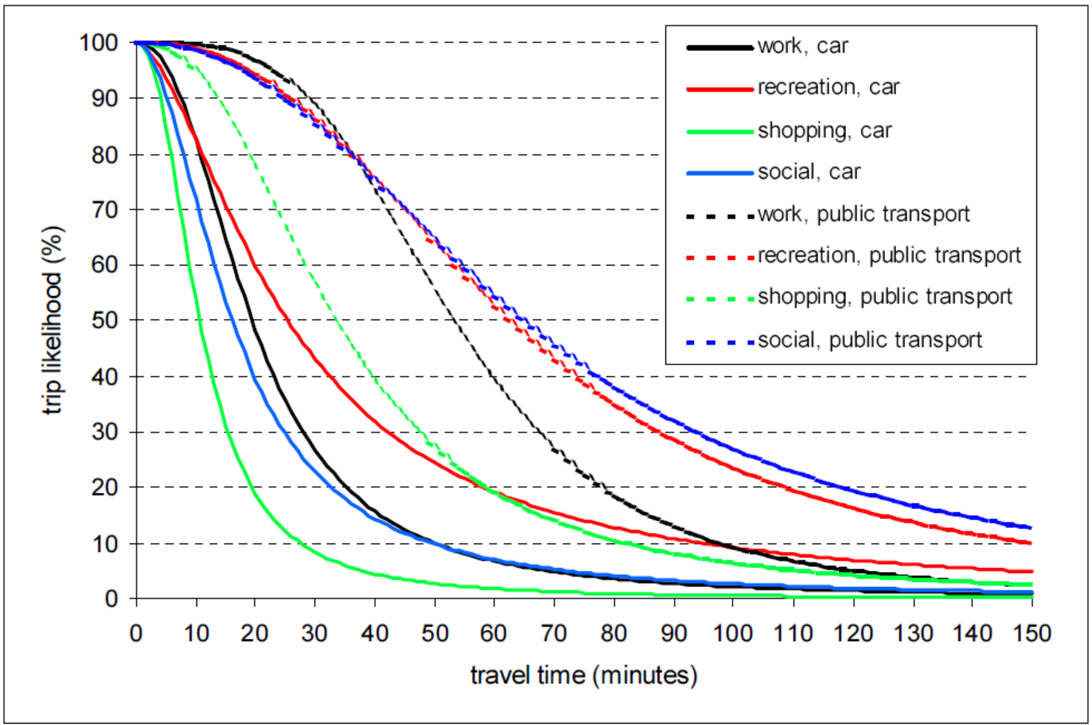
$$F(C_{ij})_{\mathrm{Car|school}} = 1.9741\exp^{-0.0502(C_{ij})} \tag{6-2}$$

$$F(C_{ij})_{\mathrm{PuT|school}} = 2.0408\ \exp^{-0.0337(C_{ij})} \tag{6-3}$$

$$F(C_{ij})_{\mathrm{Walk|school}} = 1.0986\ \exp^{-0.0523(C_{ij})} \tag{6-4}$$

The functions are of the form $f(c_{ij}) = \alpha e^{-\beta(C_{ij})}$ where α is a constant, and β is a decay parameter. Since the decay function is a probabilistic weight established to have a maximum value of 1 and a minimum value of 0, the value of the constant α becomes less significant, as the shape of the decay curve is guided by the value of β. The parameters of the functions above show that the sensitivity of the decay factor to travel time is highest for walking and lowest for public transport. In other words, for walking, there is a lesser tendency to travel for longer, compared to travel by car or public transport.

Comparing the decay curves estimated in this study to those of similar studies from literature (for example, Geurs & Ritsema van Eck 2001), shown in Figure 6-10 below, reveals similar differences in decay patterns between travel by car and by public transport. Although the study by Geurs & Ritsema van Eck (2001) utilised the log-logistic impedance functions in their estimates.



Source: Geurs & Ritsema van Eck (2001)

Figure 6-10: Decay functions by mode and trip purpose from similar studies

6.5 Measuring Travel Cost

Travel cost in this study is defined in terms of travel distance and time (for all modes of travel analysed), and in terms of out-of-pocket cost (for the case of public transport). The next subsections discuss the computation approach adopted in this study.

6.5.1 Public Transport Travel Time

While measurement of travel time for the case of car and walking is quite straightforward, public transport present more complexity as there are various time components within a single trip. A typical journey by public transport starts with walking time from the journey origin (modelled as zone centroids in this study) to the access point of the mode (bus stops/train stations or road junctions in case of minibus), a waiting time for the arrival and departure of the vehicle, boarding time, a ride time on the vehicle, and finally ending with a walk from the egress point of the last mode to the final destination. This is depicted in Figure (6-11) below.

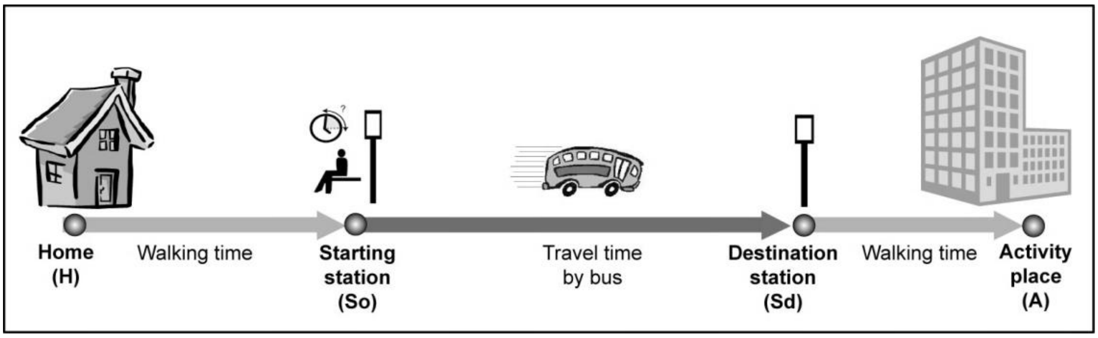


Figure 6-11: Schematic representation of public transport journey components

Figure 6-11 illustrates movement from home to workplace by a bus, whereby the first component of the journey (or the access component) involves walking time to the bus stop, and the last component is the walking time from the last bus stop to the final destination. In the case where more than one vehicle of the same mode or where more than one mode is required for the journey, there is also an egress from the first mode, followed by a transfer to the next mode. Each of these journey components takes different time and are usually weighted differently by trip makers. The total travel time for public transport can therefore be represented generally as follows:

$$T_{ij}^{\mathrm{PT}} = T_{ij(\mathrm{V})} + T_{ij(\mathrm{Wk})} + T_{ij(\mathrm{Wt})} + T_{ij(\mathrm{B})} \tag{6-5}$$

with:

$$T_{ij(V)} = \sum_{j} \frac{d_{ij(b)}}{V_{ij}} \tag{6-6}$$

where T_{ij}^{PT} is the public transport total travel time from origin i to destination j; $T_{ij(V)}$ is the total in-vehicle time for the mode(s) used from i to j; $T_{ij(\mathrm{Wk})}$ is the total walking time component of the journey from i to j. That is; access time, egress time and transfer time if applicable; $T_{ij(\mathrm{Wt})}$ represents the total of waiting times at all stops between i and j; $T_{ij(B)}$ is the total of boarding and alighting times from all stops between i and j; $d_{ij(b)}$ is the distance travelled by the mode(s) used; V_{ij} is the average travel speed of travel by the mode(s)

In this study, the travel time by public transport is calculated from trip origin TAZ centroid to the destination TAZ centroid or activity location and is made up of the various time components. Travel time from the centroid to the first transit stop as well as from the last stop to the destination centroid is modelled on the street network, within the entire multimodal network dataset (as discussed in Chapter 7) using an assumed average walking speed of 5km/hr. In-vehicle travel time is calculated on the routes of the modes, using the average travel speed of the various links of each mode. Transfer time is also recognised within the multimodal system and is modelled on the hub connectors, which link the separate network of each public transport mode to the intermodal terminal (hub) serving all the modes. The prevalence of transfers is one of the key elements that adds to the complexity of modelling multimodal public transport systems. As pointed out by Guo (2008), this complexity is reflected in two aspects; the diversity of transfer types and the complexity of transfer decisions. Although no data on transfer time were available for this study, transfers were modelled using an assumed conservative time of two minutes and defined as connector link impedance. For example, a transfer from a minibus system to the train only happens at the intermodal terminal through a connector link generated from the minibus line to the terminal and from the terminal to the train line. Further details of the network modelling procedures are discussed in Chapter 7.

Travel Time versus Generalised Cost in Impedance Functions

The representation of travel cost in impedance function in most accessibility measures has usually been in terms of time/distance (Gulhan *et al.*, 2014) or a more inclusive generalised cost (Ford et al. 2015; Koopmans *et al.*, 2013) of travel from origin to destination. The generalised cost takes into consideration both the time component and the monetary component of the journey. The time component being the summation of all the time aspects/segments of the journey (for example, network access time, waiting time at stops, boarding/alighting time, in-vehicle travel time), while the monetary component is a combination of the out-of-pocket cost for the journey as well as the monetary value of time spent travelling. The establishment of a proper generalised cost function, therefore, requires information on these time components. In this study, however, travel cost from origin to destination have been defined in terms of travel time rather than the generalised cost due to the following reasons;

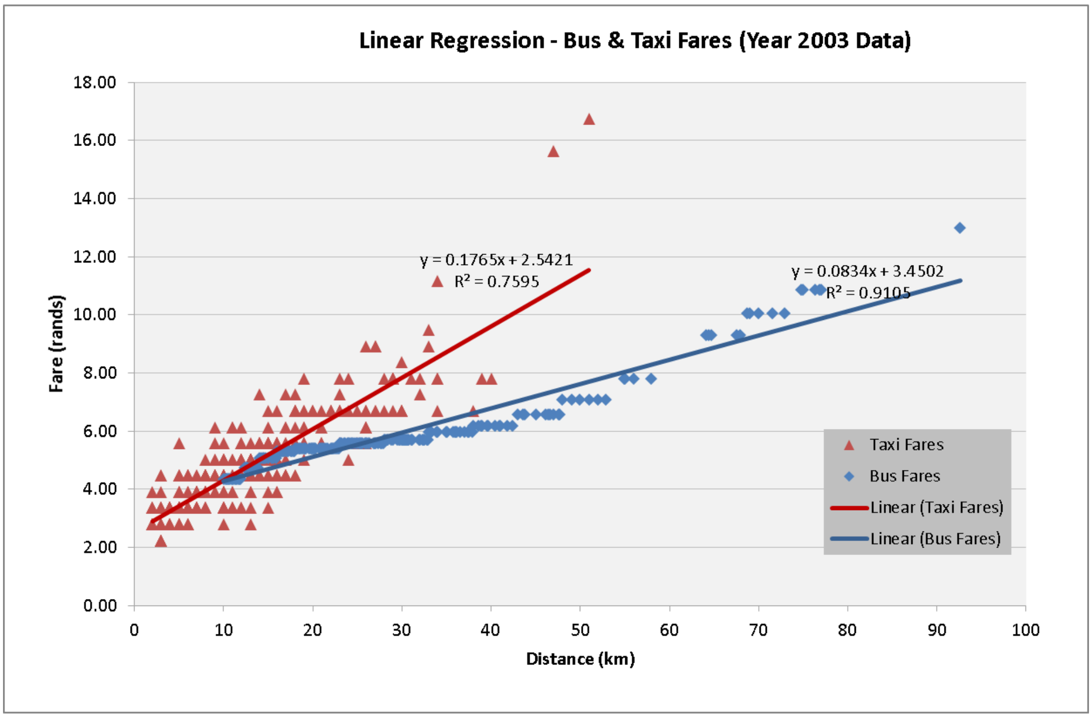
I. Lack of reliable data on an individual's valuation of time and other qualitative features of the transport system, such as reliability and safety.
II. In location-based potential accessibility measures, of interest is not just the "cost" in itself, but the "impact" of cost on interaction potential. In other words, what is of interest is establishing the weight $f(C_{ij})$ to be attributed to opportunities at different levels of separation from a given location.

III. The establishment of the weight with respect to spatial interaction, $f(C_{ij})$, can only be based on what can be measured in space. Since the generalised cost also include non-spatial elements, it is a rather difficult endeavour translating those non-spatial elements to a spatial separation weight. In other words, it is almost impractical to establish decay behaviour using a combination of variables such as travel time and value of time within a single function describing decay pattern. Generalised cost also requires having sufficient data that captures individuals' valuation of time. For this study, however, such data are not available, hence impedance functions have been based solely on time.

Based on these reasons highlighted above, impedance functions in this study have been established based on the available travel time data from the Cape Town Household Travel survey. Nevertheless, with future availability of more robust data, generalised cost functions can be established and utilised in estimating decay behaviour.

6.5.2 Monetary (Out-of-pocket) Travel Cost Functions

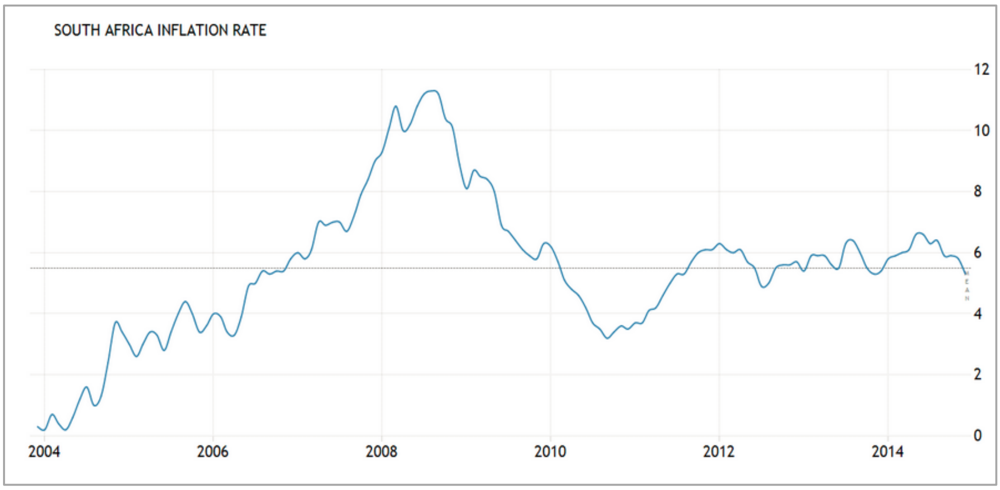
The job potential accessibility index developed in this study, which considers the affordability component of transport, requires the computation of potential journey costs for trip makers, based on public transport pricing system in the city of Cape Town. Public transport in Cape Town operates on a distance-based pricing system for all modes where users pay specific amounts depending on the distance band travelled. The relationship of fare versus distance was established for the bus and minibus modes using simple linear regression of a combination of empirical survey data of actual fares paid by users of the various modes for origin-destination pairs of pre-established distance. The regression plot of the 2003 data of fares vs distance for the regular bus and minibus (paratransit) modes are shown in Figure 6-12 below. The linear fare-distance relationship for the other modes (BRT and train) has been derived from the pre-established price per distance band for these modes.



Data Source: City of Cape Town

Figure 6-12: Bus and Paratransit fares for the year 2003

The plots in Figure 6-12 show that a linear relationship exist between fares and distance for the two modes considered in the survey, with the bus mode having a better regression coefficient of determination, R^2 of 0.91 compared to the minibus (paratransit) with an R^2 of 0.75. Due to lack of reliable data on fares for the year 2013 (for which this study is based), a linear adjustment was applied on the regression function estimated for the year 2003. The adjustment to year 2013 was carried out by applying a 10-year average inflation rate of 5.5% for the period 2004-2014. The adjustment was applied to the constant (base tariff) as well as the coefficient in the linear equations shown in Figure 6-12. The historical trend of annual inflation rate for South Africa for this period is shown in Figure 6-13.



Source: https://tradingeconomics.com/south-africa/inflation-cpi

Figure 6-13: 10-year Inflation trend in South Africa

The resultant inflation-adjusted linear relationships of fare vs distance-travelled for the various modes of public transport is represented in Equations (6-7)-(6-10) below:

$$y_{\text{Bus}} = 5.89 + 0.142x \tag{6-7}$$

$$y_{\text{Minibus}} = 5.50 + 0.333x \tag{6-8}$$

$$y_{\text{Train}} = 5.30 + 0.047x \tag{6-9}$$

$$y_{\text{BRT}} = 6.83 + 0.222x \tag{6-10}$$

The plots of the above equations are shown in Figure 6-14 below, with the y – axis representing the user fare in South African Rands (ZAR), and x – axis is the distance travelled in Kilometres.

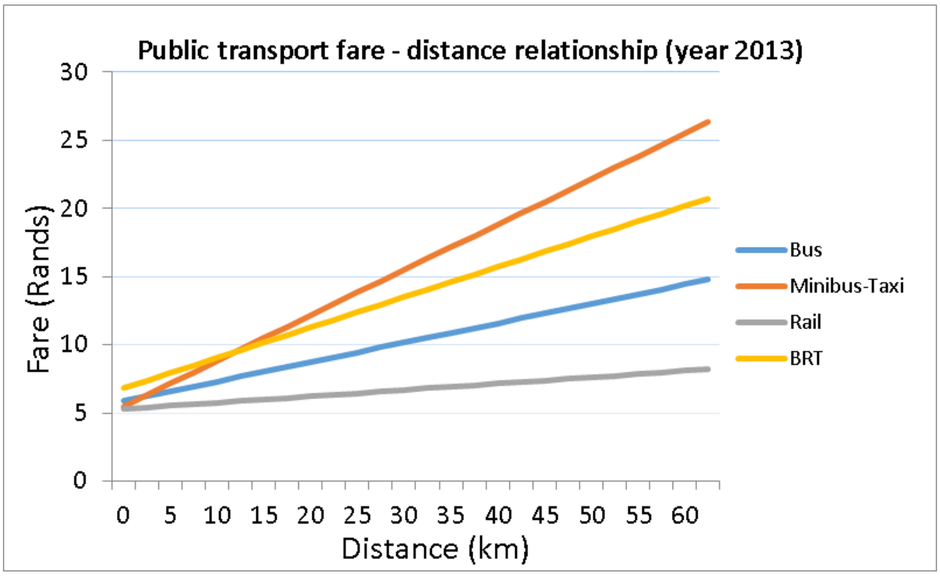


Figure 6-14: Public transport fare-distance relationship for the year 2013 (inflation-adjusted from 2003 data)

The graphs in Figure 6-14 show that for travel between 0 - 12km, the BRT (which is the most recently introduced mode in Cape Town) is the most expensive option while the minibus taxi (paratransit) becomes the most expensive option of all the modes for distances beyond 12km. Among all the modes, the train is the cheapest option and the least-sensitive to distance travelled.

In developing the network models (for accessibility calculation), the fare-distance relationships defined by Equations (6-7) – (6-10) were applied to calculate the 'potential' monetary cost associated with every origin-destination pair. The monetary cost is used to establish affordable potential accessibility as earlier discussed in Chapter 5, Section (5.5.2).

6.6 Chapter Conclusion

The distance (or time) decay rule demonstrates that the interaction effect between physical or socioeconomic entities declines along with the distance (or time) between them (Wang, 2015). This chapter discussed the estimation of the decay curves for travel by the different modes of transport, starting with a brief theoretical background on the statistics behind the estimation, and then working through to data description and processing, and with the final sections detailing the curve fitting for travel to work and for schools. A few points must, however, be noted.

The impedance function in this study is considered as probabilistic weights associated with travel time between any given origin and destination points. In other words, the weights are characteristics of only travel time, and it does not depend on any other features or attributes of the origin or destination locations. This is considered sufficient for the case of spatial accessibility investigation such as this study. In some other cases where decay curves are applied, for example, in trip distribution analyses, decays are often estimated for specific origin-destination pair. In such cases, the flows between individual O-D pairs are often employed in establishing tailor-made functions and/or parameters for decay behaviour. Such estimation is however only possible where there is sufficient data of flows between individual origin-destination pairs.

It must also be recognised that the estimation of decay behaviour is never an exact science, but statistical estimation process based on empirical data. This means that parameter values can never be accurate. As Skov-Petersen (2001) had pointed out, decay parameters are estimated as a best-fit to the current situation, represented by an empirical data-set. As such, the level of reliability in the estimates is highly dependent on the level of reliability of the base data utilised. Simply put, estimates are only as reliable as the data behind it.

While the decay behaviour in this study has been estimated based on travel time information, it is recognised that estimates of interaction decay behaviour and associated parameters are not only a function of the available transport system, but also of the general spatial structure including the local topography among others (Fotheringham 1981;Skov-Petersen 2001). However, consideration of other spatial factors (than the usual travel cost) in modelling interaction decay behaviour comes with some methodological complexities. For example, the actual prediction of interaction behaviour would demand knowledge of how every traveller value every destination from every origin. This would require knowledge of all the attributes that contribute to a person's valuation of destinations as well as quantification of those attributes in interpretable numbers. In reality, it is almost impossible to have such information for every trip maker or to model every trip maker's choice and preference. For an aggregated location-based potential accessibility analysis like this study, it is not feasible to consider such factors. Furthermore, since "potential" is evaluated as a function of spatial separation in time, and not based on actual travel decisions or utilities associated with destinations, it will be unnecessary to consider such attributes that characterise individual's choices. Utility-based measures of accessibility (which is not the subject of this study) have been developed by researchers to capture those individuals' decisions and choices. Such measures are, however, heavily dependent on rich disaggregate datasets at the person level, which was not available for this research.

Finally, it must be emphasized that parameter values estimated are sensitive to the units of the empirical travel cost data. Hence, when comparing decay parameters arising from different case studies or sources, care should be taken to ensure that the units of the empirical data are, at the least, the same or comparable. Even in situations where the same decay function is used, estimated parameters based on empirical data measures in time (say, minutes) or distance (say, miles or kilometres), will be expected to vary considerably.

The next chapter discusses the third part of the research methodology, focusing on network model development in a GIS environment.

Chapter 7

Network Model Development in GIS

"There are several paths one can take, but not every path is open to you." – Claire Bloom, actress

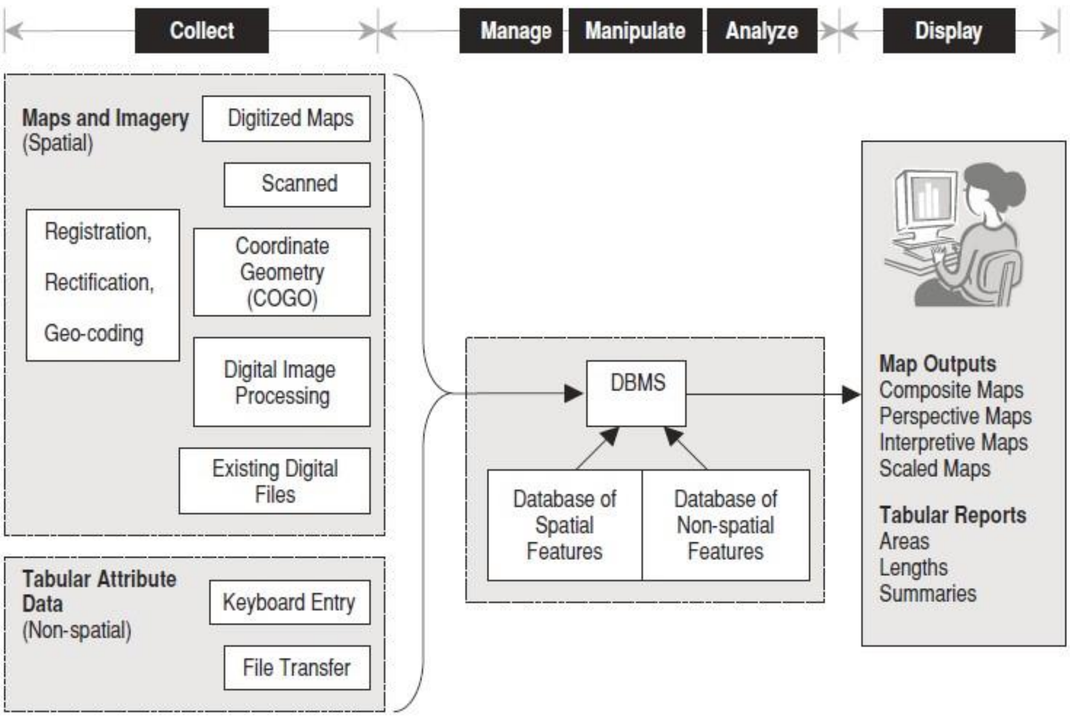
7.1 Introduction

Chapters 5 and 6 discussed the measures of accessibility, travel cost, and the estimation of decay functions. The computation of travel cost relies on having, at least, a network model of the transport system. This chapter discusses the GIS modelling methodology and techniques developed in building network data models using the available data of Cape Town's transport system. In this study, accessibility is modelled for various travel scenarios for the various opportunities considered. The four scenarios of accessibility investigated include (1) job accessibility by car (2) job accessibility by the multimodal public transport system (3) school accessibility by walking, car, and each (separate) mode of public transport (4) healthcare accessibility car. These accessibility scenarios require different network models for their computation. Thus, the network models developed include; car-based network model, unimodal public transport network model and a multimodal public transport network model. A car-based network model considers the entire road network and models travel by car, while a unimodal public transport network model considers the routes and stops for the individual mode of public transport. The multi-modal public transport network model then considers the routes and stops of all the public transport modes (bus, minibus, BRT and train) within one model that accounts for the possibility of transfers within and between the modes. For public transport, walking is considered as an access and egress mode, and pedestrian movement is assumed to use the street network.

The various network models are built using the ArcGIS Network Analyst. The development of the network models (also referred to as Network Datasets) involves several geoprocessing tasks such as; preparation of the network elements (links and stops) of the modes to be modelled, setting connectivity topology for the network elements, and setting up impedance evaluators such as travel time, distance or monetary cost. The remaining parts of the chapter discuss GIS modelling procedures.

7.2 Overview of Geographic Information Systems

Geographic Information Systems (GIS) have provided the capability as well as the flexibility to capture the dynamic nature of data that vary across space and time (Sinha and Labi, 2007). It can provide useful information on geographic elements or features, such as; their location, characteristics or attributes, logical and geometric relationships among features, and spatial interdependencies. This is usually achieved using GIS components such as drafting, polygon processing, network analysis, spatial querying and application development tools such as programming libraries (Sinha and Labi, 2007). A typical GIS, as depicted in Figure 7-1 below, can be broken into three key components: (1) the data, (2) the database management system and (3) the visualisation interface.



Source: Sinha and Labi (2007)

Figure 7-1: Typical components of a GIS

The data can either be spatial or non-spatial, while the database management system (DBMS) is the platform that enables storage and manipulation of the data. It also enables the definition of relationships between data of various kinds. The development of network models of transport systems also occurs within the database management system.

7.3 Modelling Scope and Limitations

Considering that models are a simplified representation or abstraction of real-world systems (Ortuzar and Willumsen, 2011), having a network model that correctly represents or simulates real journey scenarios is critical to the overall accuracy and reliability of an accessibility analysis. The development of a transport system model involves identifying all the components that make up the system and how they all function in themselves, and about each other. Unlike travel by car or walking, public transport systems have more complex operations, and as such, pose more challenges in terms of modelling.

The development of a comprehensive multimodal public transport network model is dependent on the availability of reliable data of both the infrastructure and services for the component modes, as well as a tool capable of modelling every aspect of the operations. In this study, model development was carried out within the geoprocessing capability limit of the ArcGIS Software and its Network Analyst extension for modelling transportation systems. In line with the scope of the study and the available data, the multimodal public transport network model developed only considers the routes and stops and does not take into account the actual service schedules for any of the component modes. The assumptions made in line with this are;

1. *Potential accessibility of a zone to any destination is based on the infrastructure presence. That is the availability of a route or stop, irrespective of the frequency of service.*
2. *The Potential accessibility indicators developed are purely static, and do not consider the temporal dimension of accessibility. Thus, schedules or frequency of operations are less relevant for the network models.*

Further, considering that the multimodal network model is intended to combine both the paratransit (which operates without schedules) and the scheduled modes (bus, BRT and rail), only the network of routes and stops can be represented within such model. A separate schedule-aware network model is, however, developed to enable computation of schedule-based accessibility by BRT using the only available General Transit Feed Specification (GTFS) data of the BRT system of Cape Town. At the time of this research, the BRT is the only public transport mode with GTFS data available among all the public transport modes in Cape Town.

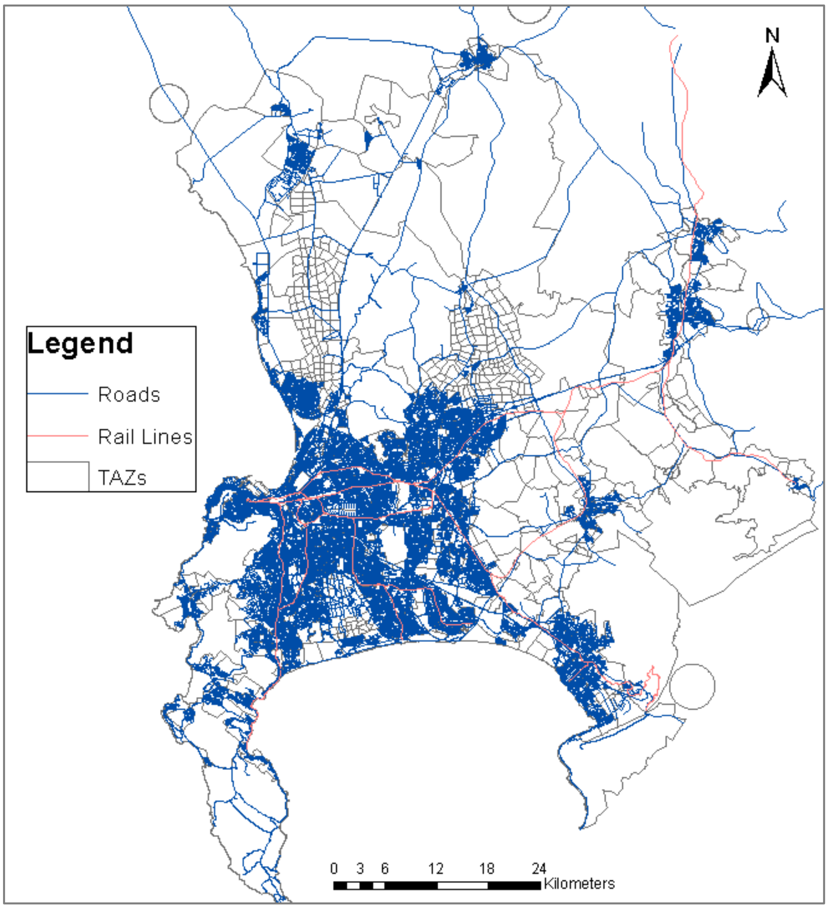
7.4 Data - Network Elements

As mentioned in the introductory section of this chapter, network models are developed for car travel as well as for the unimodal and multimodal public transport system. The network data for developing the various network models (or network datasets) include:

- The road network
- The public transport route network of each mode (bus, minibus, BRT, train)
- Stops (bus stops, train stations, multimodal terminals)

7.4.1 Road Network

The road network is the central element of the network model, as it provides the base infrastructure on which the various transport modes operate. A road can serve a single or combination of modes. The road network is also utilised in modelling walking as an access/egress mode for the public transport system, and for modelling car travel. The road network data utilised for this study was obtained from the City of Cape Town as a shapefile of polylines. It is represented in the GIS model as a combination of links (arcs) interconnected at vertices or endpoints. Each link in the network contains attributes such as link length, class of road, permissible travel speed, road name, suburb, among others. Figure 7-2 shows the entire road network of the study area.

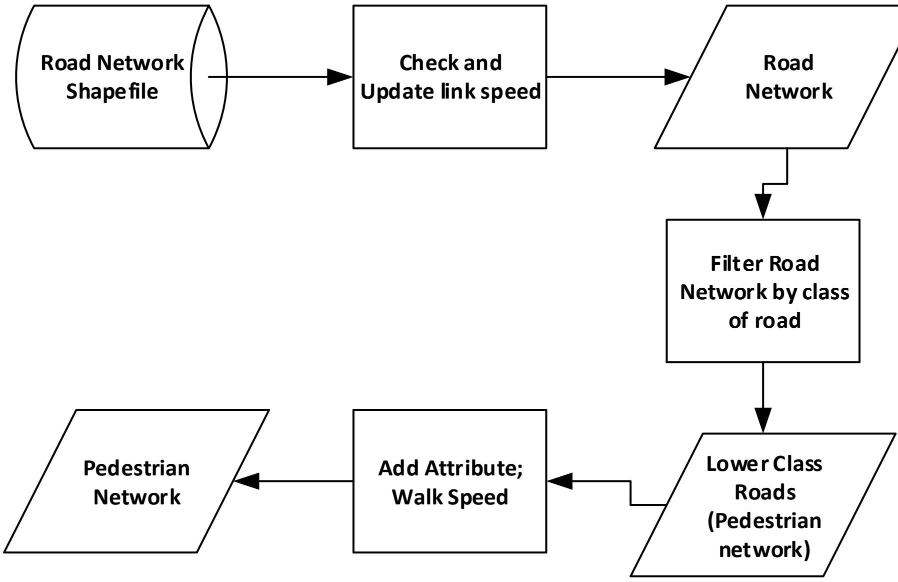


Source: Author's elaboration of the 2013 data of City of Cape Town

Figure 7-2: Road network of Cape Town and surrounding Winelands

The entire road network shown in Figure 7-2 above comprises about 105,000 link segments, with a total length of about 13,200km. The map further shows that Cape Town has a relatively dense road network, especially within the urban areas.

In utilising the road network data to model car or pedestrian movement, a set of fundamental editing tasks are first carried out on the network. For example, in creating the pedestrian network, all roads of higher hierarchies such as freeways and urban highways are eliminated as they are considered not suitable for pedestrian movements. An assumed walking speed that enables calculation of walking time is defined as an attribute in the pedestrian network. As mentioned in Chapter 5, the average walking speed for this study is taken to be 5km/h. The flowchart for editing the road network and creating a pedestrian network is shown in Figure 7-3.



Source: Author

Figure 7-3: Workflow for creating a pedestrian network from the road network

In Figure 7-3 above, the road network shapefile represents the base network obtained for the study. The first stage of editing involves a check/confirmation that every link feature has, at least, a permissible speed defined in the attribute table. Although the majority of the links already have the speed defined, there were, nevertheless, a few links with undefined speed. Such links were updated with speed values based on the class of the road and the speed indicated for such class. For example, every link classified as 'secondary', is updated with a permissible speed of 60km/hr, which is the speed defined for similar links in the network. Primary/Arterial roads are updated with a speed of 120km/hr. The resultant road network from the edits is suitable for modelling car movement. In creating the pedestrian network, the road network undergoes additional edits, which involves spatial query to filter out higher class roads which are not suitable for pedestrian movement. The filtered network is then updated with walking speed, to create a network suitable for modelling pedestrian movement either as a mode on its own or as an access/egress mode for use within a multimodal public transport network model.

7.4.2 Public Transport Network and Stops

The various public transport modes and their respective networks have earlier been discussed in Chapter 4 of this thesis, which presented the case study description. The public transport network data was obtained in the form of polyline shapefiles, with every link in the network described by the particular mode it serves. Each object (link) ID is a polyline digitised from origin to destination and showing various characteristics of the route such as mode, average speed and link length, which are the key attributes utilised in the model. The stops/stations of all the modes were also obtained as point shapefiles with location coordinates.

The multimodal public transport network model is built-up from all four modes (regular bus, minibus taxi, BRT and train). In the development of the network model, several GIS geoprocessing tasks are carried out on each of the network element. The remaining sections of this chapter discuss the data preparation and the development of the network data models within ArcGIS.

7.5 Building a Network Dataset in ArcGIS

In ArcGIS, transportation systems are modelled using Network Datasets (ESRI, 2006). A distinction must be made here between the terms, 'data of network' and 'Network Dataset'. Network Dataset is developed using the various individual network elements made up of polylines (routes) and points (stops) shapefiles of the respective modes, with all connectivity topology and impedance characteristics defined. The development of the network data models, otherwise known as the Network Dataset (ND) involves three major stages: (1) the preparation of the network data elements (2) defining and setting up of connectivity rules and topology for various network elements and (3) defining impedance evaluators in the network elements. The various Network Datasets created in this study include:

i. *Network Dataset for car travel* – This models journey by car from origin to destination TAZs centroids, based on the least-cost path algorithm within the entire road network. This network dataset enables computation of accessibility by car, for the case of jobs and schools.
ii. *Network Dataset for walking* – Models walking as a mode and is applied in calculating accessibility to schools by walking.
iii. *Network Dataset for individual public transport mode* – Models journeys by each mode of public transport and is applied in calculating accessibility (for the case of schools) by these modes.
iv. *Network dataset for multimodal public transport system* – Combines the individual network of all four public transport modes (bus, minibus, BRT, train), to create a multimodal network that models journeys from origin to destination TAZ centroids, taking into consideration pedestrian access and egress, as well as transfers within the same mode or between different modes. While intra-modal transfers (say, from one bus line to another) are modelled on regular stops or stations, intermodal transfers are modelled on the multimodal

transport hubs or terminals. This Network Dataset was applied in calculating accessibility to jobs enabled by the multimodal public transport system.

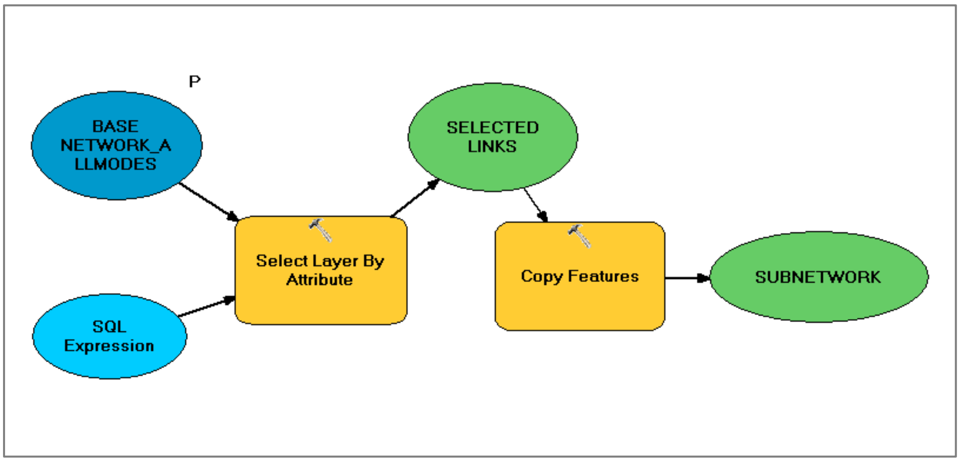
v. *Network dataset for schedule-based BRT system* – Utilised the General Transit Feed Specification (GTFS) data available for the BRT system to model accessibility by time-of-day. More details of the GTFS data structure is discussed in Section (7.6).

The network models for car travel and walking are straightforward to develop, as they each utilise only one network element, which is the road network or pedestrian street network. For public transport, however, this is more complex, as it combines several network elements, such as routes and stops of one or more modes within the network models. The next section discusses the procedure developed for preparing network elements for public transport.

7.5.1 Base data preparation

The Network Datasets described above are developed within an ArcGIS File Geodatabase which combines the various network elements. The procedures for setting up the various network elements within the geodatabase are summarised below:

i. Create new file geodatabases within ArcGIS platform
ii. Import GIS data of the road network and public transport network.
iii. Create individual mode network from the base public transport network using SQL filtering as shown in Figure 7-4 below.



Source: Author

Figure 7-4: Base network separation

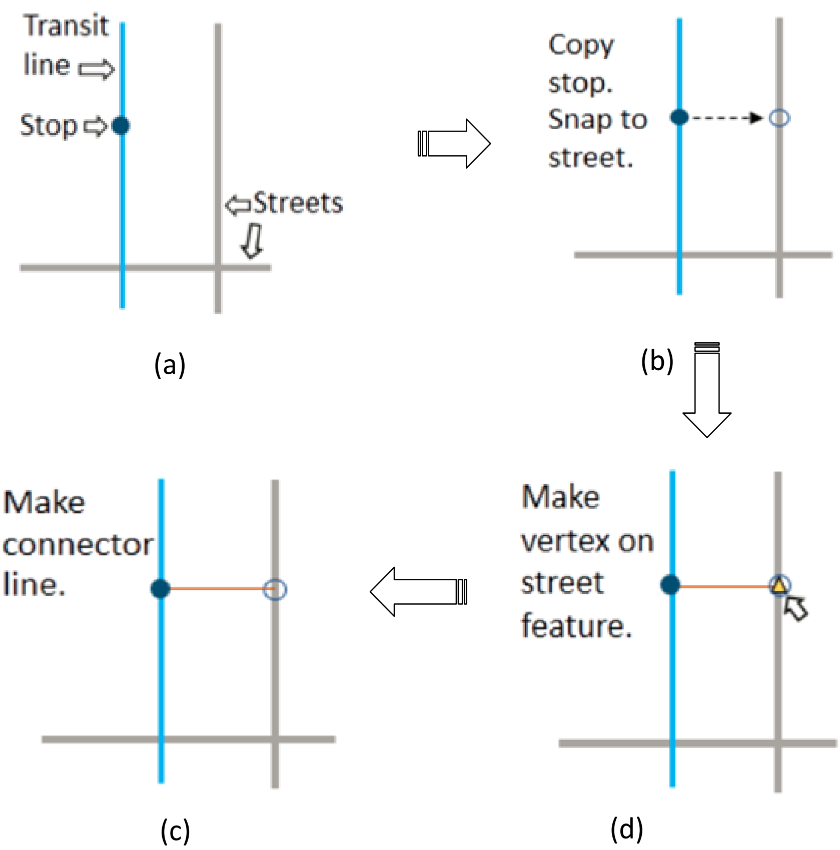
iv. Perform horizontal separation of each mode network (relative offset from pedestrian network).

v. Import point shapefile of stops for each public transport mode.
vi. Clean stops data (filtering by proximity to link) to eliminate wrongly digitised stop locations while ensuring that stops are realistically spaced, at distances of say, not less than 150m.
vii. Create stop vertices on network links using geoprocessing tools such as the near feature, snap, and split-at-point tools.
viii. Create image of stops on streets
ix. Create stops-links connectors

7.5.2 Creating stop-links connectors for public transport

A properly configured multimodal network dataset requires connectivity between all the network elements such as streets, routes, stops and interchange terminals. The idea of having a properly configured multimodal network is such that pedestrian movement along the network can be properly modelled. That is, street-to-public transport transitioning must take place at the designated stops or stations. Furthermore, a pedestrian should, for example, not get off a route in-between stops and start walking towards their destination. Getting off the public transport route must happen at the stops/stations. To realise this, connector lines are created between the streets and the routes through the stops. The procedure adopted for the creation of connector lines between streets and public transport stops/links is similar to that discussed in the ESRI guide for General Transit Feed Specification (GTFS) data integration with Network Dataset (Melinda, 2017), as made available in ESRI's open source platform[5]. An illustration of the procedure is shown in Figure 7-5.

[5] http://esri.github.io/public-transit-tools/.



Adapted from: Melinda (2017)

Figure 7-5: Creating street-public transport network connectors

The Figure shows the steps adopted for creating connectors between the pedestrian street network and the individual public transport network. The connectors are also utilised to simulate the time delay for boarding and alighting from the public transport network as well as the waiting time of the bus at every stop. Since the stops data available for this study do not contain information on boarding, alighting or waiting time at stops, an assumed average value of 1 minute was taken as the total time delay at stops. The value is then transferred as a constant impedance attribute on the street-to-route connectors. However, much of the delays across stops are assumed to be accounted for by the average speed attribute defined for the individual network. In other words, the average speed indicated for each route is assumed to have accounted for delays of boarding and alighting.

For connectors to be properly created between the street network and the public transport routes, it is necessary to carry out a horizontal separation of the individual network (polylines) of each mode to be modelled within the multimodal network setup. The horizontal separation in this study was achieved by offsetting the individual network at incremental intervals of 1 meter from the pedestrian (street) network. With such horizontal separation of the component networks, it is possible to create non-overlapping connectors from the street network to the public transport route. A similar approach of relative network offsetting was utilised in Mahrous (2012), where the authors employed both horizontal and vertical separation in their multimodal network development.

The preparation of the base network data yields the following: (1) a set of individual networks for each mode (2) street network for pedestrian movement (3) street-to-route connectors (4) stops for each mode snapped to align with the routes (4) image of the stops, snapped to align with the street network. The next section discusses the setting up of connectivity topology among the various network elements.

7.5.3 Setting up connectivity

Connectivity is the critical element that makes travel through any transport network possible. Network elements, such as edges (lines) and junctions (points), must be interconnected to allow navigation over the network. Additionally, these elements have properties that control navigation on the network. Transportation networks are undirected networks. This means that while an edge on a network may have a direction assigned to it, the agent (the person or resource being transported) is free to decide the direction, speed, and destination of traversal. For example, a person in a car travelling on a street can choose which street to turn onto, when to stop, and which direction to drive. Restrictions imposed on a network, such as one-way streets or No-U-turns-allowed, are guidelines for the agent to follow. For this study, two kinds of connectivity topologies are defined; unimodal connectivity topology and multimodal connectivity topology.

Unimodal connectivity considers the network elements of only one mode. The connectivity elements of the car network include the road links and vertices. For a bus network, the elements include the pedestrian street network, bus network, bus stops, image of the bus stops, street-to-bus line connector. The connectivity topology thus defines how each of these elements connects. The connectivity group in ArcGIS is one of the elements used to define connectivity, and it is set up to tell the network how movement is allowed between the different source features.

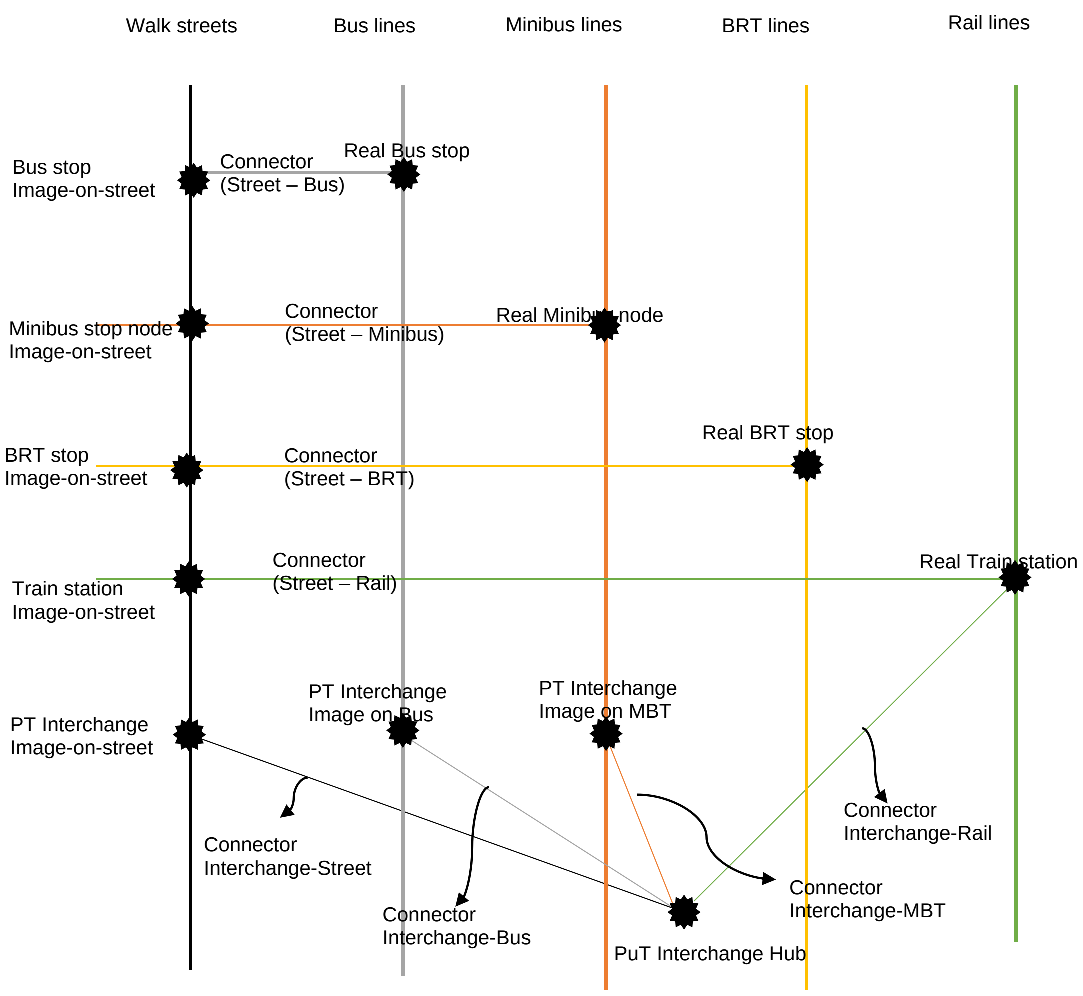
A multimodal connectivity setup defines the connection of all network elements of the component modes considered in the multimodal network dataset. Within ArcGIS, two key features that are used to define connectivity are the connectivity groups and logical elevation. While the connectivity groups create a 2-dimensional separation of all the modes within the network dataset, a logical elevation component provides an additional 3-dimensional (or vertical) separation for the network elements. Logical elevation involves creating and adding an elevation field (also known as the Z-coordinate) to the attribute of every network element participating in the multimodal network to form a 3-dimensional network dataset. Each of the network element to be vertically separated is given a unique Z-coordinate value in the form of positive integers. The introduction and usage of logical elevation component is dependent on the nature and characteristics of the system to be modelled. One of the critical characteristics of a multimodal public transport system is that several routes of the various modes often run on the same road network infrastructure resulting in a very complex system made of overlapping routes. Modelling such complexities within a generic (non-transport specific) GIS platform like ArcGIS is often a challenge, especially for an extensive network.

One approach suggested by Mahrous (2012) for dealing with the issue of overlapping routes in a multimodal system is the use of logical elevation to capture and isolate every route. The use of logical elevation to model route connectivity, however, has its limitations. The feasibility and efficacy of such approach are limited by the level of complexity and size of the network under consideration. For a small network with relatively few numbers of routes, as the case of the case study conducted by Mahrous (2012), where a multimodal transit network comprising 10 bus routes, rail and cycle routes was developed, using a logical elevation to separate all routes was feasible. However, for a relatively large network such as the one developed in this study which comprises over 900 bus routes and over 1000 minibus routes in addition to train and BRT routes, logical separation of all routes is not feasible due to the limited capability of ArcGIS to handle such separation.

Furthermore, the nature of the input network data as well as the analysis of interest, also determines if 3-dimensional separation is necessary. For this study, where the interest is on computing potential reachability of destinations, having overlapping routes does not necessarily create any problem or errors in computation of potential travel time between origin and destination since each route segment is already defined with specific average travel speed, and connectivity between routes is only permitted at the stops. Based on the already defined assumption that stops serve all the routes running across it, it will be practical to have switching of movement between routes. However, the utilised route between any origin and destination will still follow the path of least impedance. Therefore, for this study, in addition to the limitations posed by network size, 3-dimensional separation of the routes was considered unnecessary, based on the assumed operational structure of the routes and stops of individual modes. As such, connectivity was defined using a 2-dimensional setup.

In the 2-dimensional connectivity setup, each network element of the different modes as well as the created access and egress connectors, are allocated to different connectivity groups. Streets serve as the walking network and are connected to the various public transport modes by connectors. The connectors are created in GIS using a combination of proximity and line creating tools, as discussed in Section (7.5.2). In Network Analyst, connectivity of two-line features (which belong to different connectivity groups) is only possible at points common to both connectivity groups. Therefore, it is required that the image of the bus stops/stations are mirrored on the streets. The mirrored stops are snapped and aligned with the street, and the street is split at those mirrored stop points. The connectors from the street to each public transport (PT) mode are therefore created between the mode stops and the mirrored stops (see Figure 7-5).

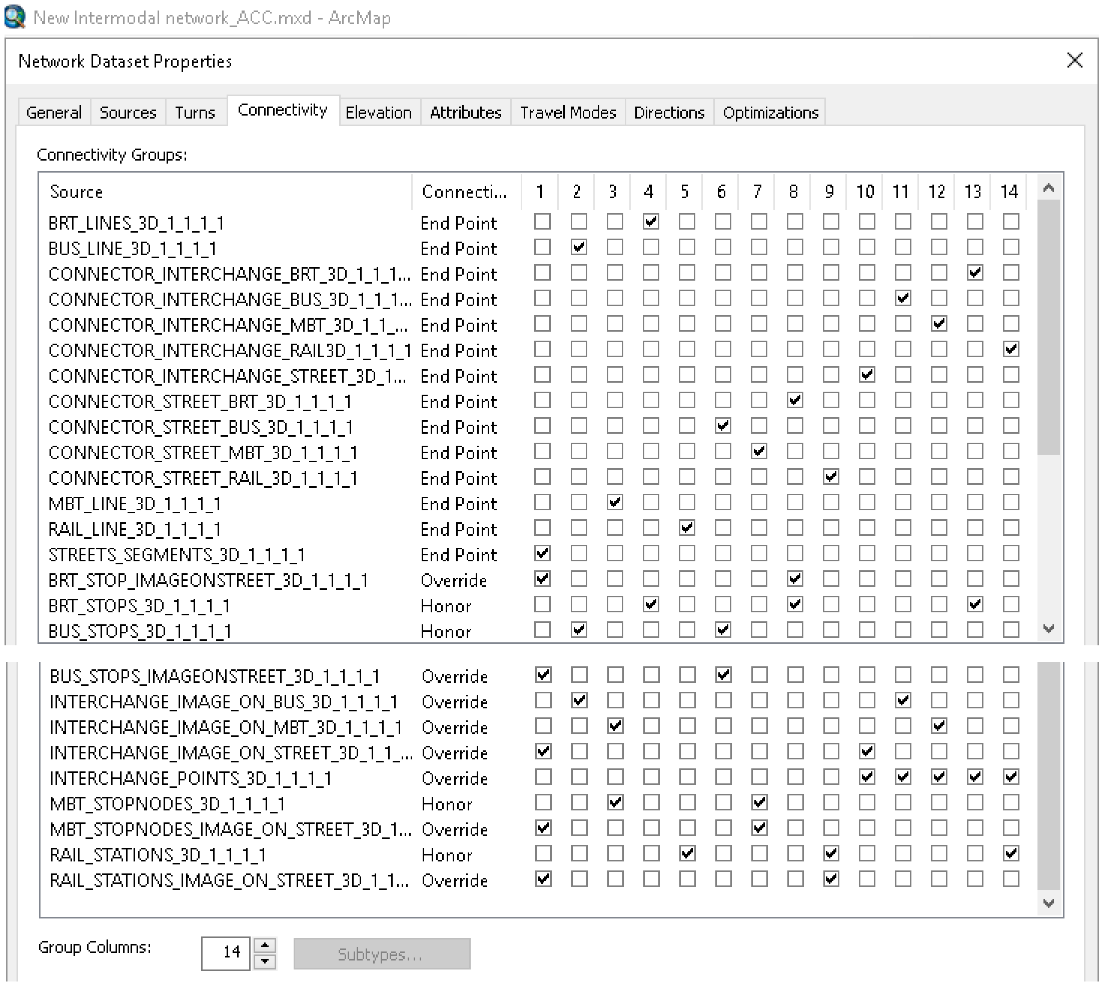
Since each PT mode network and the walking (street) network are split at the stops and mirrored stops location respectively, an end-point connectivity rule is defined for the connection. Public Transport interchange locations (terminals) are also defined in the connectivity setup. There are about 38 terminals across the study area and these terminals are usually the bus and minibus hubs and primarily act as transfer points between the bus and minibus taxi mode. However, at some locations (such as the CBD), terminals act as transfer points between all public transport modes, including rail and BRT. In other words, while all terminals connect to the bus and minibus lines, they only connect to the rail and BRT network at a few specific locations. Connectors are generated to connect the interchanges (terminals) to the bus and minibus networks. Connection of the terminal to the rail and BRT network is based on a predefined rule of proximity to nearest stops of those modes. If the closest rail station or BRT stop is within walkability radius of 400m from the interchange point, then the interchange act as transfer points for those modes as well, and connectors are created from the interchange points to those stations/stops. The entire structure of the multimodal network setup is depicted in Figure 7-6.



Source: Author

Figure 7-6: Connectivity structure for a multimodal public transport network model

The Figure shows all the component network elements that form the multimodal network data model (network dataset), as well as the connection between each element. In the connectivity setup, the PT interchanges are mirrored on the bus and minibus network, and the network is split at those points. Interchange connectors are created between the interchange points and the mirrored interchange points, and end-point connectivity policy is also defined. For rail and BRT, the connectors are created from the interchange points to the stations/stops that are within the specified radius of 400m. An end-point connectivity policy is defined for the network elements. A snapshot of the overall connectivity matrix for the multimodal public transport network elements in ArcGIS is shown in Figure 7-7.



Source: Author

Figure 7-7: Snapshot of the connectivity matrix for the multimodal public transport network model setup in ArcGIS

The Figure shows a total of 14 connectivity groups. The networks for each of the four public transport modes are assigned to separate connectivity groups, while the street network and each set of connectors are also assigned to individual connectivity groups. The respective stops and image-of-stops for each mode are assigned to the connectivity groups containing that mode and the corresponding connector lines, to define the entire connectivity. In other words, the network lines from any two connectivity group will only connect if there is a common stop point between them.

7.5.4 Setting-up Impedance Evaluators

The last part of setting up the Network Datasets is the definition of impedance evaluators or travel cost. As discussed in Chapter 5 (Section 5.6), travel impedance in this study is defined in terms of travel time, distance and the monetary cost of travel between origin and destination. The cost functions discussed in Section (5.6) were defined in the component network (of each mode) in the multimodal network dataset.

A built network data model (or Network Dataset) is, therefore, the main input required for other accessibility calculation processes such as Origin-Destination (O-D) cost matrix calculation, which involves specifying the origins and destinations of interest, as well as other parameters, such as, the threshold value of travel cost. A model that was developed to automate such computation of O-D travel cost matrix using ArcGIS Model Builder is presented in Figure 7-8.

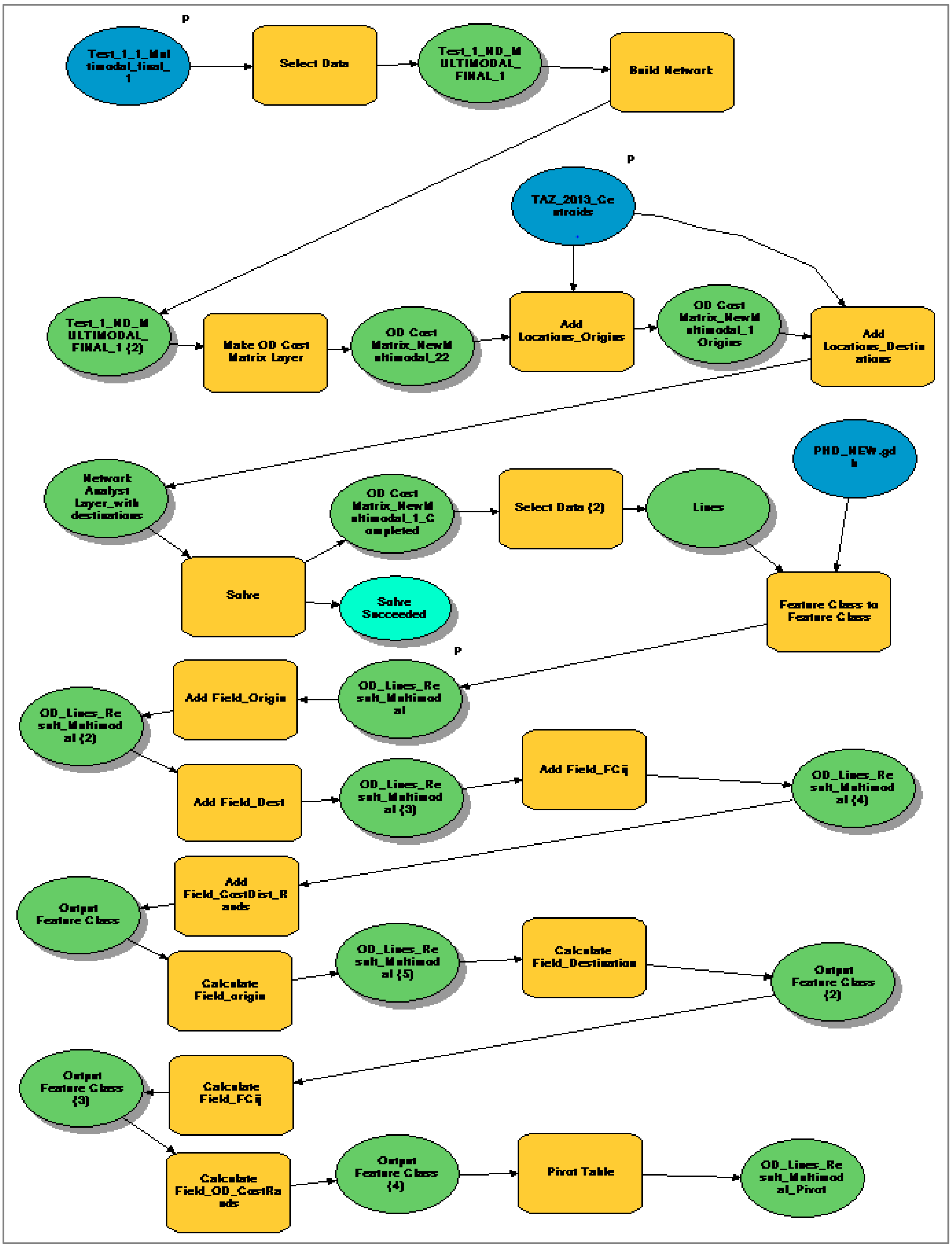


Figure 7-8: ArcGIS Model for O-D cost matrix computation

The Model Builder in ArcGIS utilises several geoprocessing tools to automate tasks. In the model presented in Figure (7-8) above, an already developed Network Dataset serves as the key input data. Another input data is the origin and destination locations, which is given as the TAZs centroids. The rectangles represent the various geoprocessing tools, while the green ovals are outputs from a process. An output from one process often feeds as input to subsequent processes until the final output is computed, which is the matrix of O-D travel time.

At the final steps of accessibility computation, the impedance functions and parameters estimated in Chapter 6 are applied to the computed O-D travel times from these network models, and accessibility is computed according to the measures proposed in Chapter 5.

7.6 Schedule-Based Network Model of BRT using GTFS Data

The previous sections in this chapter discussed the development of a series of network models using data of the routes and stops, to allow the calculation of spatial accessibility. The spatial accessibility indicators that can be computed from the network models (as will be presented in Chapter 8) are static indicators, which do not consider the influence of schedules or trip frequencies on accessibility levels across the day. Although temporal accessibility is not the focus of this research as the majority of the data utilised do not contain schedule information, this section discusses the development of a separate network model of the BRT system that has schedule data in General Transit Feed Specification (GTFS) format, to enable a schedule-based evaluation of job accessibility by the BRT.

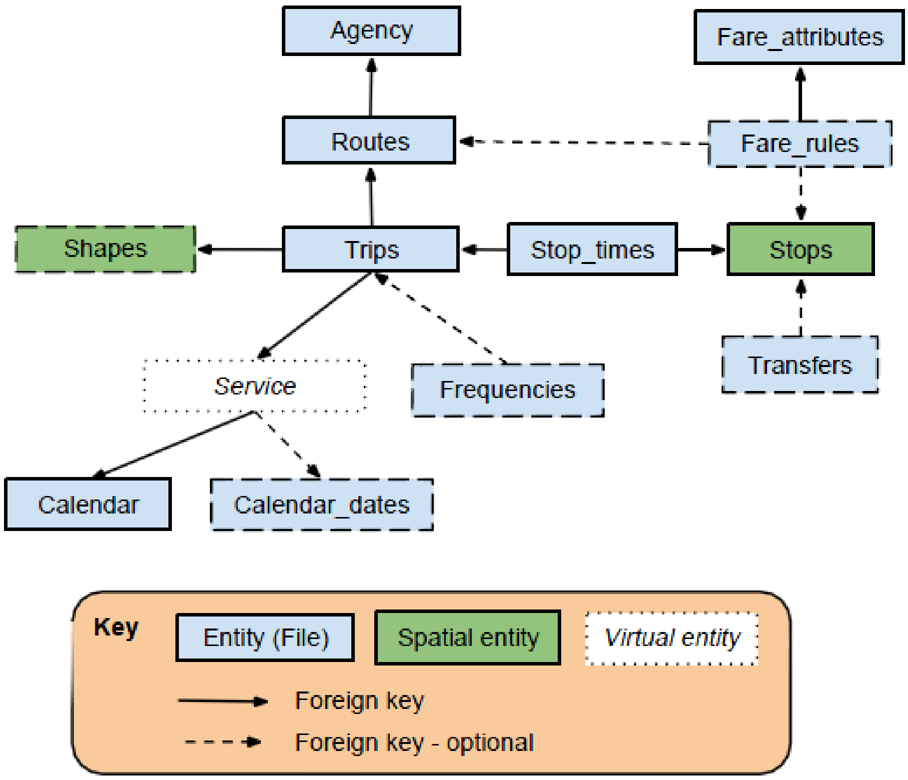
7.6.1 Overview of the GTFS Data Model

The General Transit Feed Specification (GTFS) was first launched in 2005 by Google in collaboration with TriMet in Portland, Oregon, and it defines a standard (open source) format for public transportation schedules and associated geographic information (Google, 2012). GTFS feeds allow transit agencies across the world publish their transit systems data, and developers create applications that can read these data and perform several kinds of transit-related analyses[6]. In Cape Town, the only mode with GTFS data is the BRT (also known as MyCiTi) system.

A typical GFTS feed is made up of a series of comma-delimited text files which are compressed into a ZIP format, with each file containing information on a particular aspect of the transit system such as; stops, routes, trips, and other schedule data. The details of each of these files are defined in the GTFS reference. GTFS datasets are also used in a wide array of applications, some of which include Google maps, mobile route applications, timetable generation software, tools for transit planning and

[6] https://developers.google.com/transit/gtfs/

operations, among others (Google Developers, 2016). The data model for the GTFS is represented in Figure 7-9 below.



Source: Google (2012)

Figure 7-9: GTFS data model

Figure 7-9 shows the typical data items of GTFS data and the relationships among each of these items. In some cases, however, some of the items might not be available. The GTFS files for the BRT system of Cape Town, for example, do not contain information on fares, thus fare-based analysis is not feasible with such data. The data, however, allows for computation of time-based accessibility.

Recently, Google has further developed an extension to GTFS, known as 'GTFS Realtime'[7], which is a feed specification that enables public transportation agencies to provide real-time updates about their fleets to developers. The live data feed is usually generated from an Automatic Vehicle Location System.

7.6.2 Developing a Network Model in ArcGIS with GFTS Data

ESRI has recently developed several advanced geoprocessing tools that could read and perform analyses of public transport systems using the General Transit Feed

[7] https://developers.google.com/transit/gtfs-realtime/

Specification (GTFS) data format. One of such tools is the ‘Add GTFS to Network Dataset’ tool, which allows the integration of GTFS data into an ArcGIS Network Dataset to enable schedule-based analyses (Melinda, 2017). The tool works with the ArcGIS Network Analyst, to create network models that can perform analyses such as O-D travel cost matrix, Service Area, Routing, Location-allocation and Public transport/pedestrian accessibility.

In the development of the Network Dataset of Cape Town’s BRT system, the approach described in Melinda (2017) was adopted. The input data include (1) the pedestrian street network of Cape Town, which models the access and egress parts of the journey, as discussed in Section (7.5), and (2) the 2016 GTFS data of the BRT. It is essential that the GTFS data has valid arrival and departure times, as the Add-GTFS-to-Network-Dataset tool fails to operate if the GTFS data are without that valid time information. The entire workflow for the development of the network data model is summarised in these steps:

i. *Acquire the GTFS data and prepare the feature dataset*
   The feature dataset is a folder created within a File Geodatabase in ArcGIS, to handle all files and processes.
ii. *Generate feature classes for transit lines and stops and a SQL database of the schedules*
   This step generates transit lines and stops shapefiles from the ‘.txt’ GTFS files. The transit lines are generated such that a line comprises a series of segments created between pairs of stops. This ensures that access and egress to/from a transit line only takes place at the stops. An SQL database of schedules is also generated in this step, and all these are stored in the Feature dataset and File Geodatabase created in step 2 above.
iii. *Create connector features between the transit lines/stops and other data*
   As mentioned in Section (7.5.1), a proper network model requires connectivity among all the network elements. This step employs the ‘Generate Stop-Street-Connector’ tool to automatically generate connector lines between the transit lines and the pedestrian (street) network through the stops. This step is similar to that employed for the multimodal network model development, already discussed in Section (7.5.2), whereby the image of stops is also generated and snapped to create vertices at the street network (see Figure 7-5). The outputs from this step are: (1) a copy of stops snapped to street (2) connector lines from stop to streets, and (3) a copy of the street network modified to have vertices at the locations of the snapped copy of stops.

iv. *Create and configure the network dataset*

This is the final step of the network model development, whereby connectivity structure is defined for the various network elements generated in the previous steps, and impedance evaluators are specified. The network dataset is created within the same Feature Dataset and File geodatabase containing the various network elements.

Connectivity between the various elements employs a 2-dimensional connectivity group structure (discussed in Section 7.5.3). While the multimodal network model discussed in Section (7.5.3) employs a total of 14 connectivity groups (see Figure 7-7), only 3 connectivity groups are employed for the BRT network dataset. In the connectivity matrix, each of the line feature classes (connectors, transit lines and streets) is assigned to a connectivity group and defined with an 'endpoint' connectivity policy. The stops are located at the point of connection of transit lines and street connectors and must 'honour' the 'endpoint' connectivity policy of the line. The copy of stops snapped to streets are located at the points where the connectors join the streets. The stops can join the streets whether at an endpoint or any vertex. Hence an 'override' policy is defined to override the 'endpoint' policy defined for the streets.

With connectivity defined, the impedance evaluator is then defined on the network. For this case, impedance is defined by travel time on the network elements. The computation of travel time along the transit lines utilises a special 'Transit Evaluator' file, which queries the schedule information generated from the GTFS flies in step (iii) above. The walk time along the pedestrian street network is established by referencing the traversed feature length and applying an assumed walk speed of 5km/hr (Section 5.4).

Further definitions required on the network model include; analysis time of day, day of the week or specific date for analysis. The built network model is applied to perform schedule-based job accessibility computation. The results are further discussed in Chapter 8.

7.7 Chapter Conclusion

The computation of accessibility by any mode or combination of modes requires a network model that 'reliably' simulate potential journeys between origin and destination. Hence having a well-built network model is vital for accessibility model accuracy. This Chapter presented the last part of a 3-part methodology on accessibility modelling, and it discussed the procedures developed for building network data models to enable accessibility computation.

Although the network models discussed in this chapter have been developed in line with reasonable assumptions for spatial accessibility analyses, the course of model development has nevertheless, revealed several limitations with the use of GIS packages such as ArcGIS Network Analyst in modelling a multimodal public transport system with extensive and complex network. As already mentioned in Section (7.5.2), the issue of modelling multiple overlapping routes along a link for an extensive network is one such challenge. Although, for the case of Cape Town, it was not considered much of an issue, due to the manner of operations of the stops, where every stop for a mode practically serves all routes that run adjacent to the stop. However, for cases (such as in The Netherlands or other developed cities) where stops are assigned to serve specific routes, modelling overlapping routes will become an issue for large networks, especially where 3-dimensional separation by logical elevation is not feasible.

Another limitation with the use of ArcGIS Network Analyst is related to the manner with which the results of network analysis is reported. For a travel cost calculation performed on a multimodal network model that comprises several modes, only an output of total cost from origin to destination is reported, and not the individual costs associated with the component modes. For example, an O-D travel time calculation for the multimodal network dataset only give the output of the total travel time from origin to destination, without revealing the specific times spent on the access/egress part, or, on the component modes. Although such output of total travel cost is sufficient to enable computation of accessibility (considering that impedance weight is estimated from travel cost data measured from origin to destination), it cannot be applied for further individual evaluation of the component modes. Also, for analyses situations where the various cost components of a multimodal journey (such as the walking access and egress, or the in-vehicle components) need to be weighted differently, having an output of only the total travel cost, will be of little use.

Despite the limitations noted above, this chapter has demonstrated multimodal network model development that combines multiple modes within one model, using relatively sparse data of routes and stops. Also demonstrated in the last section of the Chapter is the recent advancement in the capability of GIS to utilise more comprehensive public transport data in GTFS format, for schedule-aware accessibility evaluation. The next chapter (Chapter 8) presents the indicators of accessibility computed using the measures proposed in Chapter 5, the decay functions estimated in Chapter 6, and the network models developed in this Chapter.

Chapter 8
Results & Discussions – Access & Accessibility Indicators

"You do not get results by focusing on results. You get results by focusing on the actions that produce results." – Mike Hawkins

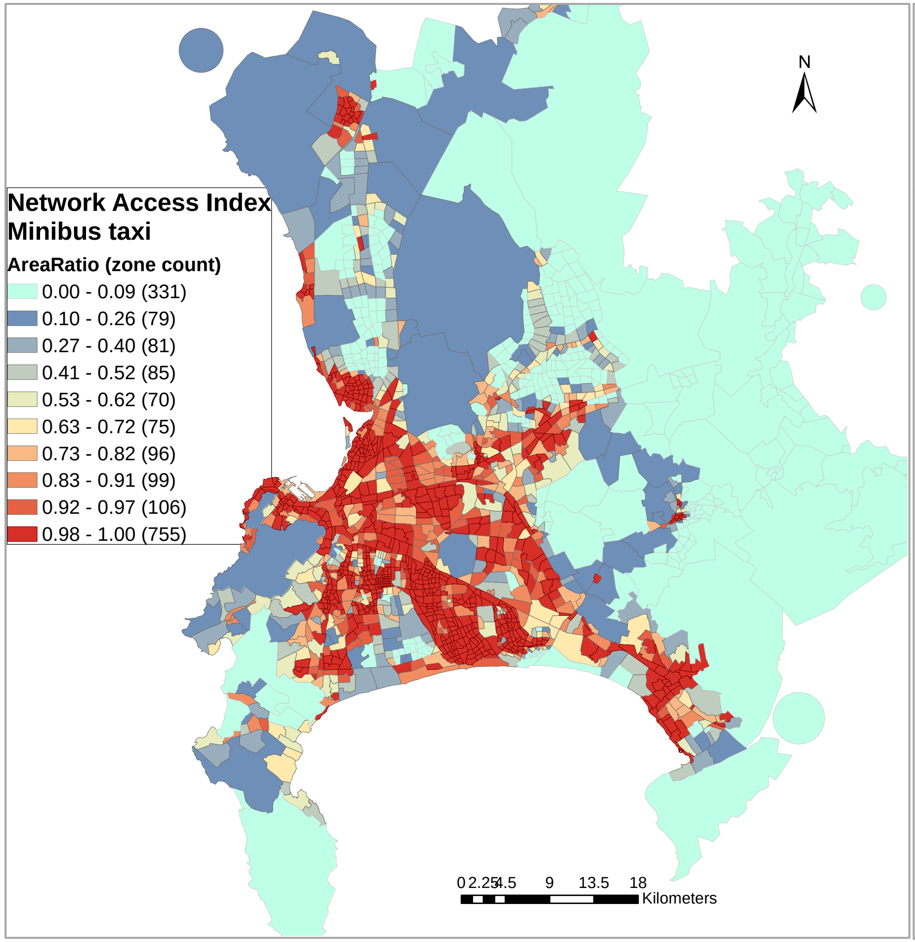
8.1 Introduction

In Chapter 5, the various measures of accessibility proposed in this study were discussed. Presented in this chapter are the various set of indicators computed with those measures. Two categories of indicators are presented: (1) indicators of public transport network access and (2) indicators of opportunities accessibility. The indicators of network access are presented for each of the four public transport modes (regular bus, minibus taxi, BRT and train), while the opportunities accessibility indicators are presented by mode and opportunity type. The opportunities, in this case, are jobs, schools and public healthcare facilities. Jobs are further classified according to the four income categories as discussed in Chapter 4, that is, from low-income to high-income jobs, and accessibility to jobs is measured for both the multimodal public transport system and car travel. School accessibility is measured for each mode of public transport, car and walking. While accessibility to jobs and schools is based on the gravity potential model, healthcare accessibility is measured using the 2-Step Floating Catchment Area (2SFCA) method. Also presented, are the results of the schedule-aware accessibility to jobs as measured by a GTFS-enabled network data model, which was developed and discussed in Chapter 7 (Section 7.6). The remaining sections present each of these indicators.

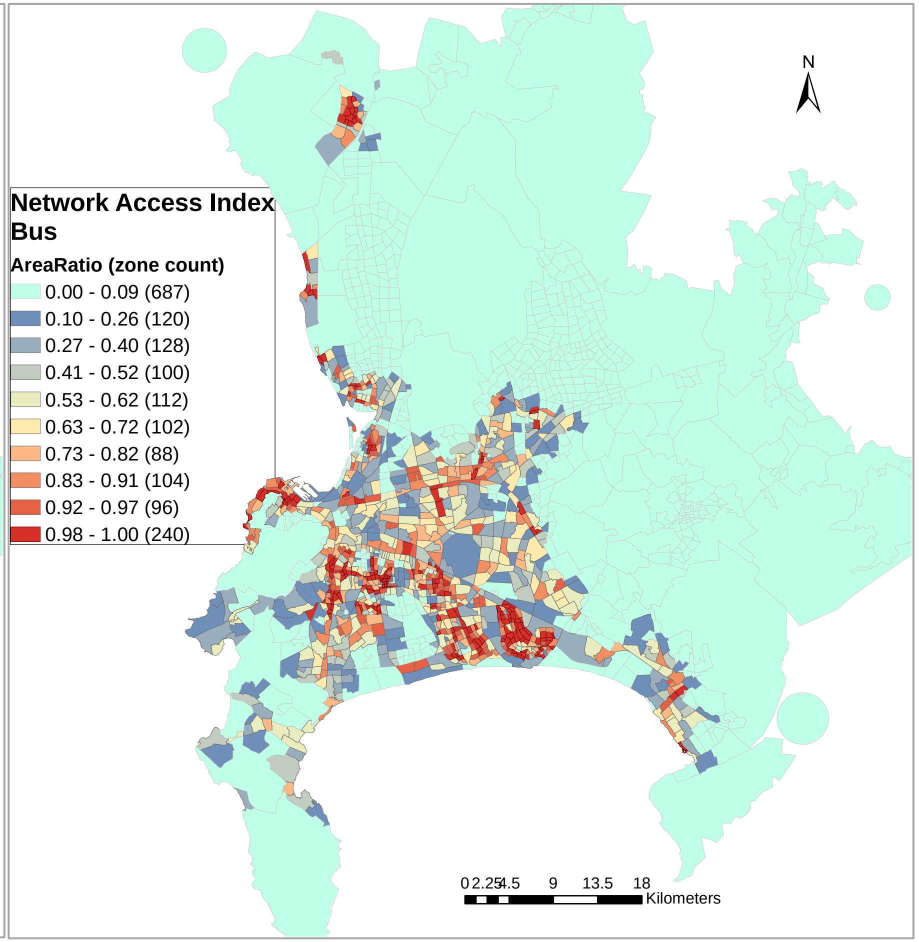
8.2 Public Transport Network Access Index (PTNAI)

As discussed in Section (5.4), the Network Access Index or Area Coverage Index of public transport (Equation 5-1), is a measure of service presence within any given zone. The index is calculated for each of the available public transport modes; the minibus taxi, regular bus, BRT and train. This is to enable a comparison and evaluation of the level of access provided by each mode, considering that the modes have distinctive operational characteristics. The minibus-taxi (paratransit) system, as described in Chapter 4 (Section 4.4.1), operates on a fixed route with unscheduled services. In other words, the minibuses run with no designated stops, with access usually at any point along the route. As such, the Network Access indicator has been calculated using line buffers rather than point (stops) buffers as was done for systems that operate on schedules at designated stops, such as regular bus, BRT and train (see Section 5.4).

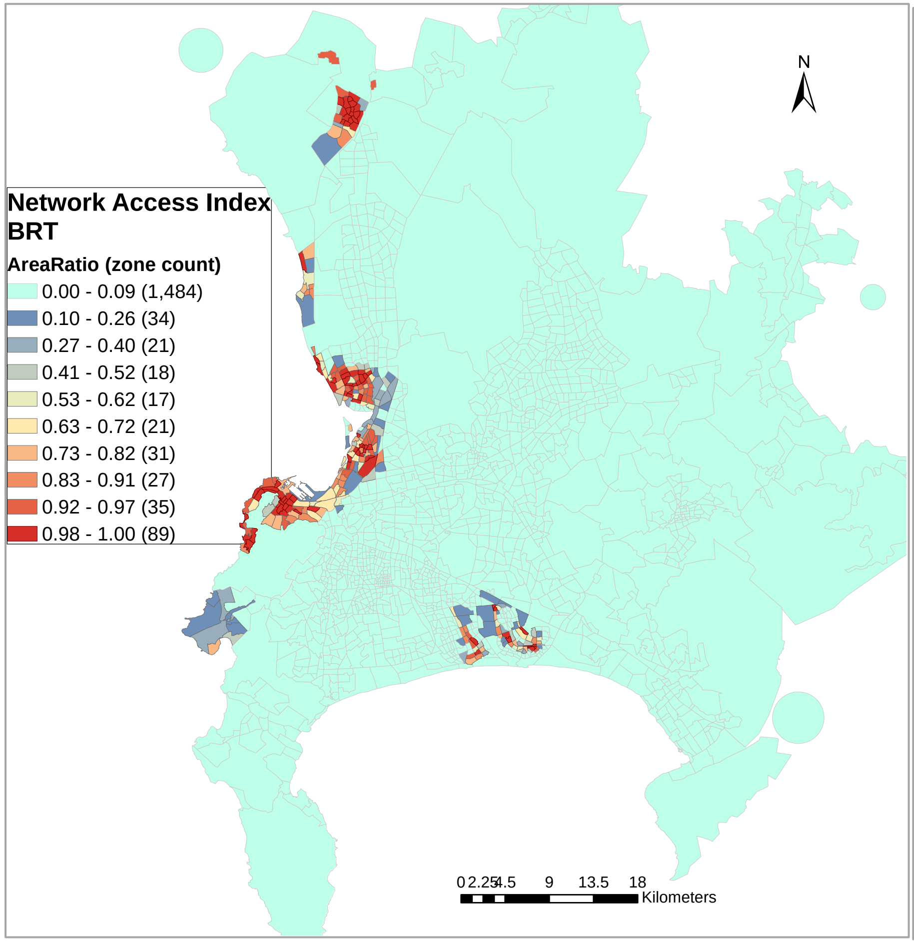
Figures 8-1 (a) – (d) present the mapped Public Transport Network Access indicators across the zones for all four modes.


Network Access Index
Minibus taxi
AreaRatio (zone count)
0.00 - 0.09 (331)
0.10 - 0.26 (79)
0.27 - 0.40 (81)
0.41 - 0.52 (85)
0.53 - 0.62 (70)
0.63 - 0.72 (75)
0.73 - 0.82 (96)
0.83 - 0.91 (99)
0.92 - 0.97 (106)
0.98 - 1.00 (755)
N
0 2.25 4.5 9 13.5 18
Kilometers

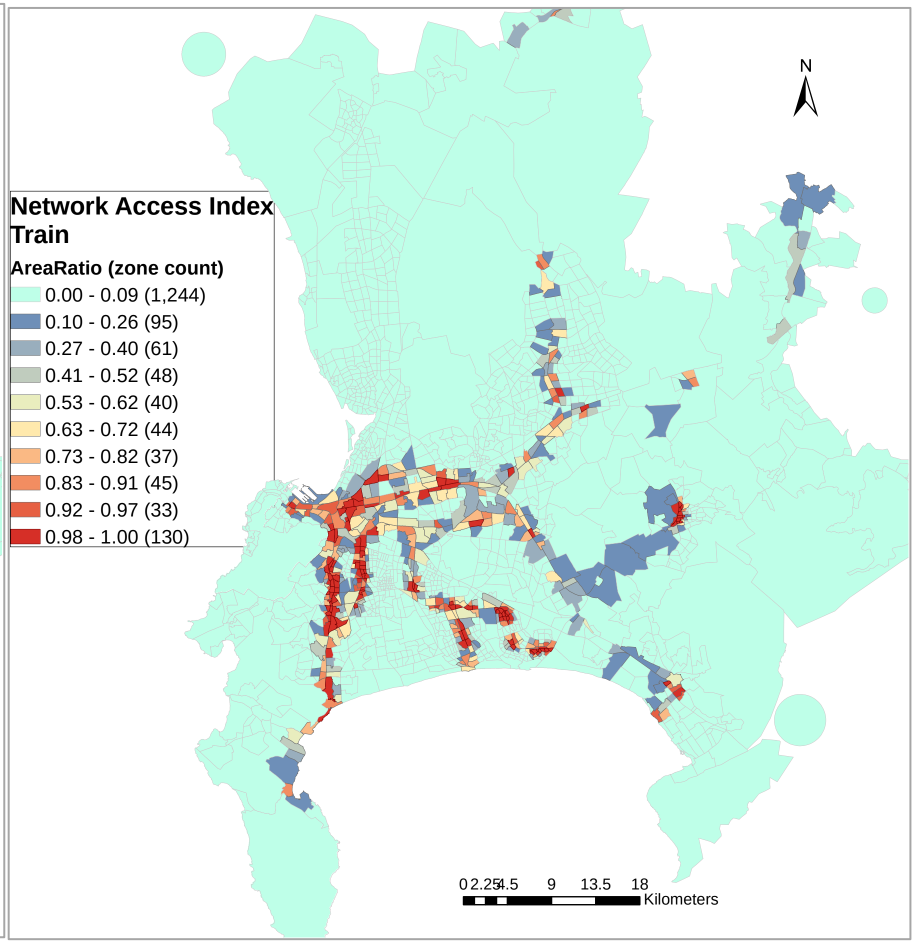
(a)


Network Access Index
Bus
AreaRatio (zone count)
0.00 - 0.09 (687)
0.10 - 0.26 (120)
0.27 - 0.40 (128)
0.41 - 0.52 (100)
0.53 - 0.62 (112)
0.63 - 0.72 (102)
0.73 - 0.82 (88)
0.83 - 0.91 (104)
0.92 - 0.97 (96)
0.98 - 1.00 (240)
N
0 2.25 4.5 9 13.5 18
Kilometers

(b)



(c)



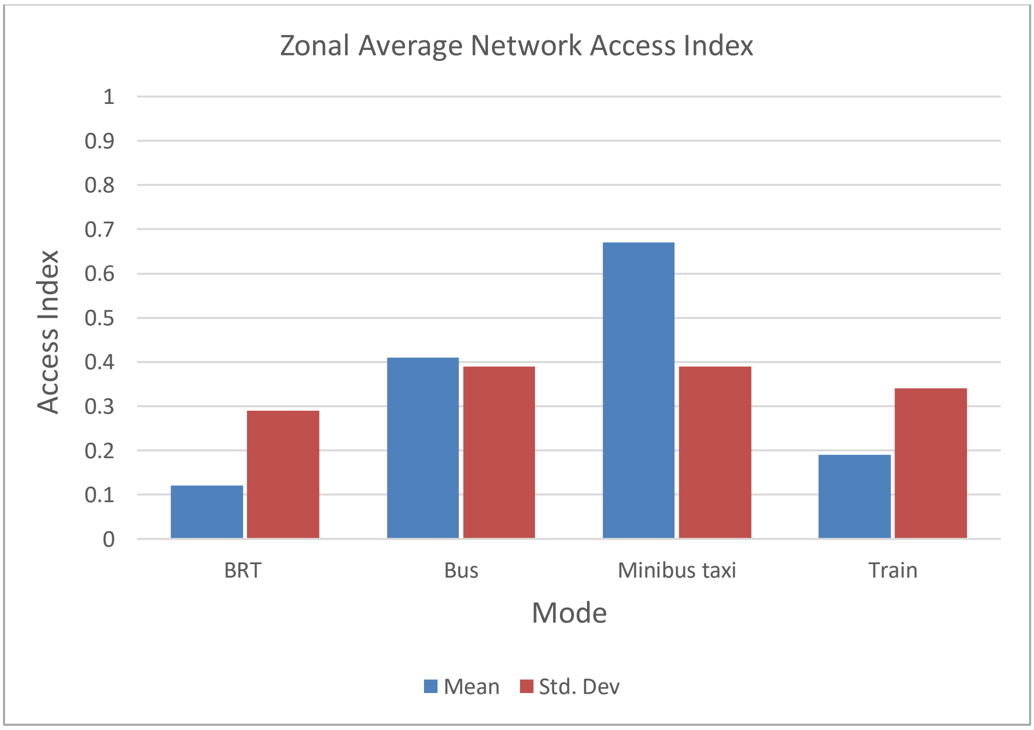
(d)

Figure 8-1: Public Transport Network Access Indicator by mode (a) minibus (b) bus (c) BRT (d) train

The access indicators in Figures 8-1 (a) – (d) have been calculated at the zone level using Equation (5-1) already discussed in Chapter 5. As discussed in that chapter, the indicators show the proportion of a zone within coverage by the respective modes. It is also be interpreted as the proportion of the population within a zone, that has access to the public transport mode, with the assumption that the population are evenly distributed across the zone. The values in the bracket indicate the number of zones associated with the indicator values.

The maps show clustering of high access level over a wider coverage area for the minibus taxi system, compared to the other public transport modes. There is also some similarity in the coverage pattern of the minibus taxi system and that of the regular bus (GABS). This can be attributed to the similar network pattern for these two modes. These modes are also seen to cover most of the lower-income zones (see Figure 4-4) compared to modes like the BRT which mostly covers the CBD, the Atlantic Seaboard and Westcoast areas up to Tableview. These are mainly middle to high-income zones

The average access level across the zones is further shown in Figure 8-2 below.



Source: Author

Figure 8-2: Average Access level by mode

The Figure shows the average access level and standard deviation by mode across all zones in the study area. As shown, the minibus taxi system provides the highest coverage of about 0.65, or 65%, while the BRT provides the lowest at about 0.12 or 12%. The interpretation of this is that, on the average, about 65% of a zone area/population of a zone is within access coverage of the minibus taxi system, while for the BRT, it is about 12% of the zone on the average. For bus and train, it is about 40% and 20% respectively. The maximum possible value of access is 1 or 100%, a situation where all parts of every zone in the entire study area are within access coverage of the public transport system. The relatively high values of standard deviation further suggest that the measured values of access across zones are quite dispersed from the indicated averages.

8.3 Potential Accessibility to Jobs

This section presents the indicators of potential accessibility to jobs, computed based on the gravity model discussed in Section (5.5.1). These are job accessibility values that have not yet incorporated the affordability dimension (discussed in Section 5.5.2), which is a key consideration for vertical equity analysis (discussed in Chapter 10). Accessibility is measured by job category (income level of jobs), for travel by public transport comprising all four modes (using the multimodal network model in Chapter 7, Section 7.5), and for travel by car. Although the gravity model weighs opportunities by travel time, a threshold travel time of 60 minutes has been defined for the analyses. These thresholds have been informed by the observed average travel time to work across various modes, as revealed by the Household Travel Survey (Chapter 6, Section 6.4.1). According to the survey, average time by public transport is just over an hour, while for the car, it is about 45 minutes.

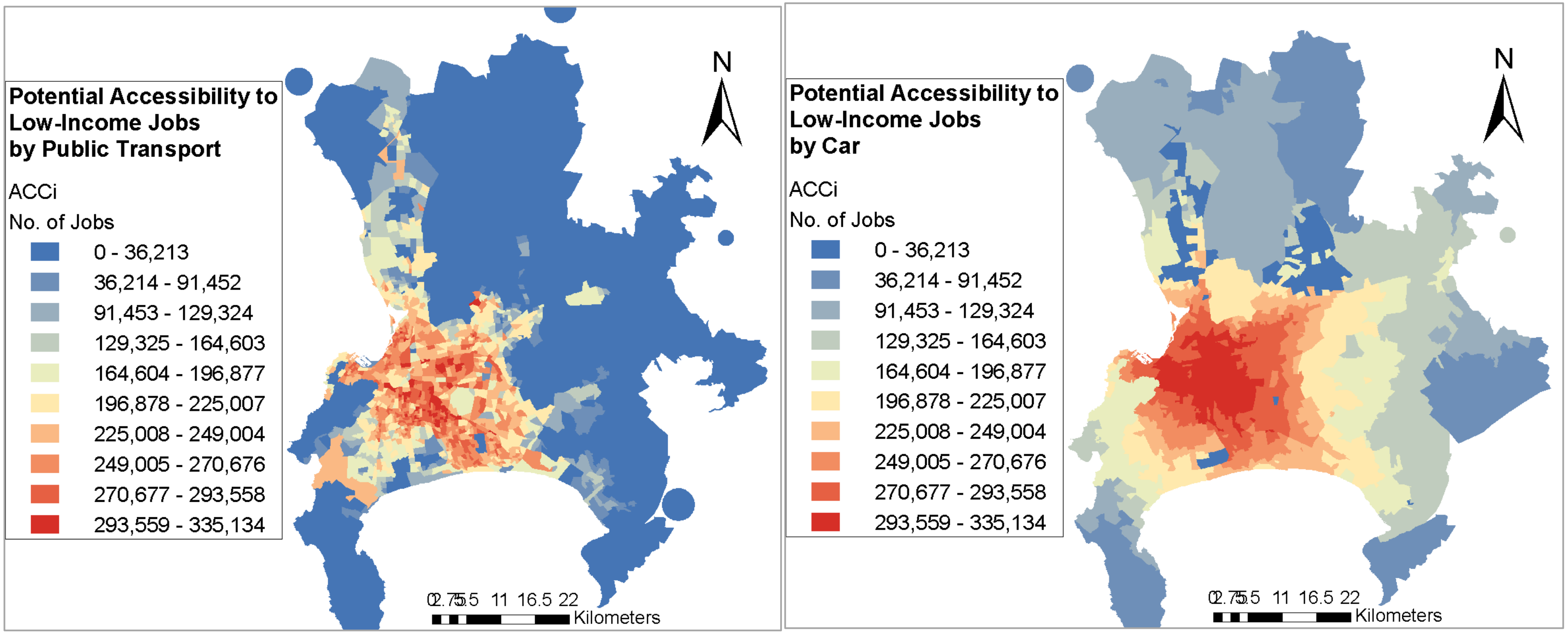
8.3.1 Public Transport versus Car-based Accessibility to jobs

Potential accessibility measured by the multimodal public transport system is compared against that of the car, for each category of jobs. The job categories, as discussed in Chapter 4, are; low-income, lower-middle-income, upper-middle-income and high-income jobs. The accessibility indicator is presented in two forms: (1) as an absolute index, given in terms of the number of jobs potentially reachable from a zone and (2) as a relative index, given in terms of the proportion of total jobs of each income category in the study area that is potentially reachable. These two measures have been presented as Equations (5-2) and (5-3) respectively in Chapter 5.

Figures (8-3) – (8-10), show the potential accessibility to the four categories of jobs for travel within 60 minutes by public transport and car. For each job category, an absolute and a relative indicator is presented for both modes of travel. Due to the wide difference in the absolute numbers of the different categories of jobs, different interval scales have been applied to symbolise accessibility values for each category of jobs, to enable better visualisation of accessibility values. The same interval scale is, however, applied for public transport and car accessibility values for each job category, to enable comparison across these two modes. The applied intervals, in this case, is set using the Jenks natural breaks of car accessibility values (since the values are relatively higher than that of public transport). A total of 10 intervals have been applied to the range of values for each job category.

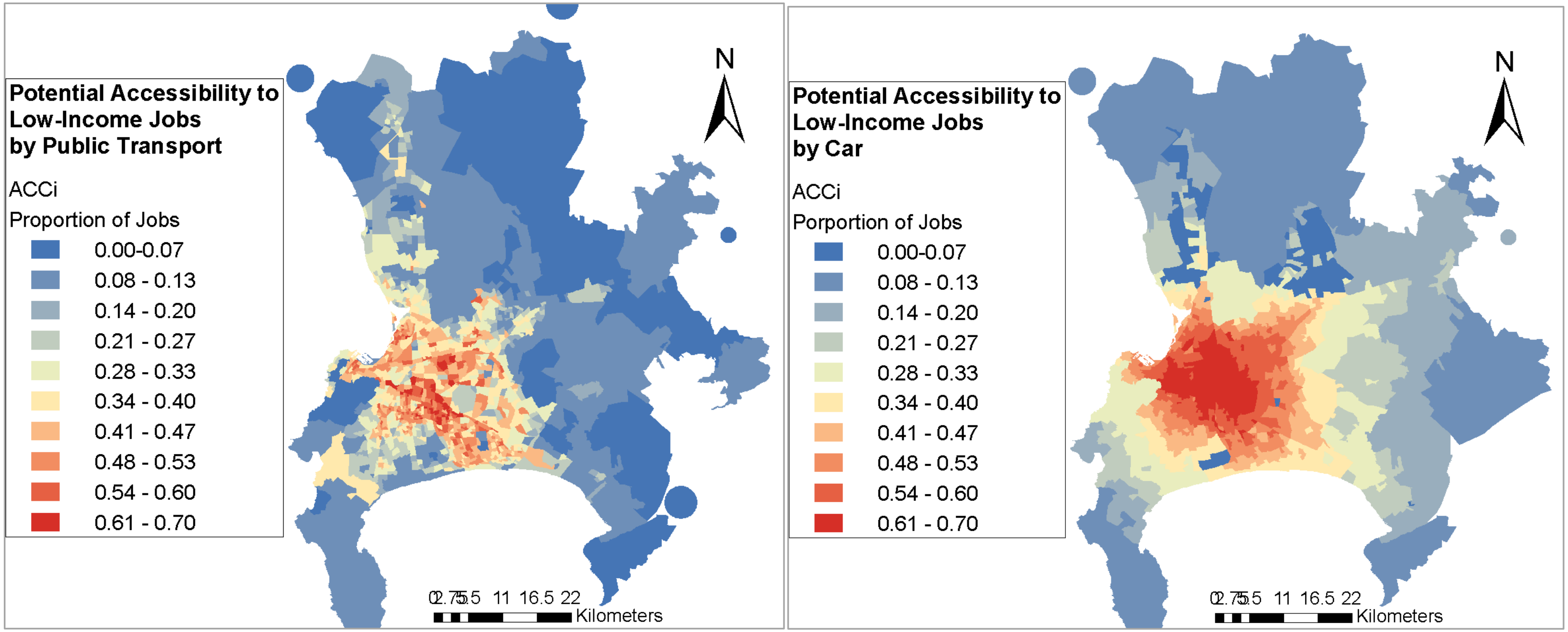
The indicators in Figure 8-3, presented as relative values (that is, as proportions of the total available low-income jobs) is as shown in Figure 8-4. The relative indicators are read as the proportion of total low-income jobs potentially reachable within 60 minutes of travel by public transport or by car.

The absolute and relative indicators of potential accessibility to jobs of the other income categories are presented in Figures (8-5) – (8-10).



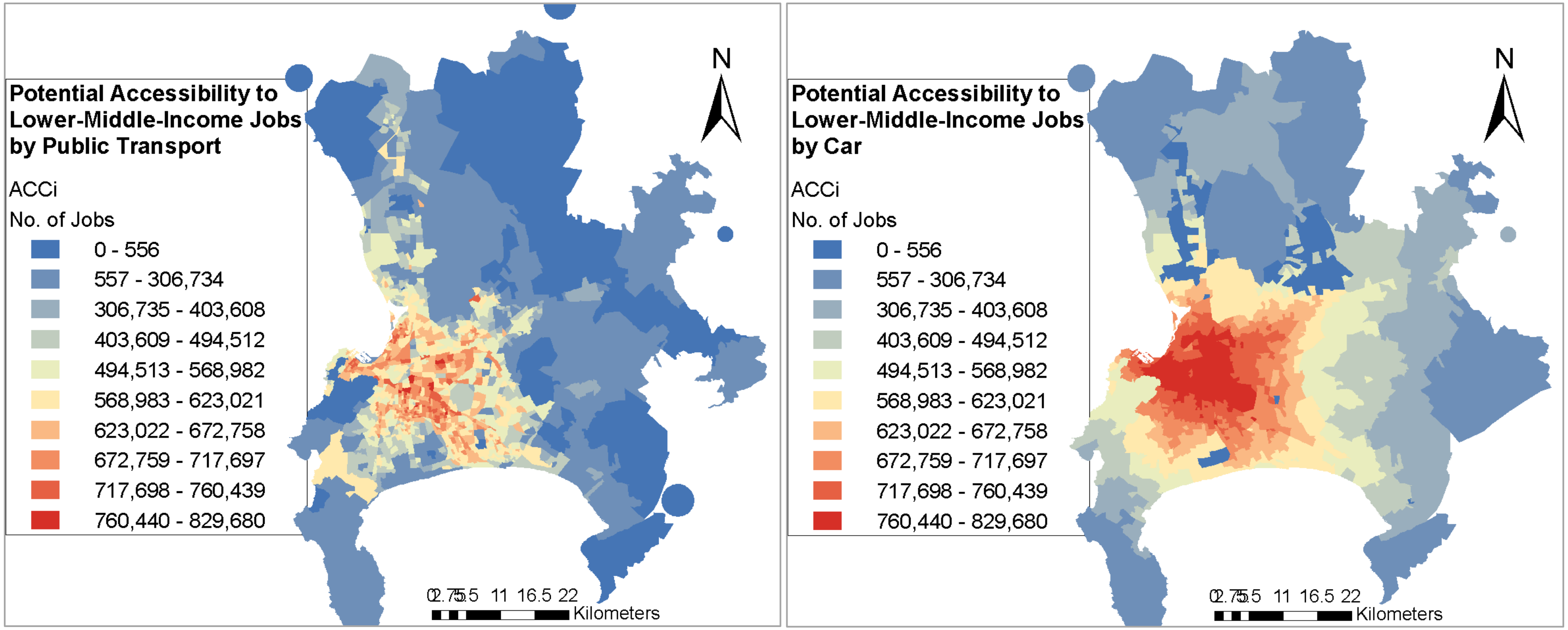
(a) (b)

Figure 8-3: Potential Accessibility to Low-Income Jobs within 60 Minutes by (a) Public Transport (b) Car



(a) (b)

Figure 8-4: Potential Accessibility to Low-Income Jobs (as relative indicators) by (a) Public Transport (b) Car



(a) (b)

Figure 8-5: Potential Accessibility to Low-Middle Income Jobs within 60 minutes by (a) Public Transport (b) Car

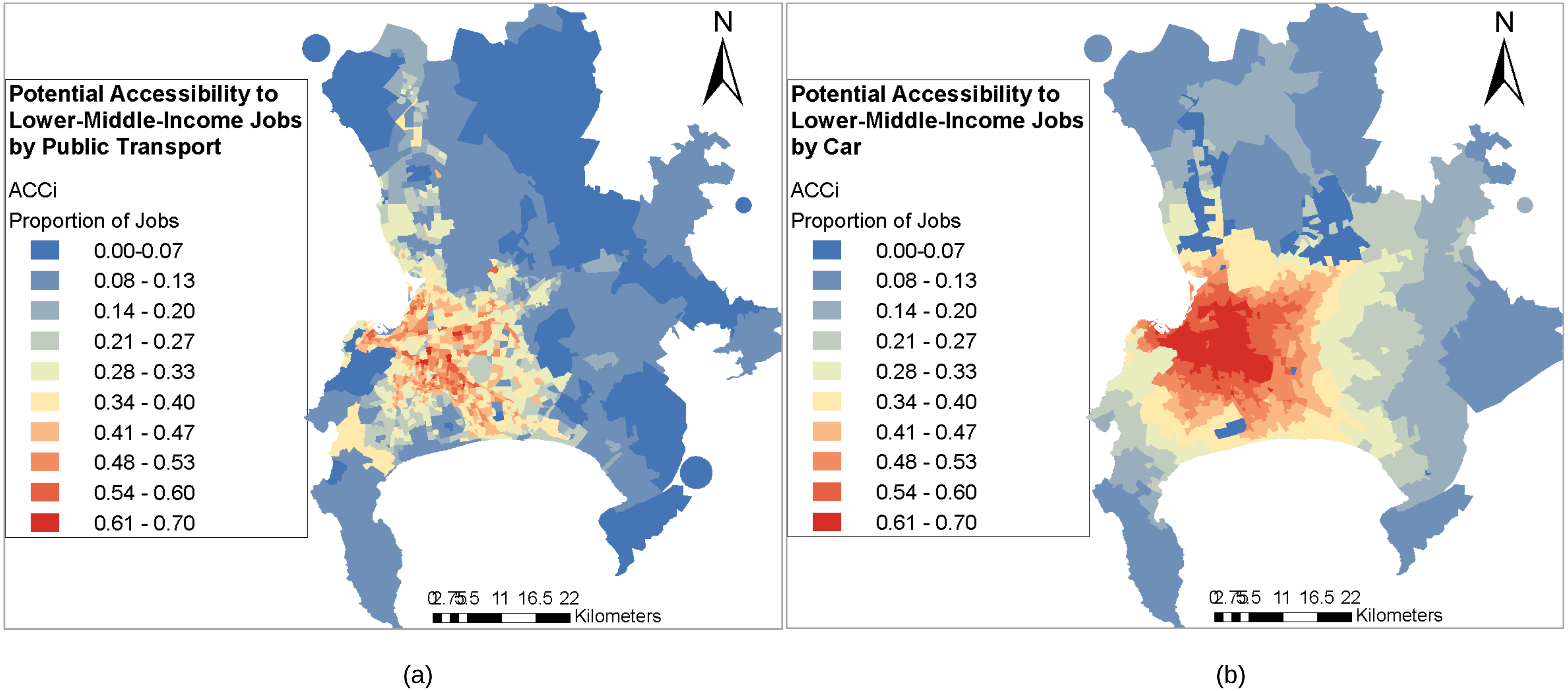
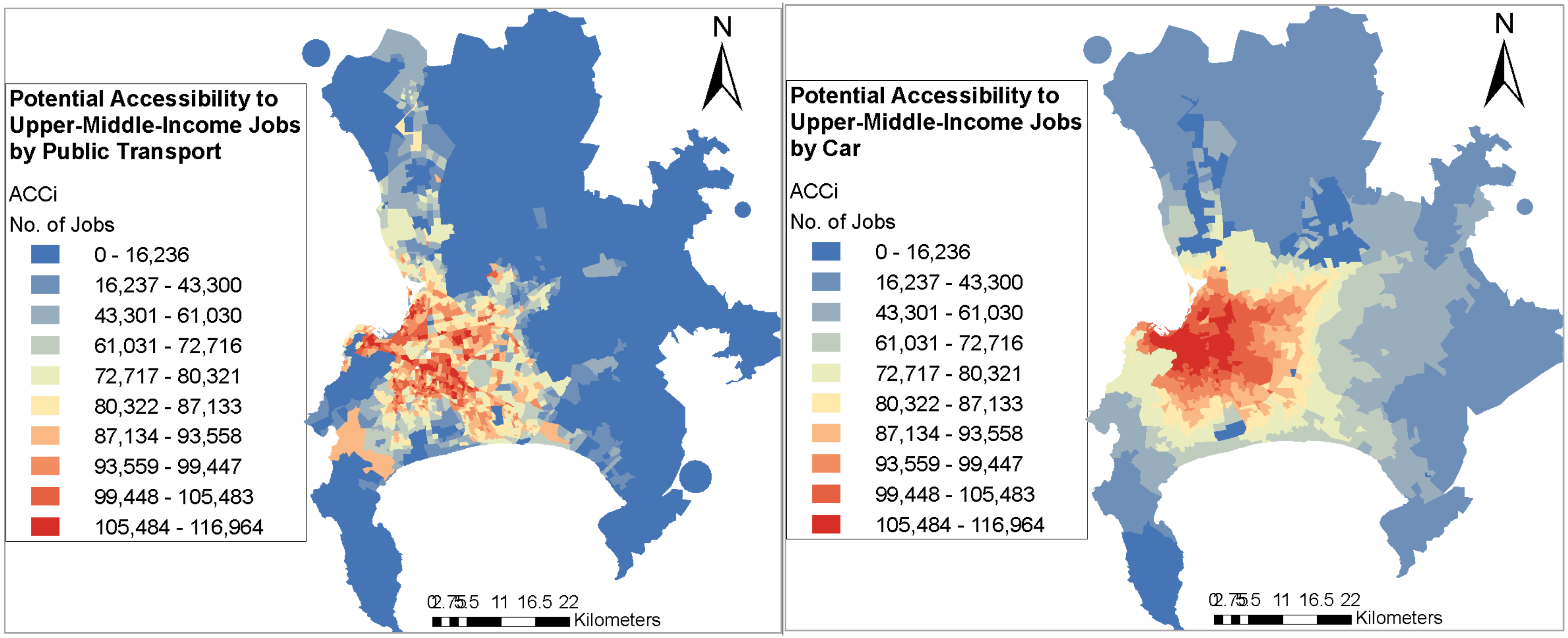
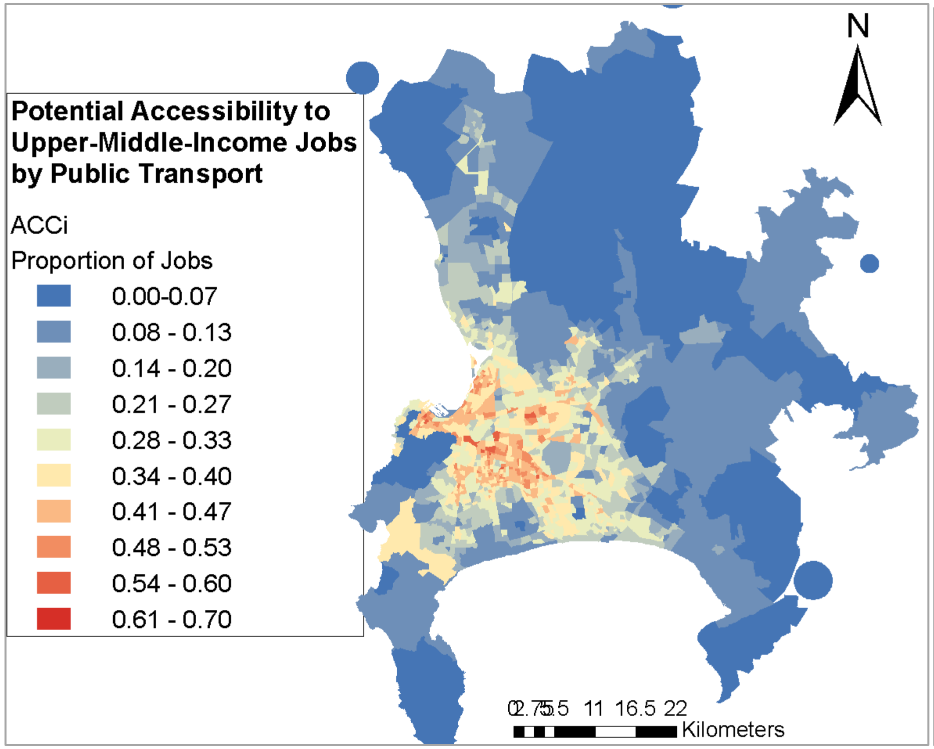


Figure 8-6: Potential Accessibility to Low-Middle Income Jobs (relative indicators) by (a) Public Transport (b) Car

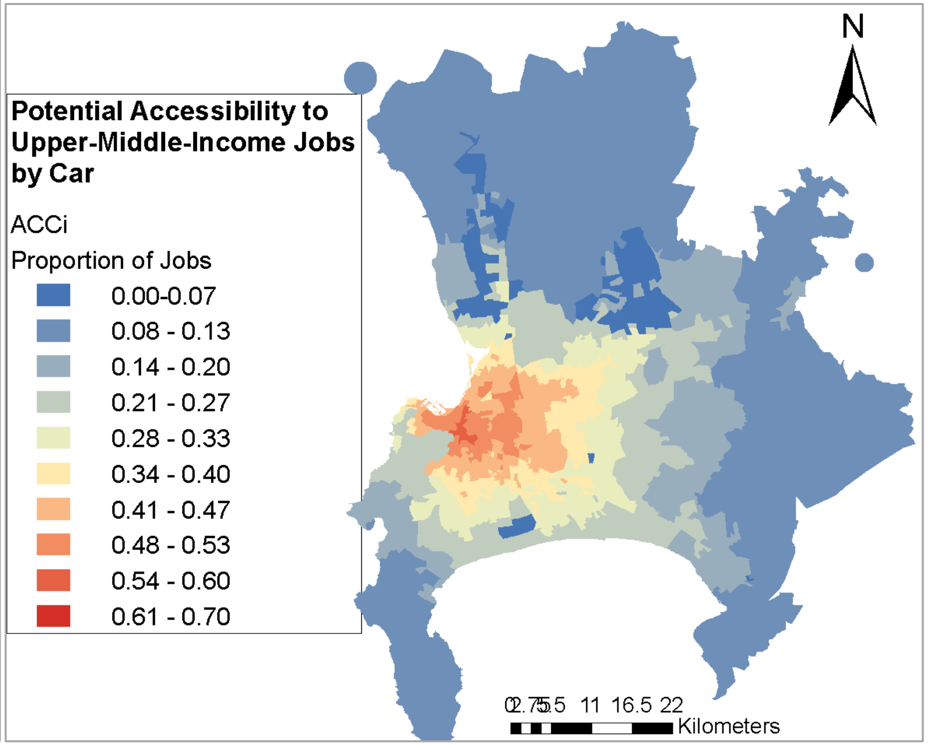


(a) (b)

Figure 8-7: Potential Accessibility to Upper-Middle-Income Jobs within 60 minutes by (a) Public Transport (b) Car

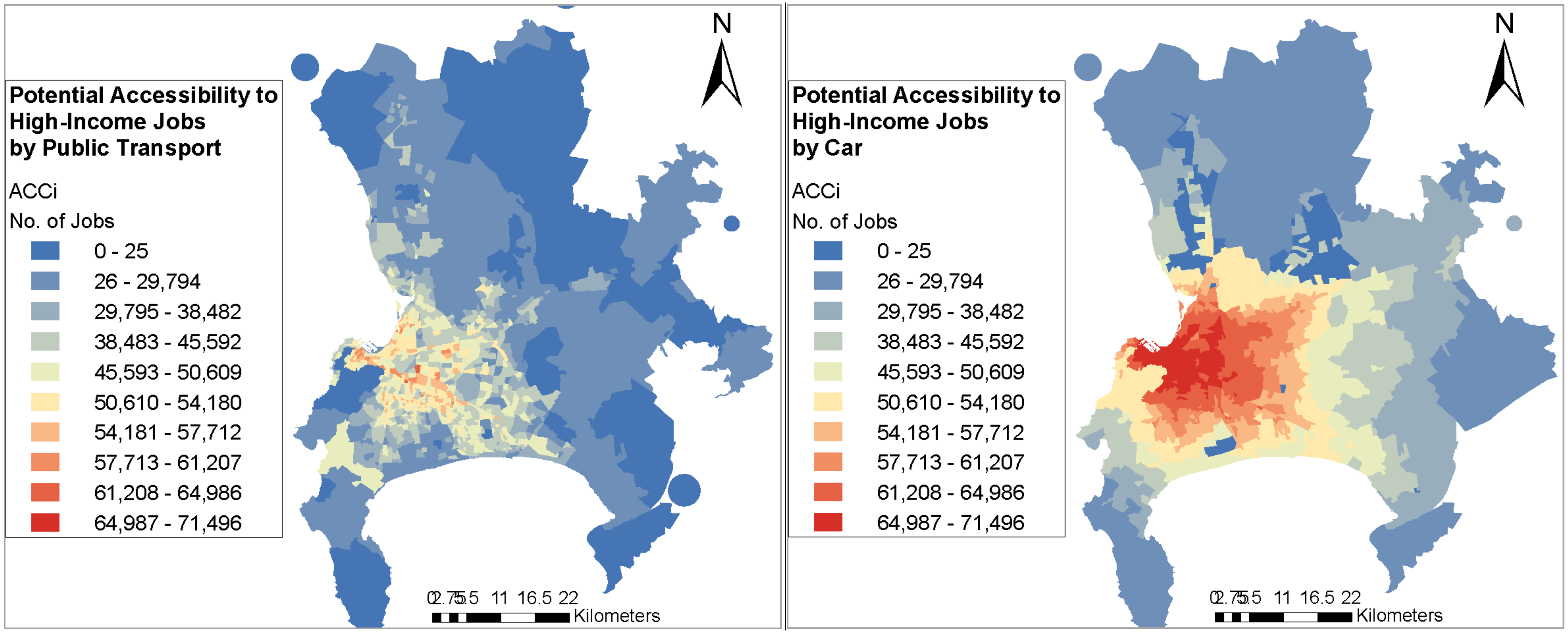


(a)



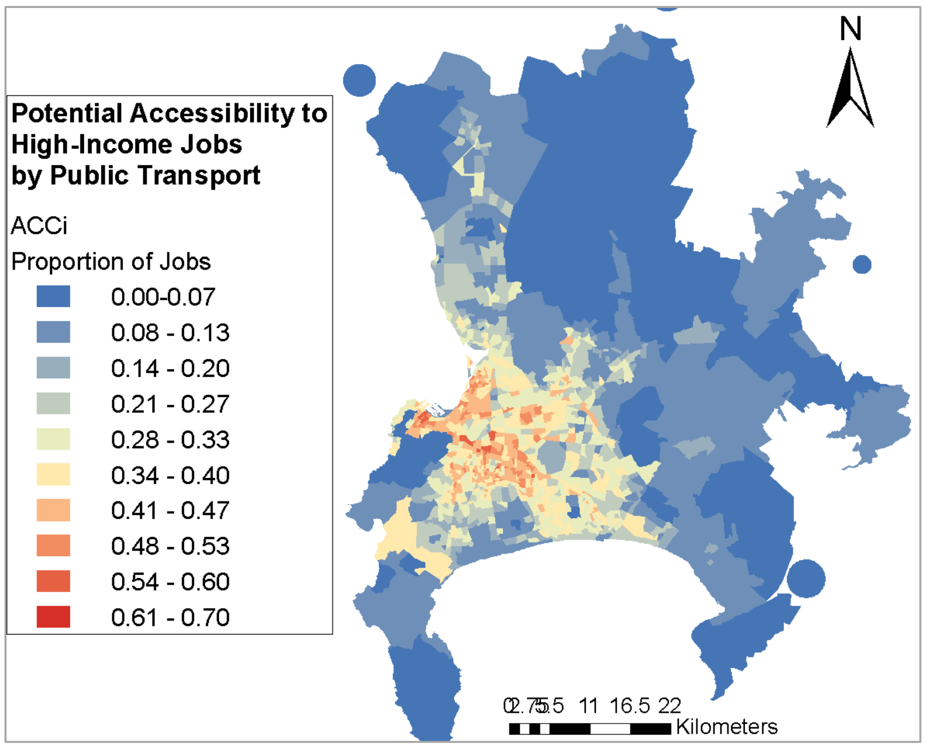
(b)

Figure 8-8: Potential Accessibility to Upper-Middle-Income Jobs (relative indicators) by (a) Public Transport (b) Car

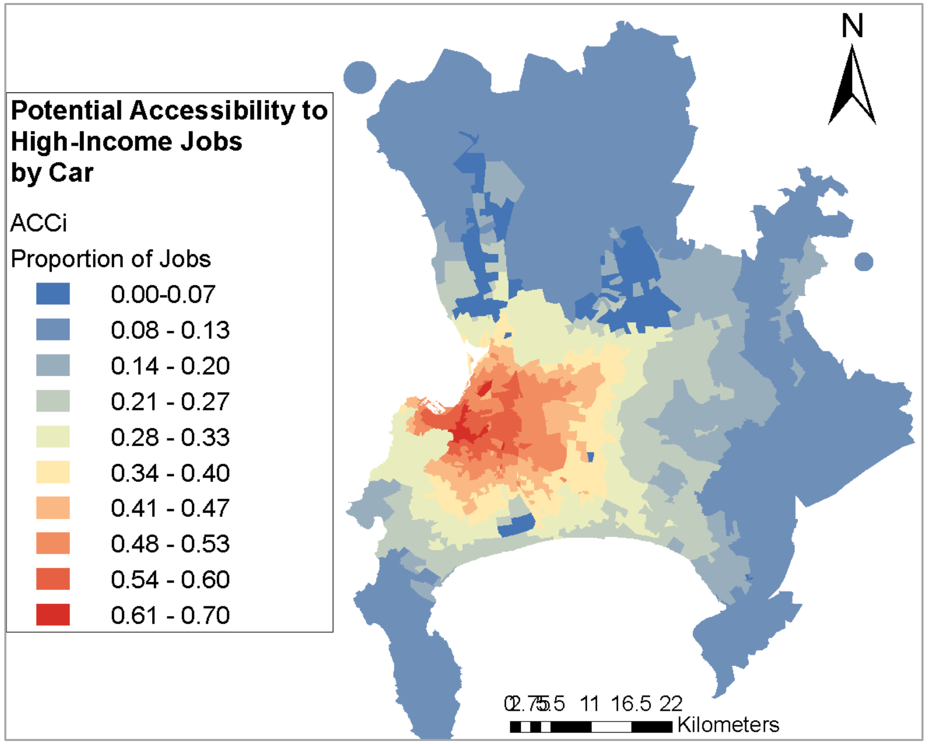


(a) (b)

Figure 8-9: Potential Accessibility to High-Income Jobs within 60 minutes by (a) Public Transport (b) Car



(a)



(b)

Figure 8-10: Potential Accessibility to High-Income Jobs (relative indicator) by (a) Public Transport (b) Car

A comparison of each pair of maps from Figures (8-3) – (8-10) reveals that potential accessibility achievable by car for travel within 60 minutes is relatively higher than that of public transport. The relative indicators of potential accessibility are the absolute indicator normalised by the total available jobs (for each income category) in the entire study area. In other words, this index shows the proportion of the total available jobs that can be potentially accessed within the specified travel time threshold of 60minutes. Table 8-1 below further summarises both the absolute and relative indicators of accessibility for travel by public transport and car.

Table 8-1: Summary statistics of Job Potential Accessibility

Job categories (Income level)	Total available jobs (‘000 jobs)	Accessibility within 60 minutes							
		Public Transport				Car			
		Absolute Index (‘000 jobs)		Relative Index (proportion of jobs)		Absolute Index (‘000 jobs)		Relative Index (proportion of jobs)	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Low	550.60	165.58	104.80	0.30	0.19	212.06	93.50	0.38	0.17
Lower-middle	1320.72	406.27	259.36	0.31	0.19	546.82	237.38	0.41	0.18
Upper-middle	207.31	59.60	38.01	0.29	0.18	70.54	32.46	0.34	0.16
High	107.51	31.12	19.65	0.29	0.18	47.03	19.86	0.43	0.18

Table 8-1 shows the total available jobs of the various income category and the summary of accessibility indicators. The Table shows that, on the average, about 30% of the jobs (all categories) are potentially accessible from a zone, for travel by public transport within 60 minutes. For travel by car, the average is seen to be higher at about 40% within the same time threshold.

While 60 minutes has been considered an appropriate threshold for analysis in line with the observed average travel time by these modes, accessibility to low-income jobs were also computed and compared for thresholds of 30, 45, 60 and 120 minutes travel time by public transport. A summary showing the total potential accessibility across all zones, as well as the average accessibility per zone for these various thresholds, are presented in Figure 8-11.

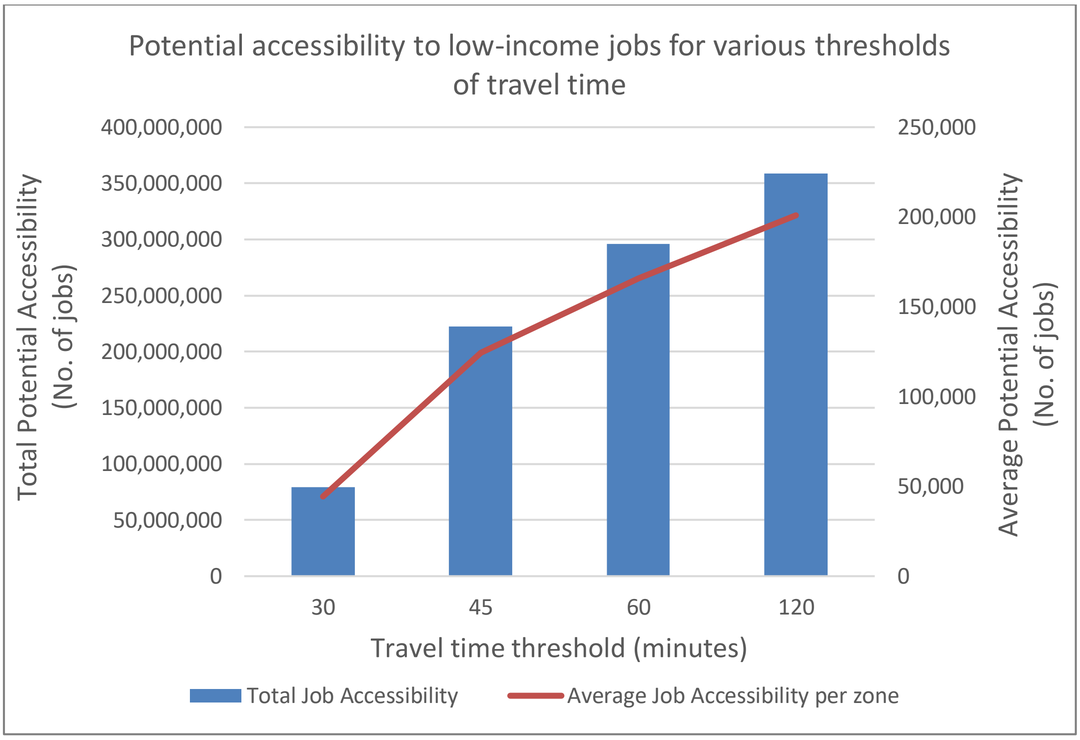


Figure 8-11: Variation in Potential Accessibility to low-income jobs for various thresholds of travel time

In the Figure above, the total potential accessibility is the sum of the potential accessibility across all zones. Since the magnitude of these values, as expected, are much higher than the total available jobs (see Table 8-1 above) across all the zones, the values are only of significance for comparative purposes across the various time thresholds. What is of essence, however, is the average accessibility per zone for each of the thresholds, as shown on the secondary vertical axis. Although travel within 120 minutes yields the highest average potential job accessibility of about 200,000 jobs (compared to about 50,000 jobs for travel within 30 minutes), such travel time can, however, be considered excessive in the context of Cape Town, where average travel time is observed to be at about 60 minutes. The 120 minutes travel threshold of accessibility has further been applied in a proposed measure of Potential Accessibility Loss (Section 5.5.3, Equation 5-7), which is developed as a function of Affordable Potential Accessibility (Section 8.4) and applied as a measure of equity. The indicators of Potential Accessibility loss are further presented in Chapter 10 (Section 10.3.1).

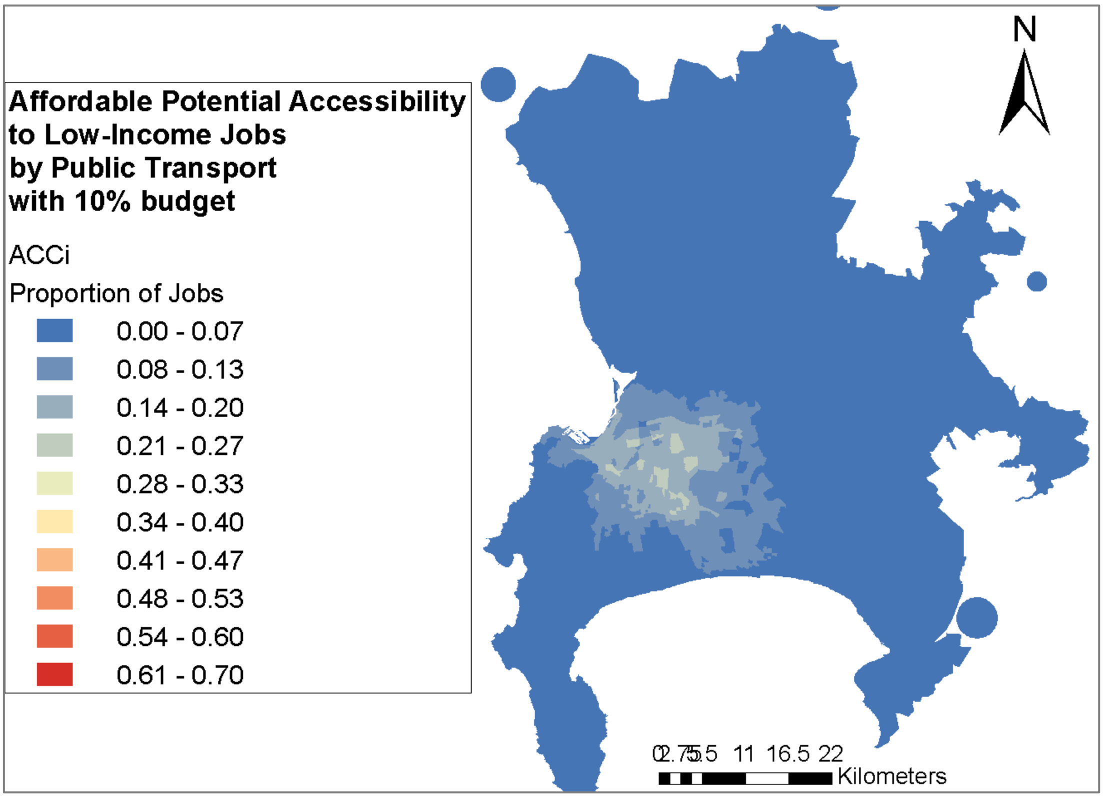
8.4 Affordable Potential Accessibility to Low-income Jobs by Public Transport

In Sections 8.3, potential accessibility to jobs using the gravity model described by Equations (5-2) and (5-3), were presented to evaluate travel by public transport and car. A modified potential accessibility index that considers the monetary cost of travel, as well as affordability, have been proposed, as presented in Section 5.5.2 (Equations (5-4) and (5-5)). This section presents the indicators, otherwise regarded as the 'Affordable Potential Accessibility indicators' for the case of low-income jobs, for travel by public transport.

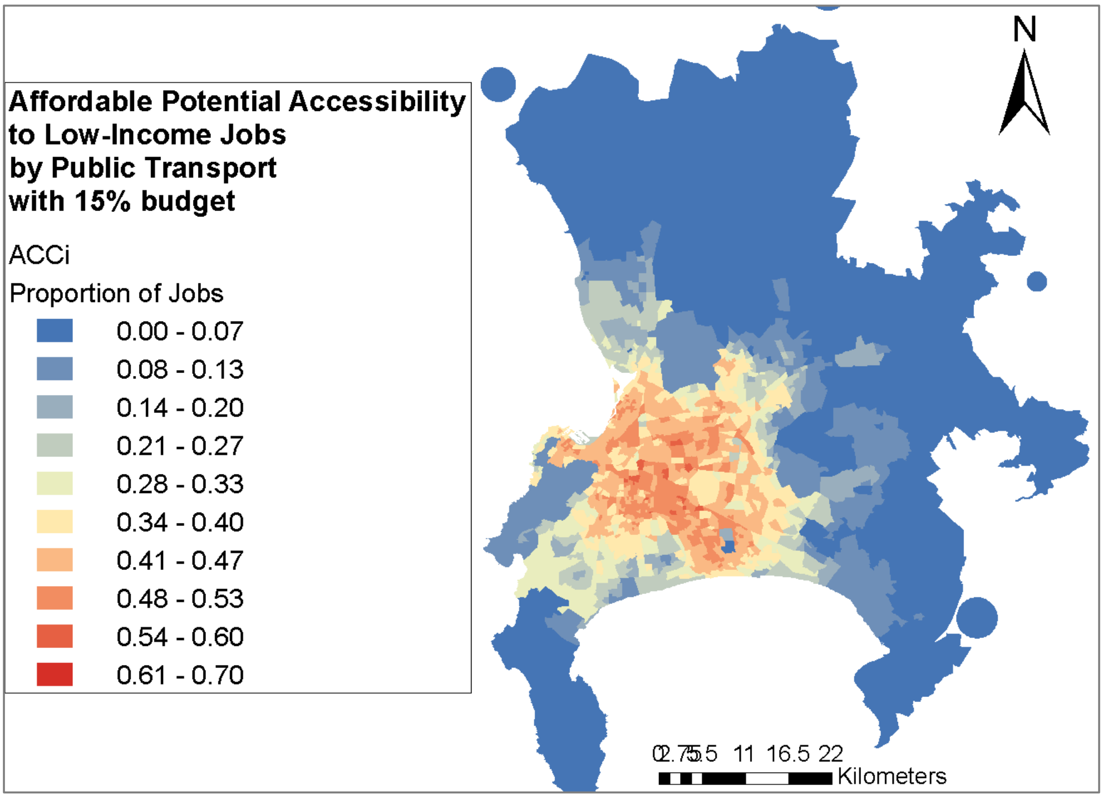
The Affordable Potential Accessibility (accessibility under affordability constraints) is measured by considering various thresholds of affordability, defined as a percentage of income. Since affordability of travel is a problem of the poorest income group, accessibility under budget constraint is measured for the low-income jobs, for a typical low-income household with one source of income. The analyses assume a maximum earnable income of ZAR3200[8] per month for the low-income household (as defined in Section 4.3). Accessibility, measured for an affordability threshold of 10% income, for example, implies the daily potential accessibility achievable with a maximum monthly budget of ZAR320. This translates to a daily return trip budget of ZAR16 (or ZAR8 one-way), assuming a 5-day work week. An affordability threshold of 20% of income will translate to a daily one-way trip budget of ZAR16. Considering that the monetary cost of travel is estimated for every possible origin-destination connection, accessibility under any threshold of affordability is computed by aggregating the opportunities reachable within the corresponding daily monetary budget for travel. Within the GIS platform, this is achieved by an SQL query 'by cost', within the attributes table of the generated origin-destination lines containing the estimated monetary cost of travel.

Presented in Figures 8-12(a) – (c) below are the indicators of daily Affordable Potential Accessibility to low-income jobs for a typical low-income household with one source of income, and for travel budget thresholds of 10%, 15%, and 20% of income. The indicators are given in relative values, that is, the proportion of total low-income jobs that are potentially accessible within the various budget. The same interval scale has been applied across the values for comparability with the potential accessibility indicators (without affordability dimension) earlier presented in Section 8.3.

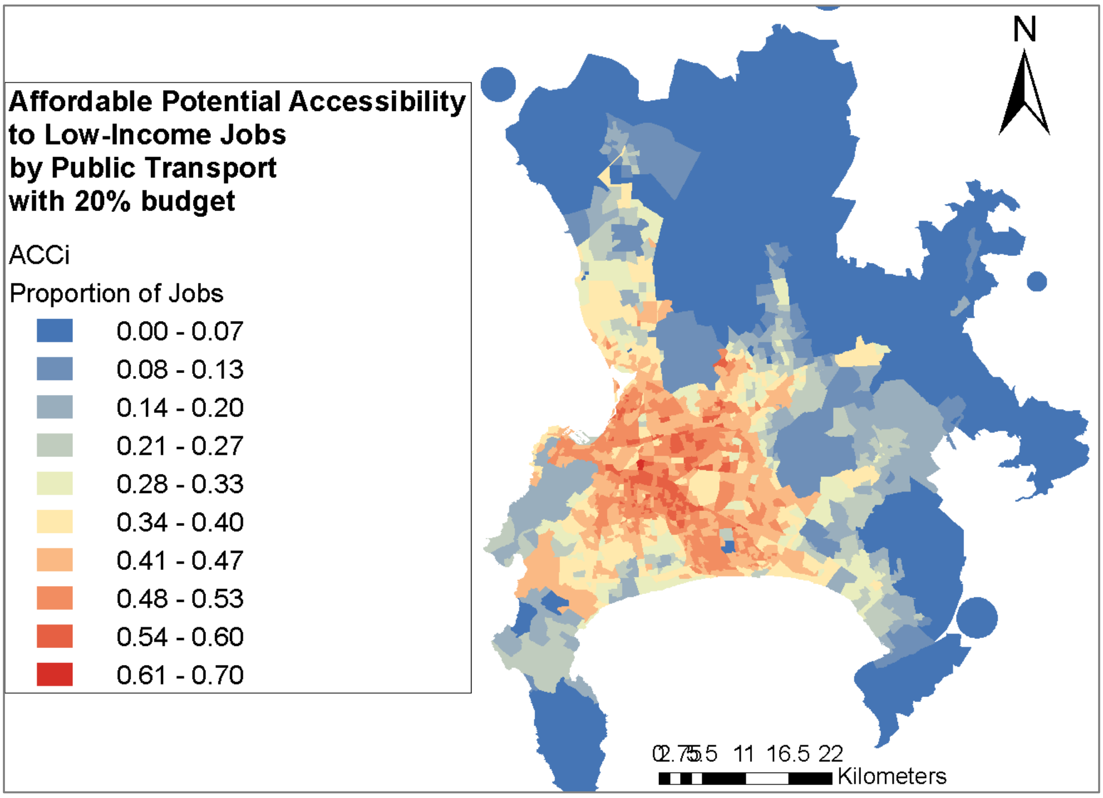
[8] ZAR or R represent the South African Rands. ZAR1 = USD 0.06 as at August 2018.


Affordable Potential Accessibility
to Low-Income Jobs
by Public Transport
with 10% budget
ACCi
Proportion of Jobs
0.00 - 0.07
0.08 - 0.13
0.14 - 0.20
0.21 - 0.27
0.28 - 0.33
0.34 - 0.40
0.41 - 0.47
0.48 - 0.53
0.54 - 0.60
0.61 - 0.70
N
0 2.75 5.5 11 16.5 22
Kilometers

(a)


Affordable Potential Accessibility
to Low-Income Jobs
by Public Transport
with 15% budget
ACCi
Proportion of Jobs
0.00 - 0.07
0.08 - 0.13
0.14 - 0.20
0.21 - 0.27
0.28 - 0.33
0.34 - 0.40
0.41 - 0.47
0.48 - 0.53
0.54 - 0.60
0.61 - 0.70
N
0 2.75 5.5 11 16.5 22
Kilometers

(b)



(c)

Figure 8-12: Affordable Potential Accessibility to Low-Income jobs for travel budget of (a) 10% (b)15% and (c) 20% of maximum earnable monthly income

Figure 8-12 (a) – (c) above show how potential accessibility vary with monetary travel budget. The analysis is based on the maximum earnable monthly income, which is taken as the upper limit of the low-income wage range, that is, ZAR3200, according to the 2013 income group classification in the city of Cape Town (see Section 4.3). As seen, the amount of opportunities potentially reachable with a 10% budget is far less than that obtainable with a 15% or 20% budget. With a 10% budget, zones with the highest accessibility level can only potentially reach a maximum of about 20% of the total available low-income jobs. With up to 20% of income as travel budget, the high-accessibility zones can potentially reach up to 60% of the total available low-income jobs.

To further show the effect of the travel budget on potential accessibility, a comparison is drawn against potential accessibility obtainable within 120 minutes of travel without monetary budget restriction. Figure 8-13 presents the comparative analysis of the aggregate accessibility with and without affordability consideration.

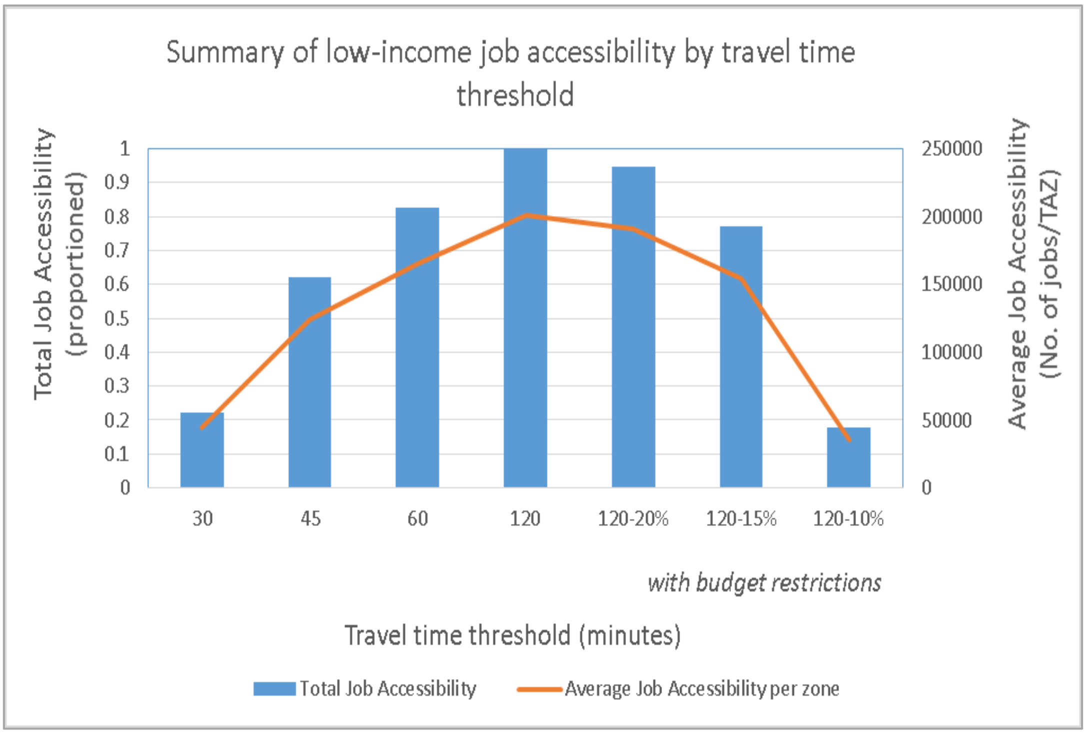


Figure 8-13: Low-income job accessibility by travel time and budget threshold.

In the Figure, the first four bars show aggregate accessibility indicator under four thresholds of time (30, 45, 60 and 120 minutes) without restriction on budget, while the last 3 bars show accessibility level when budget restrictions are factored in at the respective percentage of income. Although 120 minutes is applied as the reference travel time threshold regarding the number of opportunities reachable, it is not considered as the ideal travel time for public transport.

The analysis framework provides the flexibility of adopting lesser travel times, of say, 60 or 45 minutes. For this case, however, aggregated potential accessibility within 120 minutes is taken as the maximum and is thus, normalised to a value 1. Normalisation is necessitated since the absolute value of total accessibility (sum of potential accessibility of all zones) becomes a huge number, which is of little significance, in terms of interpretative meaning. Of more significance, is the average potential accessibility per zone, shown by the line drawn across the bars.

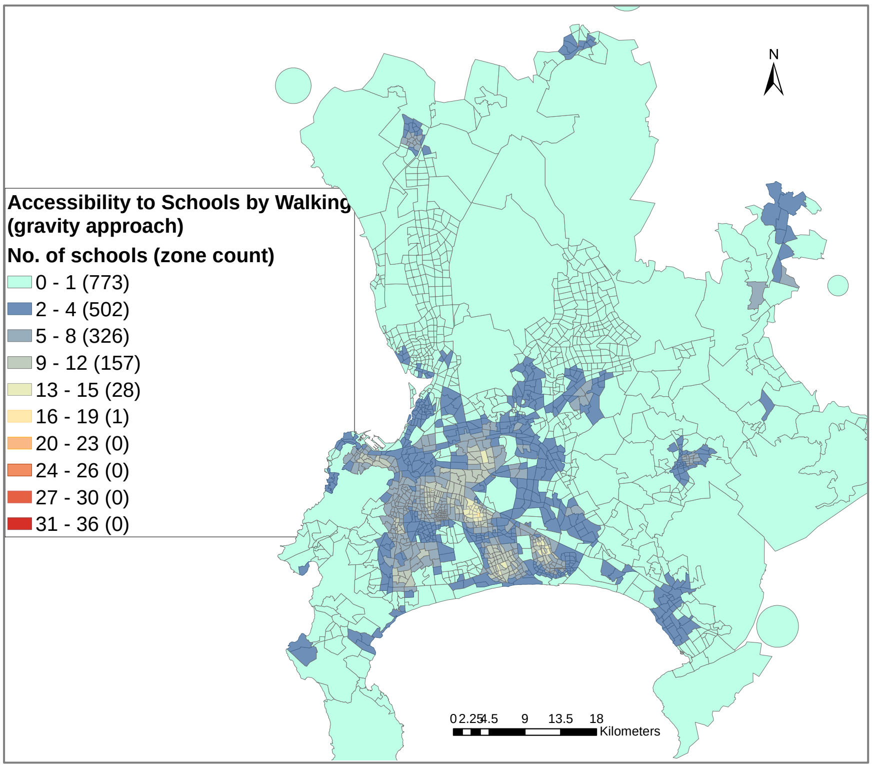
The chart shows that, for a restriction of 10% income as budget, the zonal average potential accessibility obtainable within 120 minutes of travel shrinks from about 200,000 jobs to just about 35,000 jobs. This amounts to about 82.5% reduction. In other words, on the average, over 80 % of the low-income jobs that can potentially be reached within 120 minutes, becomes unreachable when restricted to a travel budget of 10% of the low income. Reachability is, however, much improved for increased percentages (15% and 20%) of income travel budget. The chart further shows that the potential accessibility under a 60 minutes travel time threshold is achievable with a little more than 15% (but less than 20%) of income travel budget. In other words, all low-income jobs that can be reached within 60 minutes, are reachable with 20% of income travel budget.

Since travel budget is taken as a function of income earnable from the jobs, the potential loss in accessibility as a result of budget restriction further serves as a measure of vertical equity in accessibility across the various population groups. The proposed indicator of Potential Accessibility Loss (Section 5.5.3) is presented in Chapter 10 of this thesis, which focuses on equity evaluation. The remaining sections of this chapter present the indicators of accessibility to schools and healthcare facilities, as well as an evaluation of schedule-based accessibility by the BRT.

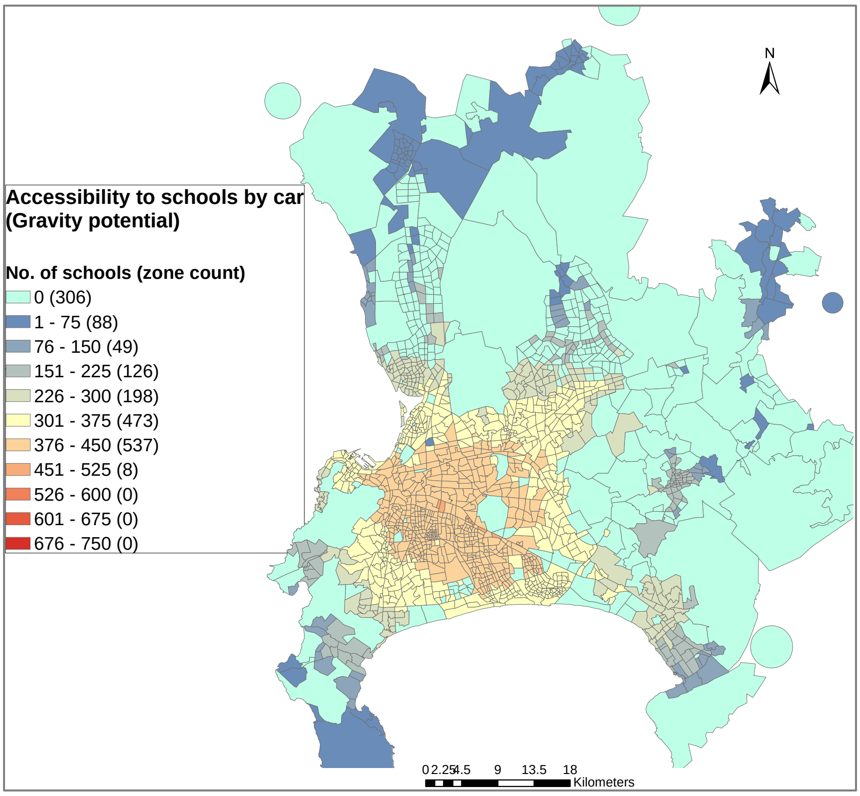
8.5 Accessibility to schools by public transport, car and walking.

As the case for jobs, accessibility to schools is computed using the gravity measure as discussed in Section 5.5.4. The indicator is computed at the TAZ level for each of the four modes of public transport, as well as for walking and travel by car. Origin points are taken as the TAZ centroids while the destinations are each of the 883 primary and secondary school locations across the study area (based on the 2013 data from the city of Cape Town). Various travel time thresholds have been applied across the modes, based on the idea of observed travel time for educational trips, as revealed from the household travel survey (see Section 6.4.4, Figure 6-8). For walking and travel by car, a threshold time of 30minutes has been applied, while the public transport modes are analysed for 60 minutes travel.

Figures 8-14 (a) - (b) present the indicators for walking and car travel, while Figures 8-15 (a) – (d) present the indicators for each mode of public transport. Apart from walking, the indicator values across all modes have been symbolised using the same interval scale, for comparability.



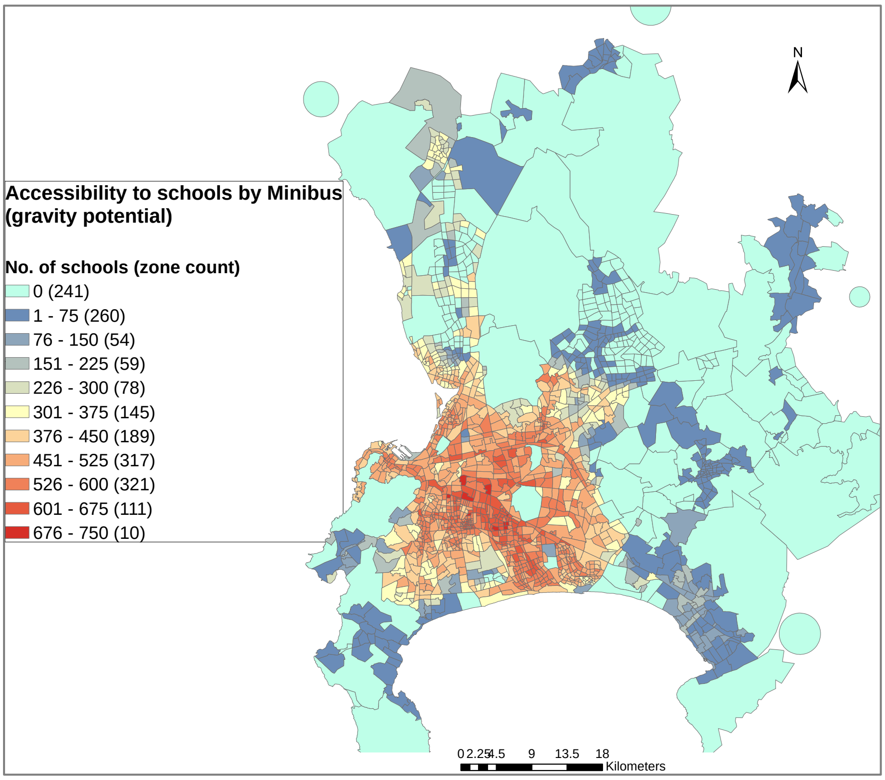
(a)



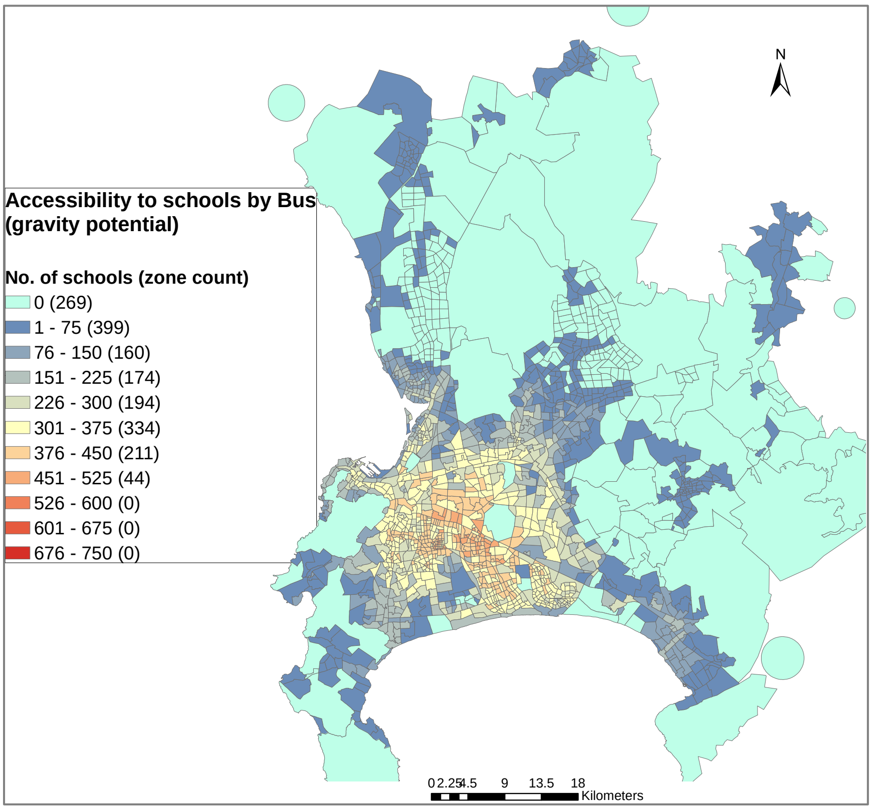
(b)

Figure 8-14: Accessibility to schools for 30minutes travel by (a) walking (b) car

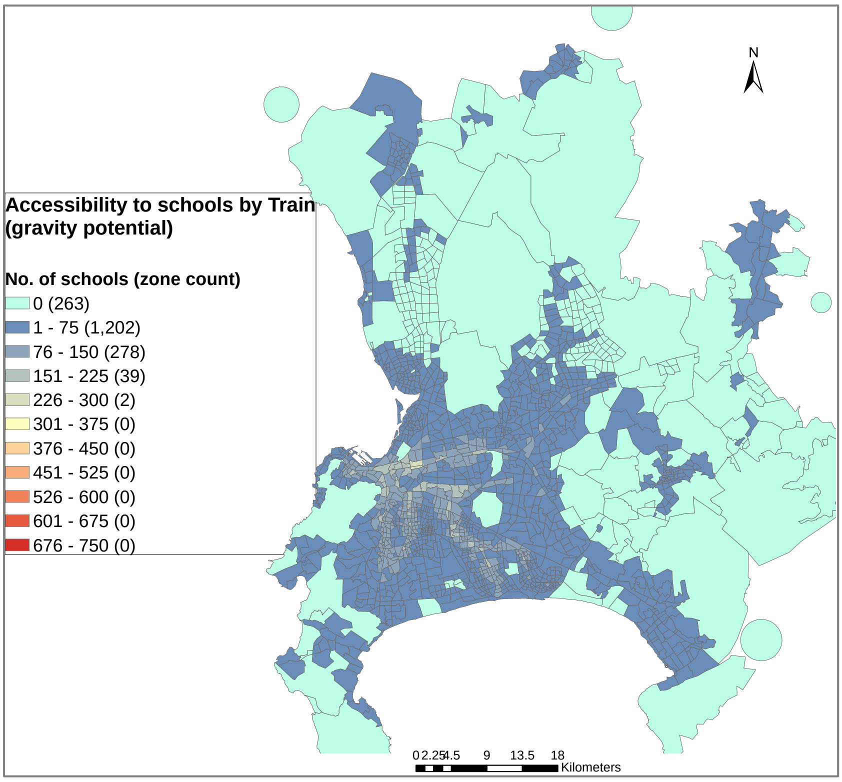
Accessibility for each mode of public transport is shown in Figure 8-15 (a)- (d)



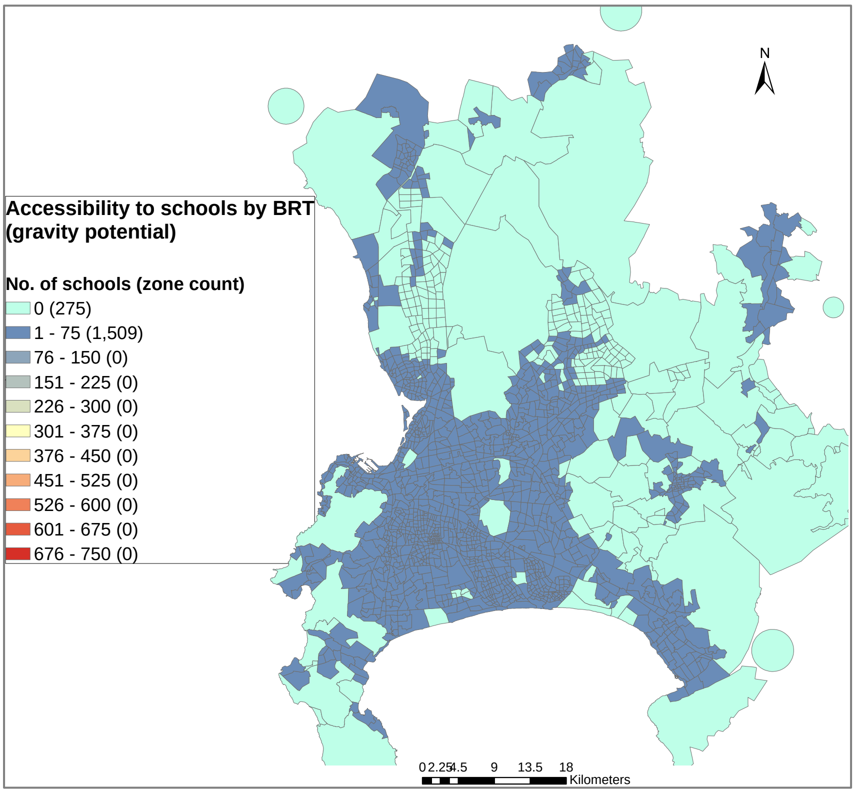
(a)



(b)



(c)



(d)

Figure 8-15: Potential Accessibility to schools within 60minutes by (a) minibus-taxi (b) regular bus (c) train (d) BRT

From Figures 8-14(a) – (b) and Figures 8-15(a) - (d), it is seen that the minibus provides the highest level of accessibility across all the public transport modes considered, while the BRT provides the lowest level of accessibility. A summary statistic of the indicators, showing the average accessibility across all zones is presented in Table 8-2 below.

Table 8-2: Summary statistics of school accessibility indicators

	Zonal average accessibility to school (No. of schools)	
Mode / Time threshold	Mean	Std. Dev
Walk _30mins	3	3
Car_gravity_30mins	262	155
Minibus_gravity_60mins	327	230
Bus_gravity_60mins	185	158
Train_gravity_60mins	36	44
BRT_60mins	17	16

The school accessibility indicator is a measure of the potential number of schools reachable from the zones. The relatively high standard deviation across modes show that the measured indicators across the zones are quite spread out from the mean. From a spatial equity perspective, the indicators are reflective of the options of schools available to households from a given location. No distinction has been made of school types, implying all schools from primary level and above, whether private or public, have been weighted equally in the calculation. The approach can, however, be replicated to investigate accessibility to specific school types.

Although the indicators above show the potential accessibility, it is recognized that in the practical sense, schools that can be considered 'accessible' for households, will also depend on other factors such as the type of school and the affordability of the school for various households. For example, households that can only afford the cheaper public schools will invariably experience zero accessibility to schools by walking, if all schools within, say 15 minutes of walking, are all expensive/non-affordable private schools. It must, therefore, be emphasized that the accessibility indicators are purely from a transport perspective, and do not consider the likely school choices of households as a result of these other factors.

8.6 Accessibility to Public Healthcare Facilities (2SFCA Method)

As discussed in Chapter 5 (Section 5.5.5), accessibility to public healthcare facilities (government-owned hospitals) has been measured using the Two-Step Floating

Catchment Area (2SFCA) method. The 2SFCA method is well suited for healthcare accessibility by the automobile, as it considers the mobility from the supply and demand points. The accessibility indicator, based on Equation (5-11), for a 15 minutes free flow travel by car, is presented in Figure 8-16 below.

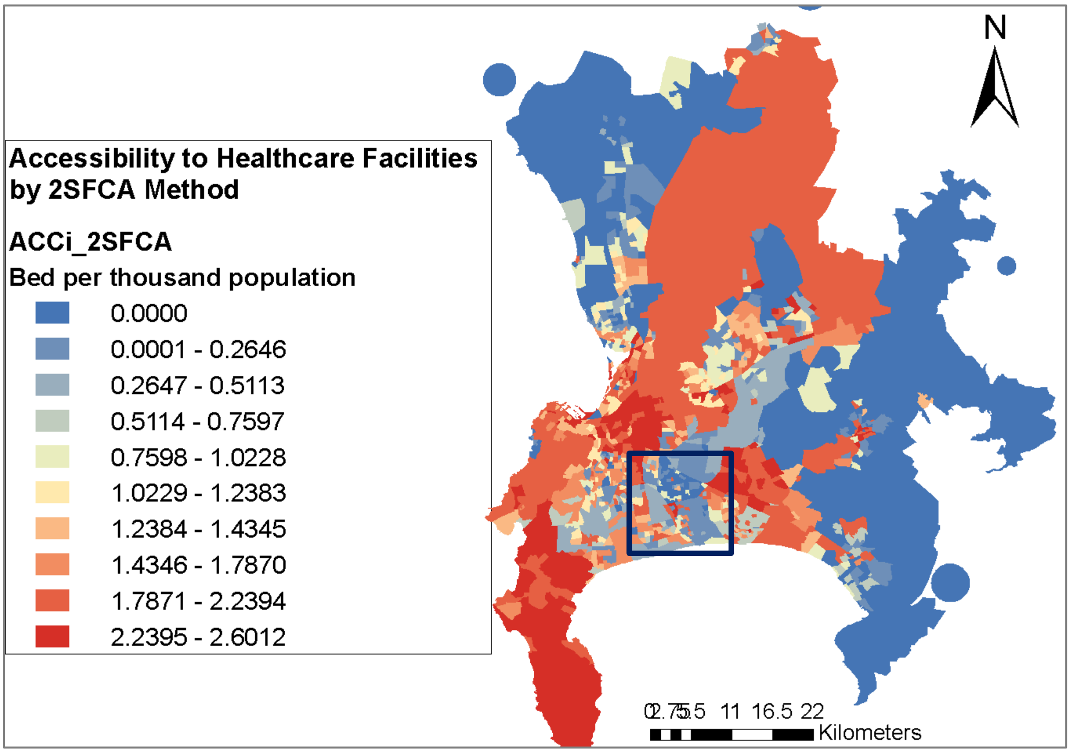


Figure 8-16: Accessibility to Public Healthcare Facilities by the 2SFCA Method

The indicator in Figure 8-16 above is given as the number of hospital beds available per thousand population. The indicator only considers public hospitals, as data on other health facilities such as private hospitals and clinics were not available for this study. From the map, it is seen that some of the areas with relatively high level of accessibility (red-coloured zones) are uninhabited areas, such as mountains or farmlands. Since facilities catchment spill onto these uninhabited zones as well, a relatively high value of bed/population ratio is computed for these less-populated zones. Nevertheless, by comparing the map above with the population dot-density of the low-income population (Figure 8-17 below), it is seen that the areas with high concentration of low-income dwellers (bounded by the square outline) have relatively low accessibility values.

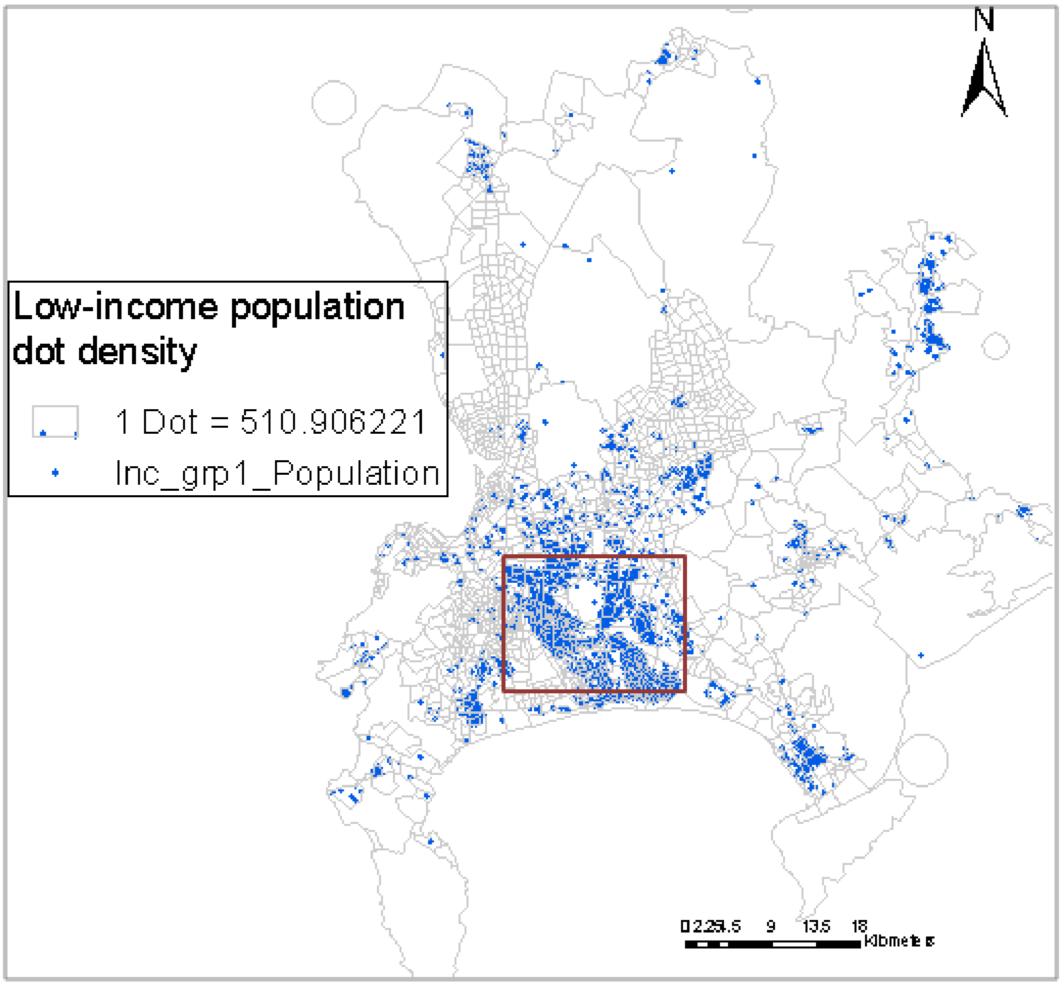


Figure 8-17: Low-income population dot density

The accessibility indicator shown in Figure 8-16 is based on the service area around a healthcare facility as defined by a 15-minute travel time by car on an uncongested road network. Although the infrastructure supply has been defined by the number of available beds (based on available data), it is recognised that service availability is also a function of other factors, such as the available number of physicians at the respective facilities at any given point in time. For this research, however, such information is not available. Thus, the indicator presented in Figure 8-16 is interpreted in terms of potential opportunity available, and not necessarily concerning the potential service quality.

Indicators such as Figure 8-16, can inform healthcare policymaking, for example, in identifying residential areas that are less served or poorly served by health facilities. The indicators can, thus, guide the optimal location of new healthcare facilities in areas that have low accessibility values.

8.7 Schedule-based Accessibility Evaluation based on GTFS Data

Section 8.3 presented potential accessibility indicators computed using data of the transport network (routes and stops for the case of public transport, and the road network in the case of the car). The public transport accessibility indicator is a static indicator which only shows the potential opportunities ‘reachable’ based on the presence of routes and stops. There is, nevertheless, some limitation with such static indicators as they do not consider the influence of schedules and timetables on the level of accessibility. Accessibility by public transport can be dependent on the service frequencies, considering that individual’s activity participation is in most cases tied to time. Although temporal accessibility is not the central focus of this research (mainly due to lack of comprehensive public transport data), the objective of this section is to present an analysis of accessibility that demonstrates the influence of schedules on accessibility level, using the GTFS data of the BRT system as discussed in section7.6.

The analyses of accessibility using GTFS data within ArcGIS have been discussed in some recent studies such as Farber & Fu (2017) and Fayyaz et al. (2017). Considering that GTFS data carries comprehensive information on the schedules and trips timetables, the results of accessibility analyses using a GTFS-enabled network dataset (Section 7.6) can vary considerably depending on the period of the day or day of the week used for the accessibility computation. In other words, accessibility is dependent on the actual operational schedules of the public transport service. For example, an analysis run at say 7:00 AM might yield a different result to one run at 7:01 AM. In which case, a given origin might have access to a given destination at 7:00 AM but not at 7:01 AM if, by starting at 7:01 AM, the traveller has just missed the bus by 1minute (Melinda, 2017).

Using the Network Dataset developed with GTFS data of the MyCiTi BRT of Cape Town, and the “calculate accessibility matrix” tool from ESRI, as discussed in Section (7.6), accessibility to all jobs (all income categories combined) was computed across two time periods (1) morning AM peak period (0700-0900 hours) and (2) the afternoon off-peak (1200-1300 hours). The computation is run at incremental intervals of 1 minute across these time windows. This yields a total of 120 runs for the selected AM period of 2 hours, and 60 runs covering the afternoon off-peak period of 1 hour. Since it becomes impractical to report accessibility at every incremental minute of start time, the results are grouped by percentages of start times within the time window.

The resultant indicator measured for a zone is given as the percentage of total available jobs that can be reached from that zone, for at least, the various percentages of start times within the analysis periods. The resultant summary of accessibility for AM peak period (00700 -00900 hours) is shown in Table 8-3.

Table 8-3: Summary statistics of Accessibility values by proportion of start time within AM peak period, 0700 – 0900 hours

% of start times	100	10	20	30	40	50	60	70	80	90
N (TAZs)	1787	1787	1787	1787	1787	1787	1787	1787	1787	1787
Accessibility (% of total available jobs)										
Mean	4.41	4.04	3.89	3.77	3.67	3.58	3.49	3.40	3.31	3.20
Median	2.96	2.91	2.88	2.86	2.81	2.78	2.75	2.72	2.69	2.56
Std. dev	5.52	4.97	4.73	4.55	4.39	4.25	4.10	3.96	3.84	3.65
Max.	28.26	25.87	24.81	24.10	23.72	23.35	22.96	22.77	22.52	21.79
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The table shows the mean, median, standard deviation and the maximum values of accessibility across all zones (N=1787), according to the percentage of start times. From the table, it is seen that average accessibility reduces slightly as proportion of start times increases. Accessibility at 100% of start times shows what can be achieved, irrespective of the start time of journey. It must be noted that the accessibility level combines walking with transit, and it is measured for a total threshold of 60 minutes. Distribution of the accessibility values is further represented in the cumulative plots shown in Figure 8-18 below.

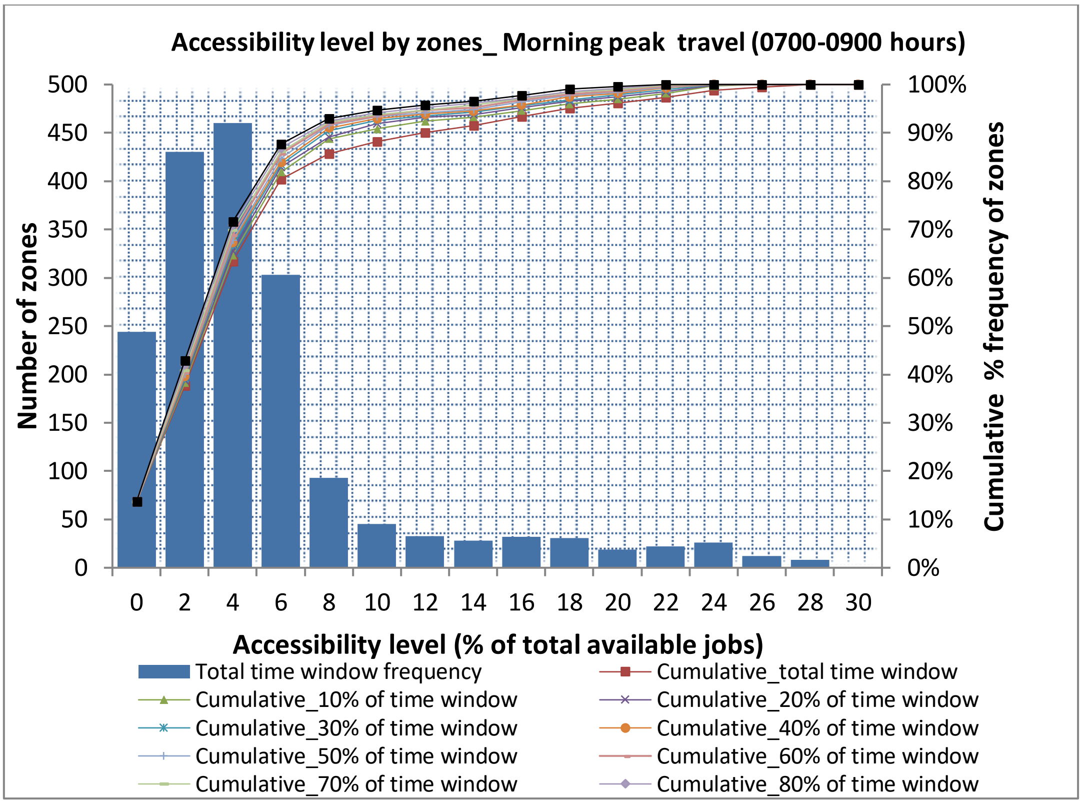


Figure 8-18: Distribution of Accessibility across zones by the proportion of start times within morning peak period 0700—00900 hours

The Figure shows a histogram of computed accessibility indicators across the zones. On the horizontal axis are the indicators, represented as percentages of total available jobs reachable from a zone. Each bar shows the frequency of zones corresponding to a range of accessibility value. The lines further show the cumulative percentage frequency of zones across the range of accessibility values, which range from 0 – 30%.

The distribution shows that about 60-70% of zones have accessibility value of about 4%, for the various percentages of start times within the travel time window. A cumulative of about 90% of the zones have accessibility below 8%. Also, not much difference is observed across the various proportion of start times for which accessibility is analysed.

Similarly, accessibility summary for the off-peak window is shown in Table 8-4 below.

Table 8-4: Summary statistics of Accessibility values by proportion of start time within off-peak period, 1200 – 1300Hrs

% of start times	100	10	20	30	40	50	60	70	80	90
N (TAZs)	1787	1787	1787	1787	1787	1787	1787	1787	1787	1787
Accessibility (% of total available jobs)										
Mean	3.70	3.44	3.27	3.17	3.09	3.03	2.96	2.90	2.85	2.80
Median	2.81	2.69	2.54	2.44	2.42	2.41	2.39	2.36	2.31	2.30
Std. dev	4.42	4.09	3.87	3.70	3.54	3.40	3.25	3.13	3.02	2.92
Max.	22.95	22.13	21.42	20.64	20.34	19.85	18.94	18.36	17.74	17.05
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

A comparison of the output for off-peak (Table 8-4) with that of the peak period (Table 8-3) shows that average accessibility is slightly less in the off-peak period, with a value that ranges between 2.3% to 2.8%. The distribution of the accessibility values across all zones is further shown in Figure 8-19.

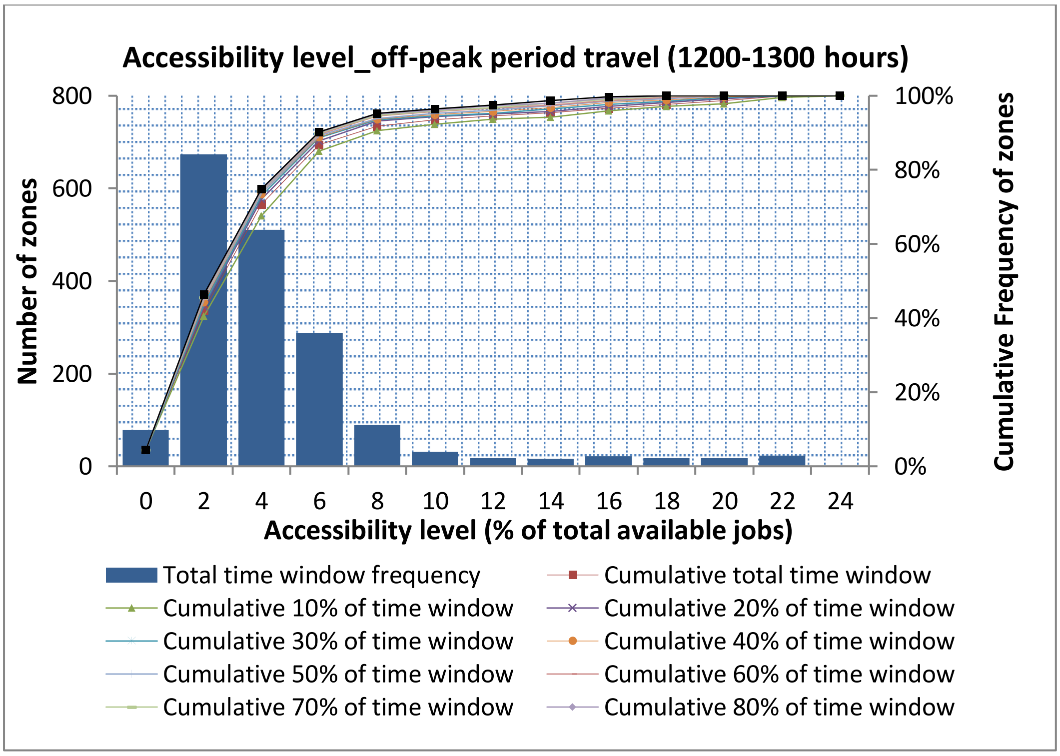


Figure 8-19: Distribution of Accessibility across zones by the proportion of start times within off-peak period, 1200—1300hrs

The Figure is a combined chart of the histogram of accessibility level within a total off-peak period, as well as the cumulative frequencies of zones for the various percentages of start times within the total time window. The total time window frequency represents the number of zones by accessibility level within a 1hr time-frame for the off-peak period considered (1200-1300 hours), with accessibility computation run at 1-minute intervals. The 1-minute interval yields an accessibility computation for 60 different start times (departure time). The accessibility level for the total time window indicates a summation of all opportunities reached at least once within any departure time that falls within the 60 different possible start times.

What is evident from the cumulative frequency plots is that variation in accessibility is seen to be minimal across the various percentages of start times within each window. This might be attributable to the nature of the schedules of the BRT service. A schedule with, say, constant headways across all times of the day would be expected to yield such results.

With future availability of more GTFS data for other modes of public transport in Cape Town, time-of-day evaluation of accessibility, such as this, can be achieved.

8.8 Chapter Conclusion

This chapter presented the various indicators of access and accessibility developed in this research. The network access indicators for public transport show that most parts of the city are well covered by public transport network, with the paratransit mode providing the most extensive coverage and the BRT mode providing the lowest. These indicators have been developed to suit the nature of data available for public transport, which is limited to routes lines and stop locations, without detailed information on schedules.

The public transport network access indicators are relevant to planning, as it finds application in the strategic level assessment of network coverage across the entire city of Cape Town. There are nevertheless, some limitations in its application for temporal assessment of access, as it does not show possible access variation across various times of the day based on scheduling and frequencies of the public transport services. Since some of the modes investigated in this research do not have schedule information, comparison of coverage areas can only be carried out based on the individual network of the modes. Also, no distinction has been made between a route that runs limited service (say few morning and evening peak trips) and a route that runs more frequent service, in which case, access would be expected to vary considerably by time of day. There is also the challenge of developing a schedule-based measure of access for modes like the paratransit (minibus taxi), which, characteristically, do not operate on fixed schedules.

Despite these limitations, the indicator of access presented in this chapter can be used to evaluate public transport infrastructure coverage at a macroscopic level. For microscopic analysis of access, the index can further be expanded to incorporate variables relating to service quality, such as frequencies, reliability and safety. Perceived safety of stops can, for example, be a vital indicator of access. Hence, the development of a comprehensive access index for public transport in Cape Town, which considers these components, would be a recommended area for further research. This would, however, depend on the availability of rich dataset of the public transport infrastructure and services, including users' perceptions of aspects, such as safety of stops, the reliability of service or walkability.

On the accessibility aspect, a set of indicators has been developed for three key opportunities; jobs, healthcare and education. While these indicators have been developed from existing theories, modifications have been introduced to suit South Africa and Cape Town context. The Affordable Potential Accessibility indicator and the associated Potential Accessibility Loss indicators are two of the significant indicators proposed in this research. The strength of these indicators lies in their intuitiveness and relative ease of interpretation, especially in the context of job accessibility analyses for the transport-disadvantaged poor.

Although the accessibility indicators provide measures of the potentials available, it is recognised that what is of utmost importance to individuals is real access that is being enjoyed. In other words, while a job accessibility indicator might show the number of jobs that can "potentially" be reached, whether (or not) the individuals have access to those jobs is a different question entirely. The analysis presented in this research does not provide such information. Nevertheless, potential accessibility indicators such as these can be applied for comparative evaluation of various zones to identify areas with low or high levels of potential accessibility, and thus guide land use and transport planning decisions, as will be discussed in Chapter 11.

The next chapter (Chapter 9) seeks to understand some of the spatial and socioeconomic drivers of the measured potential accessibility indicator presented in this chapter. An understanding of such drivers could further inform the strategies to be recommended to improve accessibility. In Chapter 10, an evaluation of equity in accessibility, as it affects the various population groups, will be presented.

Chapter 9

Exploratory Analysis of Accessibility Drivers

"Nothing's random. Even if it looks that way, it's just because we don't know the causes" – Johnny Rich, The Human Script

9.1 Introduction

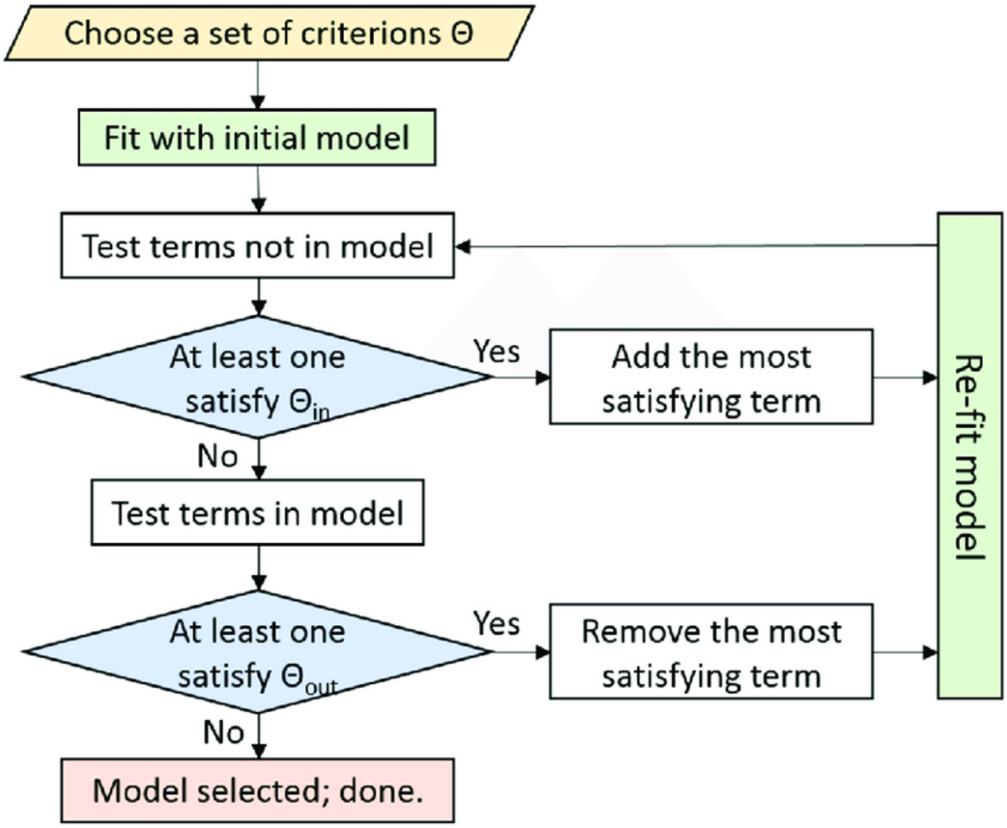
The previous chapter presented the results (indicators) of computed potential accessibility at the TAZ level for three kinds of opportunities; jobs, healthcare and schools. To further understand the likely drivers of accessibility, this chapter investigates the relationship between job accessibility indicators and a combination of socioeconomic and built environment variables, using an exploratory OLS regression technique. This regression technique (Draper and Smith, 1998) is a stepwise regression process which operates by iteratively finding the best Ordinary Least Squares (OLS) models from an array of candidate explanatory variables (socioeconomic and built environment variables in this case) to explain the dependent variable of interest, which in this case is the indicators of job accessibility. Understanding such relationship could further add another dimension to understanding the potential impacts of various land-use and spatial planning decisions on improving accessibility.

The remaining sections of this chapter present the regression procedure, variable specification, regression results and chapter conclusion.

9.2 Overview of the Exploratory (Stepwise) Regression Technique

An exploratory regression technique is a stepwise regression procedure which involves fitting regression models in an iterative procedure based on a pre-established criterion (Draper and Smith, 1998). In this procedure, the choice of explanatory variables is automatically selected. The procedure is useful when there are many potential explanatory variables that one might consider as important in explaining the variable being modelled (ESRI, 2018).

The stepwise regression technique is adopted in this research to model the relationship between job accessibility indicators (the dependent variables) and the socioeconomic and built environment features (the explanatory variables). The procedure is executed using the IBM SPSS statistical package. The algorithm of the regression procedure as described in Yang et al. (2017) is as shown in Figure 9-1 below.



Source: Yang et al. (2017)

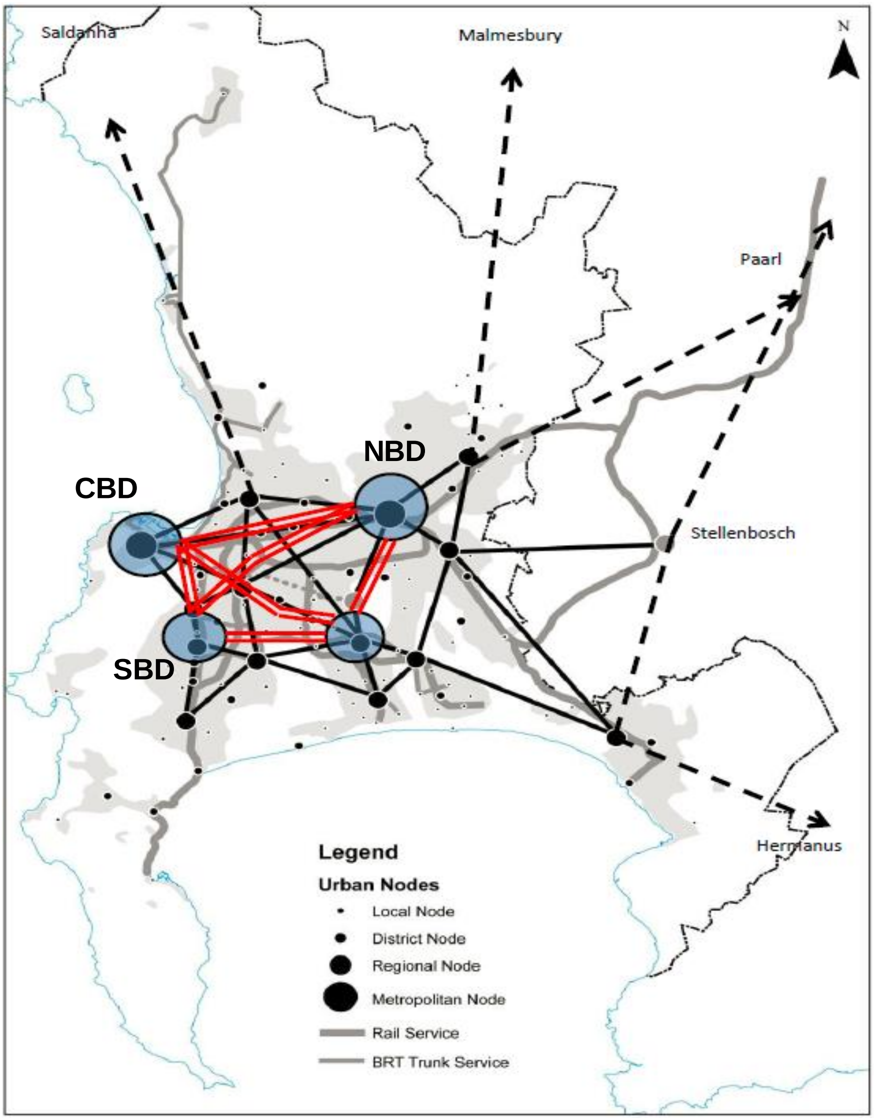
Figure 9-1: Exploratory (Stepwise) Regression Algorithm

The regression process, as illustrated above, starts with an initial model with only a constant term. This is followed by successive addition and removal of predictor variables based on a set criterion until a subset of the best predictors is identified (Harrell, 2001). The regression has also been regarded as a data mining process that utilises all possible combination of the candidate explanatory variables and looks for models that meet all of the set criterion, as well as the requirements and assumptions of the Ordinary Least Squares (OLS) method (ESRI, 2018). Although the logic remains the same, various statistical packages vary slightly in criteria-definition for the stepwise regression process. Commonly defined criterion include; minimum and maximum number of explanatory variables to be allowed in a model, thresholds of the coefficient of determination R^2, confidence intervals and p-values. The next section discusses the dependent and explanatory variables considered in the regression analysis.

9.3 Variables Definition

The dependent variables considered in the regression model are accessibility by public transport and car, to jobs of the various income categories. That is, low-income, lower-middle-income, upper-middle-income, and high-income jobs. This results in a total of eight dependent variables. The independent variables considered are (1) the socioeconomic variables, defined by the population's employment profile as well as job types, and (2) the built environment variables, defined by proximity of zones to various business districts, otherwise known as the major economic nodes of the city.

The City of Cape Town, in its spatial development framework (CTSDF), defined various urban nodes (Figure 9-2 below) as key anchor points to guide current and future urban development (City of Cape Town, 2013a).



Source: City of Cape Town (2013a)

Figure 9-2: Urban Nodes of Cape Town

As shown in Figure 9-2, there are four categories of urban nodes defined across the city, which are referred to as the local, district, regional and metropolitan nodes. There is a total of 2 metropolitan nodes, which include the city's Central Business District (CBD), and the Northern Suburbs Business district of Bellville (denoted as NBD in this analysis). In addition to these two metropolitan nodes, a total of 12 regional nodes and 23 district nodes also exist. Since these urban nodes (especially the metropolitan nodes) are considered to be the centre of major economic activities, they are expected to have a relatively high concentration of opportunities. As such, the job accessibility indicator at any location would expectedly be related to the proximity of these economic nodes.

The built environment variables in the exploratory regression analysis are, therefore, defined by the linear areal distances to these urban nodes. Since the highest-ranked nodes are expected to have a higher influence on accessibility, only the two metropolitan nodes (CBD and NBD) and 1 regional node (Southern Suburbs business district, SBD) have been considered in the regression. A major aim of the regression analysis therefore, is to establish among other variables, the level of influence the proximity of economic nodes has on accessibility.

A summary of the dependent (accessibility) and independent (socioeconomic and built environment) variables are presented in Table 9-1.

Table 9-1: Variables definition for exploratory stepwise regression analyses

S/No	Description of variables	Notation
	Dependent variables – Job accessibility by public transport and car	
1	Potential Accessibility to low-income jobs by public transport	ACC_{PT_INC1}
2	Potential Accessibility to low-income jobs by car	ACC_{CAR_INC1}
3	Potential Accessibility to lower-middle-income jobs by public transport	ACC_{PT_INC2}
4	Potential Accessibility to lower-middle-income jobs by car	ACC_{CAR_INC2}
5	Potential Accessibility to upper-middle-income jobs by public transport	ACC_{PT_INC3}
6	Potential Accessibility to upper-middle-income jobs by car	ACC_{CAR_INC3}
7	Potential Accessibility to high- income jobs by public transport	ACC_{PT_INC4}
8	Potential Accessibility to high-income jobs by car	ACC_{CAR_INC4}
	Independent variables – Socioeconomic	
1	Number of persons employed fulltime	$Empl_{Full}$
2	Number of persons employed part-time	$Empl_{Part}$
3	Number of persons self-employed	$Empl_{Self}$
4	Number of persons unemployed but not looking for jobs	$UEmpl_{NL}$
5	Number of persons unemployed and looking for jobs	$UEmpl_{L}$
6	Number of office jobs	$Jobs_{Office}$
7	Number of retail jobs	$Jobs_{Retail}$
8	Number of manufacturing jobs	$Jobs_{Manu}$
9	Number of service jobs	Job_{Serv}
	Independent variables - Built environment	
10	Distance to Central Business District (City Centre) in meters	$Dist_{CBD}$
11	Distance to Northern Suburb Business District (Bellville) in meters	$Dist_{NBD}$
12	Distance to Southern Suburb Business District (Wyndberg) in meters	$Dist_{SBD}$

In Table 9-1 above, the dependent variables are accessibility to jobs (of various income categories) by public transport and car. In the notation, the income categories are classified from 1 - 4, with 1 representing low-income, and 4 representing high-income. According to the income classification by the City of Cape Town, a low-income job, for example, means any job offering a monthly pay within the low-income range of ZAR0 - ZAR3200 (as discussed in Chapter 4). Car-based accessibility has been measured for a maximum travel time of 30 minutes, while public transport accessibility has been measured for a maximum travel time of 60 minutes (as presented in Chapter 8).

Each of the independent socioeconomic variables in Table 9-1 is also classified and organised according to income groups 1 to 4. Therefore, for each dependent variable in the regression, only the combination of socioeconomic variables within the corresponding income groups are considered. For example, a regression of accessibility to low-income jobs will consider the socioeconomic variables for the low-income category. The built environment variables are the pre-established aerial distances to key urban nodes, which are; Central Business District, Northern Suburb Business District and Southern Suburb Business District. The areal distances are computed from every zone centroid to each of the business district centroid using the point distance tool in ArcGIS. This procedure generates three distance attributes, which are then joined to the other socioeconomic attributes of the zones.

Since the exploratory regression process aims to find the best model using an iterative algorithm, it must be emphasized that the selected independent variables above are only considered as ‘candidate’ variables prior to the regression, as no implicit assumption is made of the level of influence on the dependent variables.

The next section presents the output of the stepwise regression process. This includes a total of eight regression runs, with each run involving one dependent variable and a combination of all the independent variables.

9.4 Stepwise Regression Result

The stepwise regression run generates a report of the combination of models that have been tested and shows whether (or not) the candidate independent variables being considered yield any properly specified OLS models that meet all the passing criteria. Those models meeting the criteria are then considered as the passing models. Among the criteria set for the stepwise regression run is the minimum acceptable confidence interval for each regression coefficient. For all the regression runs, a 99% confidence interval was applied. Another stepping criteria defined is the acceptable significance (or probability) of the F value of a variable for it to be entered into the regression model. Within SPSS, two values were defined; an entry value set at 0.05, and a removal value set at 0.10. A candidate variable is entered into the model if its F value is greater than the entry value and is removed if the F value is less than the removal value. The following subsections present the output of the regression run for each dependent variable listed in Table 9-1.

9.4.1 Regression Output 1 – ACC_{PT_INC1} as dependent variable

In the first stepwise regression, accessibility to low-income jobs by public transport for 60-minute travel was selected as the dependent variable of interest, while the candidate independent variables were those listed in Table 9-1 above. In this case, the independent socioeconomic variables selected were only those associated with the low-income group. For example, 'number of persons with fulltime employment' only refers to employment within the low-income group only. Similarly, for the variable, 'number of manufacturing jobs', only the manufacturing jobs within the low-income category were considered. The reason behind such consideration is based on the assumption that, since accessibility is measured to only the low-income jobs, the most logical models would be those that consider the attributes of the low-income groups. Although there is the possibility that attributes of the other income categories might as well impact on the low-income job accessibility. In this case, variable selection is limited to similar income of the dependent variable being modelled, to avoid having too many variables.

The output of the regression run is presented in Table 9-2.

Table 9-2: Regression summary- Accessibility to low-income jobs by public transport

Model	R	R Square	Adj R Square	Std. Err. of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	0.712[a]	0.507	0.507	73673.083	0.507	1834.665	1	1785	0.000
2	0.726[b]	0.527	0.527	72170.539	0.020	76.099	1	1784	0.000
3	0.735[c]	0.540	0.539	71177.042	0.013	51.150	1	1783	0.000
4	0.738[d]	0.545	0.544	70812.956	0.005	19.382	1	1782	0.000
5	0.740[e]	0.548	0.547	70588.095	0.003	12.371	1	1781	0.000
6	0.742[f]	0.551	0.549	70434.558	0.002	8.773	1	1780	0.003

a. Predictors: (Constant), Dist_CBD

b. Predictors: (Constant), Dist_CBD, Empl_full_Inc1

c. Predictors: (Constant), Dist_CBD, Empl_full_Inc1, Dist_SBD

d. Predictors: (Constant), Dist_CBD, Empl_full_Inc1, Dist_SBD, Dist_NBD

e. Predictors: (Constant), Dist_CBD, Empl_full_Inc1, Dist_SBD, Dist_NBD, Jobs_retail_Inc1

f. Predictors: (Constant), Dist_CBD, Empl_full_Inc1, Dist_SBD, Dist_NBD, Jobs_retail_Inc1, Jobs_manu_Inc1

Table 9-2 shows the summary of the 6 passing models from the stepwise regression. Also shown, are the predictor variables associated with each of the model. Out of the initial 12 candidate independent (predictor) variables considered in the regression run, a maximum of 6 variables were selected in the final model (model 6). The output shows that distance to the main CBD as well as to the Northern & Southern Suburb Business districts, all have a relationship with measured accessibility level at zones. The number of retail and manufacturing jobs, as well as the number of persons with full-time employment, are also found to be related to job accessibility. The selected variables in the models satisfy the non-collinearity requirement as revealed by the collinearity diagnostics output in Appendix 2A.

The estimated coefficients of the independent variables associated with each of the 6 passing models are further shown in Appendix 2A. As expected, the models reveal a negative coefficient with the distance variables, with distance to the CBD having the greatest negative effect. Also, in line with expectations, the number of persons with full-time employment, as well as the number of retail and manufacturing jobs all have positive coefficients associated with each variable. Considering that these estimates were carried out at the 99% confidence interval, it can be concluded that the model is fairly reliable. Although, as shown by the R-squared value, only about 55% of the variability observed in the accessibility score, is explained by the combination of variables, as revealed in model 6. From the table of regression coefficients presented in Appendix 2A, the resultant model of accessibility to low-income jobs by public transport therefore written as;

$$\begin{aligned} \mathrm{ACC_{PT\_INC1}} = \; & 290443 - 3.103\mathrm{Dist_{CBD}} + 45.14\mathrm{Emp_{Fulltime}} - 2.17\mathrm{Dist_{SBD}} \\ & - 1.039\mathrm{Dist_{NBD}} + 60.754\mathrm{Jobs_{Retail}} + 15.251\mathrm{Jobs_{Manuf}} \end{aligned} \quad (9\text{-}1)$$

Where the variables are as defined in Table 9-1.

The resultant model above shows that distance to all three business districts have a reduction effect on accessibility, with the distance to CBD having about 3 times more reduction effect compared to distance to Northern Suburb Business District (NBD). It is also quite logical that accessibility to low-income jobs for a zone is a function of the number of full-time employed low-income persons in that zone as well the number of low-income retail and manufacturing jobs within the zone.

One of the critical requirements of OLS regression models is that residuals are normally distributed with a mean centred about zero and a standard deviation of about 1. The plot of the regression residuals from output 1 is shown in Figure 9-3.

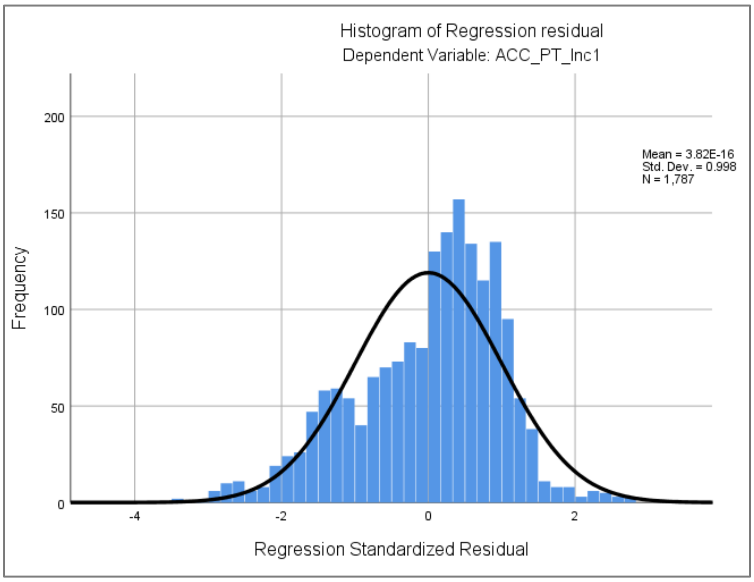


Figure 9-3: Frequency distribution of regression residual

Although not ‘perfectly’ normal, the distribution above approximate to a normal pattern, but with some skew to the right. The mean of the residuals is estimated to be about 3.82×10^{-16}, which approximates to zero, while the standard deviation of about 0.996 also approximates to 1. Thus, it can be concluded that the normality of residuals criteria is met for the regression.

The confirmation of normality is further checked with the normal probability-probability (P-P) plot as shown in Figure (9-4). The P-P plot compares the observed cumulative distribution function (CDF) of the standardized residual to the expected CDF of the normal distribution (UCLA: Statistical Consulting Group., no date), and normality of residuals is confirmed if the data points are clustered around the straight diagonal line.

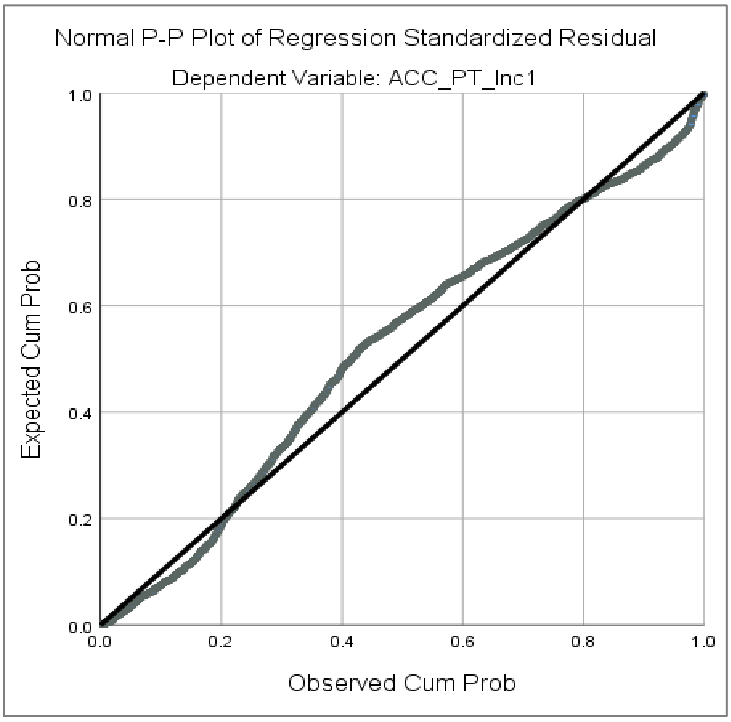


Figure 9-4: Normal P-P Plot of regression standardized residual

The normal P-P plot shows that the distribution of the regression residuals approximates to a normal distribution. Additional regression outputs, such as collinearity diagnostics are presented in Appendix 2A.

9.4.2 Regression Output 2 - $\mathrm{ACC}_{\mathrm{CAR\_INC1}}$ as dependent variable

In the second regression, the dependent variable considered is the accessibility to low-income jobs by car ($\mathrm{ACC}_{\mathrm{CAR\_INC1}}$), while the set of candidate independent variables remains the same as for the previous section (9.4.1). The regression summary is shown in Table 9-3.

Table 9-3: Regression summary - Accessibility to low-income jobs by car

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.642[a]	0.413	0.412	71860.390	0.413	1254.031	1	1785	0.000
2	0.676[b]	0.457	0.457	69094.950	0.045	146.744	1	1784	0.000
3	0.691[c]	0.478	0.477	67781.721	0.021	70.797	1	1783	0.000
4	0.700[d]	0.490	0.488	67047.694	0.012	40.254	1	1782	0.000
5	0.706[e]	0.499	0.497	66475.272	0.009	31.822	1	1781	0.000
6	0.709[f]	0.502	0.501	66249.610	0.004	13.154	1	1780	0.000
7	0.710[g]	0.504	0.502	66150.800	0.002	6.321	1	1779	0.012

a. Predictors: (Constant), Dist_CBD
b. Predictors: (Constant), Dist_CBD, Dist_NBD
c. Predictors: (Constant), Dist_CBD, Dist_NBD, Dist_SBD
d. Predictors: (Constant), Dist_CBD, Dist_NBD, Dist_SBD, Empl_full_Inc1
e. Predictors: (Constant), Dist_CBD, Dist_NBD, Dist_SBD, Empl_full_Inc1, Jobs_office_Inc1
f. Predictors: (Constant), Dist_CBD, Dist_NBD, Dist_SBD, Empl_full_Inc1, Jobs_office_Inc1, Jobs_manu_Inc1
g. Predictors: (Constant), Dist_CBD, Dist_NBD, Dist_SBD, Empl_full_Inc1, Jobs_office_Inc1, Jobs_manu_Inc1, Jobs_retail_Inc1
Dependent Variable: ACC_CAR_Inc1

Compared to the regression output for public transport (Table 9-2), in which 6 models were found to be passing the regression criteria, the regression for travel by car (Table 9-4) shows 7 passing models, although the models for car were found to have lesser R-squared values compared to that for public transport for the same set of explanatory variables. While all 6 models for public transport is found to have R-squared values above 0.5, only 2 out of the 7 models for car shows an R-squared value of up to 0.5. The associated coefficients of the explanatory variables for each of the passing models are shown in Appendix 2B.

The coefficients in Appendix 2B reveal that distance to the CBD and the Northern business district (NBD) both have a negative relationship with accessibility by car just as the case for travel by public transport. However, as against the output for public transport, where it had a negative coefficient, distance to the Southern suburb business district (SBD) is observed to have a positive coefficient for the case of travel by car. In other words, for travel by car, proximity to the SBD exerts a reverse effect compared to proximity to either the CBD or NBD. It is however not obvious from the available information what could be attributed to this noticeable variation. From the estimated regression coefficients, the accessibility model is written as;

$$\begin{aligned}\mathrm{ACC_{CAR\_INC1}} = \; & 311375.84 - 5.74\mathrm{Dist_{CBD}} + 28.35\mathrm{Emp_{Fulltime}} \\ & + 3.028\mathrm{Dist_{SBD}} - 2.98\mathrm{Dist_{NBD}} + 53.10\mathrm{Jobs_{Office}} \\ & + 52.75\mathrm{Jobs_{Retail}} + 17.14\mathrm{Jobs_{Manuf}}\end{aligned} \tag{9-2}$$

Where the variables are as defined in Table (9-1)

The regression is further checked with a test of normality of the regression residuals. The distribution of the residuals and the associated probability-probability (P-P) plot is shown in Appendix 2B. The mean value of the residual is seen to be about 1.21×10^{-14}, which approximates to zero, while the standard deviation approximates to 1. When compared to the model for public transport where the regression residuals were more normally distributed, it can be concluded that the explanatory variables have a better predictive capacity for accessibility to low-income jobs by public transport than for cars.

9.4.3 Regression Output 3 - $\mathrm{ACC_{PT\_INC2}}$ as dependent variable

The regression for accessibility to lower-middle-income jobs by public transport considers the socioeconomic attributes of the lower-middle-income group. Distances to the three business districts remain as the built environment variables. The summary from the regression run is presented in Table 9-4.

Table 9-4: Regression summary - Accessibility to lower-middle income jobs by public transport

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.723[a]	0.522	0.522	179425.263	0.522	1951.831	1	1785	0.000
2	0.736[b]	0.542	0.542	175695.147	0.020	77.598	1	1784	0.000
3	0.750[c]	0.563	0.562	171709.190	0.021	84.787	1	1783	0.000
4	0.753[d]	0.566	0.565	171105.564	0.003	13.602	1	1782	0.000
5	0.754[e]	0.569	0.568	170592.343	0.003	11.738	1	1781	0.001
6	0.756[f]	0.571	0.570	170270.302	0.002	7.743	1	1780	0.005
7	0.756[g]	0.572	0.571	170074.181	0.001	5.108	1	1779	0.024
8	0.757[h]	0.573	0.571	169899.759	0.001	4.655	1	1778	0.031

a. Predictors: (Constant), Dist_CBD

b. Predictors: (Constant), Dist_CBD, Empl_full_Inc2

c. Predictors: (Constant), Dist_CBD, Empl_full_Inc2, Dist_SBD

d. Predictors: (Constant), Dist_CBD, Empl_full_Inc2, Dist_SBD, Dist_NBD

e. Predictors: (Constant), Dist_CBD, Empl_full_Inc2, Dist_SBD, Dist_NBD, Jobs_manu_Inc2

f. Predictors: (Constant), Dist_CBD, Empl_full_Inc2, Dist_SBD, Dist_NBD, Jobs_manu_Inc2, Jobs_retail_Inc2

g. Predictors: (Constant), Dist_CBD, Empl_full_Inc2, Dist_SBD, Dist_NBD, Jobs_manu_Inc2, Jobs_retail_Inc2, UnEmpl_NL_Inc2

h. Predictors: (Constant), Dist_CBD, Empl_full_Inc2, Dist_SBD, Dist_NBD, Jobs_manu_Inc2, Jobs_retail_Inc2, UnEmpl_NL_Inc2, Empl_self_Inc2

Table 9-4 shows 8 passing models and the associated explanatory variables in the stepwise regression with final model R^2 of 0.57. The output shows distance to the CBD as a common explanatory variable in all the passing models. The associated coefficient for the independent variables are presented in Appendix 2C.

From the table of coefficients (Appendix 2C), the resultant ant model for accessibility to lower-middle income jobs by public transport can be written as;

$$\begin{aligned}\mathrm{ACC}_{\mathrm{PT\_INC2}} = \ & 718439.66 - 6.317\mathrm{Dist}_{\mathrm{CBD}} + 43.67\mathrm{Emp}_{\mathrm{Fulltime}} \\ & - 7.40\mathrm{Dist}_{\mathrm{SBD}} - 1.93\mathrm{Dist}_{\mathrm{NBD}} + 20.56\mathrm{Jobs}_{\mathrm{Manuf}} \\ & + 48.85\mathrm{Jobs}_{\mathrm{Retail}} + 95.59\mathrm{UnEmp}_{\mathrm{NL}} - 98.75\mathrm{Empl}_{\mathrm{Self}}\end{aligned} \quad (9\text{-}3)$$

Where all variables are as defined in Table (9-1).

Similar to the case for accessibility to low-income jobs by public transport, it is seen from the model that distance to all three business districts has a reduction effect on accessibility of zones. Likewise, distance to the CBD is seen to have about 3 times the reduction effect of distance to the NBD. Interestingly, accessibility at a zone is also seen to be a function of the unemployed lower-middle income population who are not looking for jobs, as well as the population who are self-employed. The number of self-employed persons has a reduction impact on accessibility of a zone. This can be considered logical. In other words, the higher the number of self-employed persons in a zone, the lower the potential accessibility of jobs from that zone.

The plot of the residuals (Appendix 2C) approximates to a normal distribution with a mean of 1.39×10^{-15} and a standard deviation of 0.998. Other regression outputs such as residual statistics and the collinearity diagnostics are also presented in Appendix 2C.

9.4.4 Regression Output 4 - ACC_{CAR_INC2} as dependent variable

The summary of the regression with accessibility to lower-middle-income jobs by car as the dependent variable is shown in Table 9-5 below. The summary shows eight (8) passing models with the final model having an R-squared value of approximately 0.5.

Table 9-5: Regression summary - Accessibility to lower-middle income jobs by car

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.651[a]	0.424	0.423	180753.449	0.424	1311.899	1	1785	0.000
2	0.674[b]	0.454	0.453	175966.926	0.030	99.429	1	1784	0.000
3	0.691[c]	0.478	0.477	172152.770	0.024	80.927	1	1783	0.000
4	0.695[d]	0.483	0.482	171293.413	0.005	18.935	1	1782	0.000
5	0.701[e]	0.492	0.490	169940.298	0.008	29.491	1	1781	0.000
6	0.704[f]	0.495	0.494	169375.464	0.004	12.898	1	1780	0.000
7	0.706[g]	0.499	0.497	168820.985	0.004	12.712	1	1779	0.000
8	0.707[h]	0.500	0.498	168653.543	0.001	4.534	1	1778	0.033

a. Predictors: (Constant), Dist_CBD
b. Predictors: (Constant), Dist_CBD, Dist_NBD
c. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc2
d. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc2, Dist_SBD
e. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc2, Dist_SBD, Jobs_office_Inc2
f. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc2, Dist_SBD, Jobs_office_Inc2, Jobs_manu_Inc2
g. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc2, Dist_SBD, Jobs_office_Inc2, Jobs_manu_Inc2, Empl_self_Inc2
h. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc2, Dist_SBD, Jobs_office_Inc2, Jobs_manu_Inc2, Empl_self_Inc2, Jobs_retail_Inc2
Dependent Variable: ACC_CAR_Inc2

The estimated regression coefficients are presented in Appendix 2D. As for the case of previous regression outputs (1)-(3), distance to the three business districts are all significant variables. From the table of coefficients, the resultant model can be written as:

$$\begin{aligned}\mathrm{ACC}_{\mathrm{CAR\_INC2}} = \ & 787230.70 - 12.96\mathrm{Dist}_{\mathrm{CBD}} - 6.23\mathrm{Dist}_{\mathrm{NBD}} \\ & + 28.34\mathrm{Emp}_{\mathrm{Fulltime}} + 5.16\mathrm{Dist}_{\mathrm{SBD}} + 18.72\mathrm{Jobs}_{\mathrm{Office}} \\ & + 24.01\mathrm{Jobs}_{\mathrm{Manuf}} + 156.31\mathrm{Empl}_{\mathrm{Self}} + 40.42\mathrm{Jobs}_{\mathrm{Retail}}\end{aligned} \tag{9-4}$$

In the model above, distances to the central business district (CBD) and the Northern suburb business district (NBD) both have a reduction impact on accessibility, with the reduction effect of the CBD being about twice that of the NBD. Accessibility is also seen to have a positive relationship with the number of full-time employed persons, as well as manufacturing, retail and office jobs.

The distribution of the regression residuals, as well as the collinearity diagnostics, are presented in Appendix 2D. The mean of the residuals is calculated as 3.69×10^{-15}, while the standard deviation is 0.998, which is indicative of an approximately normal distribution. The P-P plot is however s-shaped, indicating that the residuals are distributed symmetrically.

9.4.5 Regression Output 5 - $\mathrm{ACC}_{\mathrm{PT\_INC3}}$ as dependent variable

With accessibility to upper-middle income jobs by public transport as the dependent variable, the regression run yields the summary presented below in Table 9-6.

Table 9-6: Regression summary - Accessibility to upper-middle income jobs by public transport

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.733[a]	0.537	0.537	25890.769	0.537	2069.858	1	1785	0.000
2	0.745[b]	0.555	0.555	25377.348	0.018	73.957	1	1784	0.000
3	0.748[c]	0.559	0.558	25282.205	0.004	14.453	1	1783	0.000
4	0.749[d]	0.561	0.560	25227.426	0.002	8.752	1	1782	0.003
5	0.750[e]	0.563	0.562	25178.470	0.002	7.936	1	1781	0.005

a. Predictors: (Constant), Dist_CBD
b. Predictors: (Constant), Dist_CBD, Dist_SBD
c. Predictors: (Constant), Dist_CBD, Dist_SBD, Jobs_retail_Inc3
d. Predictors: (Constant), Dist_CBD, Dist_SBD, Jobs_retail_Inc3, Dist_NBD
e. Predictors: (Constant), Dist_CBD, Dist_SBD, Jobs_retail_Inc3, Dist_NBD, Jobs_manu_Inc3
Dependent Variable: ACC_PT60min_Inc3

The summary above shows the five (5) passing models with R-squared values between 0.53 and 0.56. From the table of regression coefficients shown in Appendix 2E, the resultant model is written as;

$$\begin{aligned}\mathrm{ACC}_{\mathrm{PT\_INC3}} = {} & 108506.36 - 1.06\mathrm{Dist}_{\mathrm{CBD}} - 1.01\mathrm{Dist}_{\mathrm{SBD}} + 60.25\mathrm{Jobs}_{\mathrm{Retail}} \\ & - 0.233\mathrm{Dist}_{\mathrm{NBD}} + 23.05\mathrm{Jobs}_{\mathrm{Manu}}\end{aligned} \tag{9-5}$$

As is the case with the other regression outputs for accessibility to lower-income jobs, proximity to the business districts is again confirmed to have reduction effect on accessibility to upper-middle-income jobs. However, distance to CBD and the Southern suburb district (SBD) is seen to have similar effect, while the effect of proximity to Northern suburb district (NBD) is seen to be about one-fifth that of the CBD or SBD. The number of upper-middle-income retail and manufacturing jobs is also significant explanatory variables for accessibility to jobs of this income category.

The distribution of the regression residuals and the associated normal P-P are shown in Appendix 2E. The plots above show that regression residuals are normally distributed, with a mean and standard deviation that approximates to 0 and 1 respectively. Collinearity diagnostics are also presented in Appendix 2E.

9.4.6 Regression Output 6 - ACC_{CAR_INC3} as dependent variable

With accessibility to upper-middle-income jobs by car as the dependent variable and same independent variables as for output 5, the regression summary is shown in Table 9-7.

Table 9-7: Regression summary- Accessibility to upper-middle income jobs by car

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.691[a]	0.477	0.477	23533.709	0.477	1629.873	1	1785	0.000
2	0.714[b]	0.509	0.509	22812.270	0.032	115.687	1	1784	0.000
3	0.725[c]	0.526	0.525	22424.613	0.017	63.214	1	1783	0.000
4	0.732[d]	0.536	0.535	22200.646	0.010	37.156	1	1782	0.000
5	0.735[e]	0.540	0.539	22097.542	0.005	17.668	1	1781	0.000
6	0.738[f]	0.544	0.543	22005.629	0.004	15.909	1	1780	0.000
7	0.739[g]	0.546	0.544	21976.729	0.001	5.685	1	1779	0.017

a. Predictors: (Constant), Dist_CBD

b. Predictors: (Constant), Dist_CBD, Dist_NBD

c. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc3

d. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc3, Jobs_office_Inc3

e. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc3, Jobs_office_Inc3, Dist_SBD

f. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc3, Jobs_office_Inc3, Dist_SBD, Jobs_manu_Inc3

g. Predictors: (Constant), Dist_CBD, Dist_NBD, Empl_full_Inc3, Jobs_office_Inc3, Dist_SBD, Jobs_manu_Inc3, Jobs_retail_Inc3

Dependent Variable: ACC_CAR_Inc3

The output in Table 9-7 shows 7 passing models with R^2 values of approximately between 0.48 and 0.55. From the table of coefficients (Appendix 2F), the resultant model is written as;

$$\begin{aligned}\mathrm{ACC}_{\mathrm{CAR\_INC3}} = {} & 106982.61 - 1.70\mathrm{Dist}_{\mathrm{CBD}} - 0.84\mathrm{Dist}_{\mathrm{NBD}} + 32.77\mathrm{Empl}_{\mathrm{Full}} \\ & + 14.08\mathrm{Jobs}_{\mathrm{Office}} + 0.50\mathrm{Dist}_{\mathrm{SBD}} + 27.70\mathrm{Jobs}_{\mathrm{Manu}} \\ & + 41.22\mathrm{Jobs}_{\mathrm{Retail}}\end{aligned} \tag{9-6}$$

In the model above, the reduction effect of proximity to CBD is twice that of proximity to the NBD. Proximity to the SBD, however, is seen to have a positive relationship with accessibility. The number of retail and manufacturing jobs, as well as the employed full-time upper-middle income individuals in a zone, are the other explanatory variables of accessibility to jobs for that zone.

The plots of the regression residuals are shown in Appendix 2F.

9.4.7 Regression Output 7 – $\mathrm{ACC}_{\mathrm{PT\_INC4}}$ as dependent variable

For accessibility to high-income jobs by public transport ($\mathrm{ACC}_{\mathrm{PT\_INC4}}$) as the dependent variable, the regression model summary is as below.

Table 9-8: Regression summary- Accessibility to high-income jobs by public transport

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.732[a]	0.536	0.536	13396.551	0.536	2062.584	1	1785	0.000
2	0.743[b]	0.552	0.551	13173.406	0.016	61.984	1	1784	0.000
3	0.745[c]	0.554	0.554	13135.638	0.003	11.273	1	1783	0.001
4	0.746[d]	0.556	0.555	13112.703	0.002	7.243	1	1782	0.007
5	0.747[e]	0.558	0.556	13096.303	0.001	5.466	1	1781	0.020
6	0.747[f]	0.559	0.557	13085.144	0.001	4.039	1	1780	0.045

a. Predictors: (Constant), Dist_CBD

b. Predictors: (Constant), Dist_CBD, Dist_SBD

c. Predictors: (Constant), Dist_CBD, Dist_SBD, Jobs_retail_Inc4

d. Predictors: (Constant), Dist_CBD, Dist_SBD, Jobs_retail_Inc4, Jobs_manu_Inc4

e. Predictors: (Constant), Dist_CBD, Dist_SBD, Jobs_retail_Inc4, Jobs_manu_Inc4, Dist_NBD

f. Predictors: (Constant), Dist_CBD, Dist_SBD, Jobs_retail_Inc4, Jobs_manu_Inc4, Dist_NBD, Empl_self_Inc4
Dependent Variable: ACC_PT60min_Inc4

The resultant model based on the estimated coefficients in Appendix 2G can be written as;

$$\begin{aligned} \mathrm{ACC_{PT\_INC4}} = \; & 56208.78 - 0.59\mathrm{Dist_{CBD}} - 0.48\mathrm{Dist_{SBD}} + 93.85\mathrm{Jobs_{Retail}} \\ & + 37.38\mathrm{Jobs_{Manu}} - 0.92\mathrm{Dist_{NBD}} - 12.63\mathrm{Empl_{Self}} \end{aligned} \quad (9\text{-}7)$$

The model shows that distance to all three business districts has a reducing effect on accessibility to high-income jobs by public transport. Retail and manufacturing jobs have a positive relationship with accessibility. The negative coefficient for self-employment implies that the higher the number of self-employed high-income earners is in a zone, the lesser the accessibility to high-income jobs. These coefficients are logical, although only about 55% of the observed variability in accessibility can be explained by this model, as indicated by the R^2 value in Table (9-8) above.

The regression residuals (shown in Appendix 2G) approximate to a normal distribution, with a mean and standard deviation of approximately 0 and 1 respectively.

9.4.8 Regression Output 8 - $\mathrm{ACC_{CAR\_INC4}}$ as dependent variable

For accessibility to high-income jobs by car ($\mathrm{ACC_{CAR\_INC4}}$) as the dependent variable, the regression model summary is as shown in Table 9-9.

Table 9-9: Regression summary- Accessibility to high-income jobs by public transport

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.635[a]	0.403	0.403	15395.703	0.403	1205.562	1	1785	0.000
2	0.649[b]	0.422	0.421	15158.431	0.019	57.318	1	1784	0.000
3	0.655[c]	0.429	0.428	15060.843	0.008	24.194	1	1783	0.000
4	0.664[d]	0.440	0.439	14920.592	0.011	34.677	1	1782	0.000
5	0.668[e]	0.446	0.445	14843.548	0.006	19.547	1	1781	0.000
6	0.671[f]	0.450	0.448	14805.050	0.003	10.274	1	1780	0.001
7	0.672[g]	0.451	0.449	14786.269	0.002	5.525	1	1779	0.019
8	0.673[h]	0.453	0.450	14771.909	0.001	4.460	1	1778	0.035

a. Predictors: (Constant), Dist_CBD
b. Predictors: (Constant), Dist_CBD, Dist_NBD
c. Predictors: (Constant), Dist_CBD, Dist_NBD, Jobs_office_Inc4
d. Predictors: (Constant), Dist_CBD, Dist_NBD, Jobs_office_Inc4, Dist_SBD
e. Predictors: (Constant), Dist_CBD, Dist_NBD, Jobs_office_Inc4, Dist_SBD, Empl_full_Inc4
f. Predictors: (Constant), Dist_CBD, Dist_NBD, Jobs_office_Inc4, Dist_SBD, Empl_full_Inc4, Jobs_manu_Inc4
g. Predictors: (Constant), Dist_CBD, Dist_NBD, Jobs_office_Inc4, Dist_SBD, Empl_full_Inc4, Jobs_manu_Inc4, Jobs_retail_Inc4
h. Predictors: (Constant), Dist_CBD, Dist_NBD, Jobs_office_Inc4, Dist_SBD, Empl_full_Inc4, Jobs_manu_Inc4, Jobs_retail_Inc4, Empl_self_Inc4
Dependent Variable: ACC_CAR_Inc4

The regression summary above shows eight passing models, but with relatively low R^2 values of between 0.40 and 0.45. The resultant model based on the estimated coefficients (Appendix 2H) can be written as

$$\begin{aligned} \mathrm{ACC}_{\mathrm{CAR\_INC4}} = {} & 66769 - 1.15\mathrm{Dist}_{\mathrm{CBD}} - 0.44\mathrm{Dist}_{\mathrm{NBD}} + 12.77\mathrm{Jobs}_{\mathrm{Office}} \\ & + 0.50\mathrm{Dist}_{\mathrm{SBD}} + 15.29\mathrm{Empl}_{\mathrm{Full}} + 54.20\mathrm{Jobs}_{\mathrm{Manu}} \\ & + 85.77\mathrm{Jobs}_{\mathrm{Retail}} + 16.50\mathrm{Empl}_{\mathrm{Self}} \end{aligned} \tag{9-8}$$

For the model above, distance to CBD and NBD have a negative relationship with accessibility to high-income jobs, while distance to SBD is observed to have a positive relationship. Although most of the variable coefficients seem logical, less than 50%

of the variability in accessibility can be explained by this model, as revealed by the relatively low R^2 value of 0.45.

9.4.9 Summary of Model Coefficients

The various regression models presented in the previous sections are summarised in Table 9-10 in the next page.

Table 9-10: Summary of regression models coefficients

Explanatory variables / Dependent variables			Distance to CBD	Distance to NBD	Distance to SBD	Employed fulltime	Employed part-time	Self-employed	Unemployed and not looking for job	Unemployed and looking for job	Number of office jobs	Number of retail jobs	Number of manufacturing jobs
		R^2	$Dist_{CBD}$	$Dist_{NBD}$	$Dist_{SBD}$	$Empl_{Full}$	$Empl_{Part}$	$Empl_{Self}$	$UEmpl_{NL}$	$UEmpl_{L}$	$Jobs_{Office}$	$Jobs_{Retail}$	$Jobs_{Manu}$
Accessibility according to mode and income category of jobs	ACC_{PT_INC1}	0.55	-3.10	-1.03	-2.17	45.14	---	---	---	---	---	60.75	15.25
	ACC_{CAR_INC1}	0.50	-5.74	-2.98	3.02	28.38	---	---	---	---	53.10	52.75	17.14
	ACC_{PT_INC2}	0.57	-6.31	-1.93	-7.40	43.66	---	-98.75	95.59	---	---	48.85	20.56
	ACC_{CAR_INC2}	0.50	-12.96	-6.23	5.16	28.34	---	156.31	---	---	18.71	40.42	24.01
	ACC_{PT_INC3}	0.56	-1.06	-0.23	-1.01	---	---	---	---	---	---	60.25	23.05
	ACC_{CAR_INC3}	0.55	-1.70	-0.84	0.50	32.77	---	---	---	---	14.08	41.22	27.70
	ACC_{PT_INC4}	0.56	-0.59	-0.09	-0.48	---	---	-12.63	---	---	---	93.85	37.38
	ACC_{CAR_INC4}	0.45	-1.15	-0.44	0.50	15.29	---	16.5	---	---	12.77	85.77	54.20

The summary in Table 9-10 shows that proximity to the Central business district (CBD) as well as the Northern suburb business district (NBD), both have a direct correlation with potential accessibility by public transport and car, for all the job categories. In other words, zonal accessibility indicator increases as the distance from the zone centroid to the business districts decreases, and vice versa. For proximity to CBD, the value of the coefficients is seen to be relatively higher for car accessibility than for public transport, for a similar job category. For proximity to the Southern suburb business district (SBD), there is, however, a slight variation in the pattern of influence on accessibility. Increase in distance is seen to have a reducing impact on accessibility by public transport only, but not for car travel. In other words, accessibility to jobs by public transport increases (or decreases) as the distance to the SBD decreases (or increases). However, for car accessibility, the reverse is the case. This holds for accessibility to all job categories. Among the socioeconomic variables, the number of full-time employment, as well as number of retail, manufacturing and office jobs, were found to be the most significantly correlated with accessibility, both for public transport and car travel.

9.5 Chapter Conclusion

As mentioned in the introductory section (Section 9.1), the overall objective of this chapter was to understand 'possible' drivers of accessibility through a regression analysis of job accessibility indicator as the dependent variable, and a combination of various socioeconomic and built environment variables of the study area. The establishment of such relationship is significant on two front (1) it enables the validation of measured accessibility indicators based on 'presumed' or 'hypothesised' influence of some known variables (2) determination of the level of influence of the variables on accessibility level.

Considering that no defined framework currently exists for validating the indicators of potential accessibility (say, against empirical data), exploring the relationship between such indicators and other known variables can be useful in establishing the level of reliability of the indicators. For example, given a monocentric city, where there is a high concentration of opportunities in the urban core, there will be an expectation that distances of zones from the urban core would have a direct impact on the accessibility of the zones. For the case of Cape Town investigated, one of the major findings from the regression analyses is the significance of distances to the three major urban nodes on accessibility level, from among the pool of candidate explanatory variables considered. This has a major implication for spatial planning as it enables the determination of the potential impact of planning strategies (such as decentralisation) on accessibility.

Apart from the coefficient of determination (R^2), the two vital requirements with which the output of the regression models have been evaluated is the distribution of the regression residuals (which is expected to be normally distributed), and the non-collinearity among the explanatory variables. These requirements have been met in the stepwise regression, as shown in the residuals plot (which showed an approximately normal distribution) and the table of collinearity diagnostics (see Appendix 2), which showed no significant collinearity among the explanatory variables considered in the models.

Although the stepwise regression procedure has its limitations in its application as detailed in Harrell (2001), it nevertheless, provides a suitable way of 'exploring' relationships for situations where there is no 'prior' assumption on what variables to be considered the 'most suitable' in a regression. While most of the issues raised concerning the regression method involve the variable selection procedure (Harrell, 2001), it must be pointed out that the availability of advanced statistical software such as the IBM SPSS (utilised in this study) and SAS, enables variable selection through iterative process against predefined regression criteria such as the minimum F values, confidence intervals and a host of other criteria. Variable selection through an iterative process is, however, not meant to replace expert judgement, but to merely provide a guide, and possibly, serve as a first process to further investigation or testing.

In conclusion, it is recognised that other methods (for example, factor analysis) can also be employed for variable reduction/selection just like the stepwise process. Thus, alternative models can also be realised. However, the stepwise procedure can be considered adequate in situations such as this case study, where there is no prior assumption on which variables might be influencing accessibility, and where the focus is on 'exploring' of potential relationship rather than the realisation of best or optimal models.

Chapter 10

Evaluating Equity in Accessibility to Jobs and Schools

"Everyone has an equal right to inequality" ~ John Ralston Saul, Canadian writer

10.1 Introduction

Chapters 8 and 9 presented the indicators of accessibility and an analysis of its relationship with socioeconomic and built-environment attributes. While the indicators of accessibility revealed the potentially accessible opportunities, as enabled by the transport system in relation to the location of residents, it does not show the level of 'fairness' or 'equity' in the distribution of accessibility benefit for the population. The focus of this chapter is therefore to evaluate the 'fairness' or 'equity' in the distribution of accessibility across zones. Since every zone is a composition of persons of the various income groups, the evaluation establishes how much each population (income) group is benefiting from accessibility.

The remaining sections of this chapter discuss the approaches applied for performing an equity evaluation, followed by the evaluation outcome for job and school accessibility. The chapter is concluded with a summary discussion of the relevance of the equity analysis and outcomes to land use-transport planning and decision making.

10.2 Approaches for Equity Evaluation

Equity, as it relates to transportation and land use, can be considered as the fairness with which the benefit of the integrated transport and land use system is distributed across a population (Geurs et al. 2009; Litman 2016; Lucas et al. 2016). Equity, therefore, is about distribution as well as a judgement on who is benefiting the most, and who are worse of, or disadvantaged (Wee & Geurs 2011). Although equity can be analysed from various dimensions (Thomopoulos et al. 2009), this study specifically looks at vertical equity across the population groups and horizontal equity within each population group.

Two approaches have been employed in evaluating equity in accessibility (1) a travel cost affordability framework to evaluate vertical equity, and (2) the Gini-based approach to evaluate horizontal equity. Vertical equity evaluates, for example, the accessibility potential for a high-income individual/household compared to that of a low-income person/household, based on the cost of travel and the imbalance in budget outlays across the two income groups. Horizontal equity looks at the entire population of each income group and evaluates the proportion of the population benefiting from accessibility.

10.2.1 Affordability-based framework

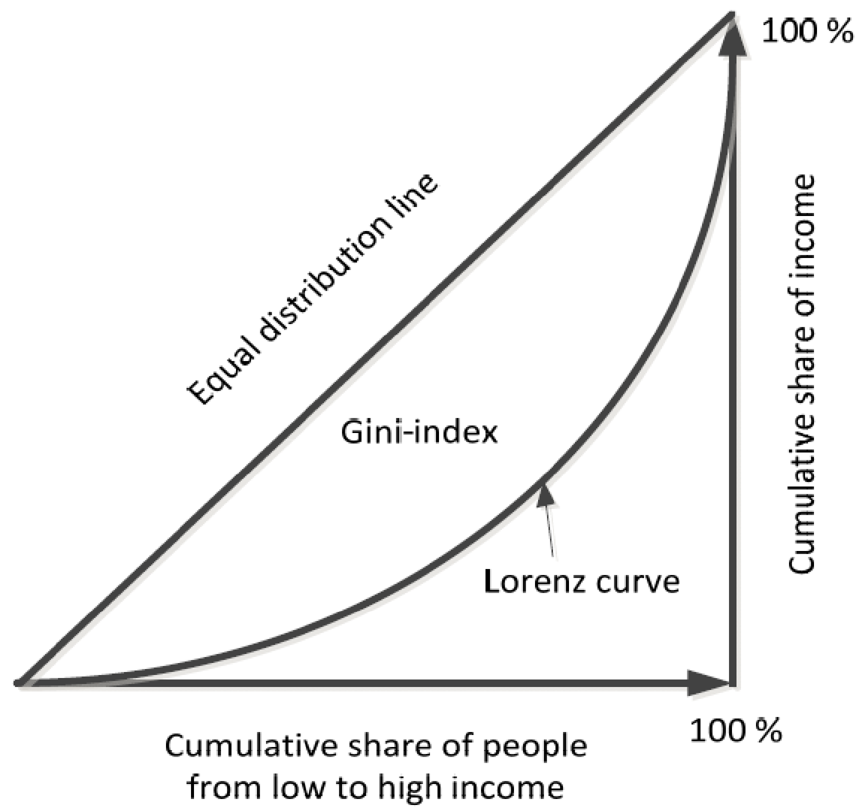
The travel affordability approach evaluates the fairness in the distribution of accessibility benefit across the various population groups, taking into consideration the monetary cost of travel and the 'potential' implication of budget constraints across households in the various income groups. The approach is based on the notion that the higher income population would invariably have higher budget outlay for travel, compared to the low-income population, and thus enjoys more reachability of opportunities. This applies, for example, to systems that operate on a distance-based pricing scheme, such as is the case in Cape Town, where the potential for destination reachability is also dependent on the amount of money the trip maker is willing to spend on travel. Although propensity to pay can vary from person to person irrespective of the income level (mostly as a result of other household expenditure), the analysis of equity using this approach assumes a common affordability benchmark for transport, given as a percentage of income.

A common percentage of income applied across all income levels will invariably translate to different budget outlays for households, depending on their income level. As is to be expected, the lowest income population would be the worse-off. An affordability-based equity analysis, therefore, allows to show the disparity in potential accessibility as a result of the disparity in income and travel budget. Under this approach, two indicators are proposed; (1) an accessibility loss indicator and (2) aggregated potential curves. An accessibility loss indicator measures the potential loss for a person group at a zonal level, while the aggregated opportunity curve evaluates equity at an aggregate level by showing the sum potential accessibility achievable according to various travel cost thresholds. These two indicators are operationalised for the cases of accessibility to jobs and schools.

10.2.2 Gini-based framework

Developed initially to evaluate inequality in the distribution of wealth across a population (Cowell 2000; Betti & Lemmi 2008), the Lorenz curves and associated Gini coefficients are applied in this study to evaluate equity in the distribution of accessibility across zones. The Gini coefficient has also been used in similar studies on accessibility (Lucas et al. 2016; Guzman et al. 2017; van Wee & Geurs 2011) for evaluating equity in the distribution of accessibility benefit across various population groups. The coefficient ranges from a value of 0 to 1, where 0 indicates perfect equality (that is, the same level of accessibility for everyone) and 1 indicates perfect inequality, that is, all accessibility for only one individual and 0 accessibility for the others (Guzman *et al.*, 2017).

A typical Lorenz curve is drawn by plotting the cumulative percentage of the population against the cumulative share of the collective wealth or income available for the entire population. From an accessibility perspective, such collective wealth is considered as the aggregated potential accessibility across the entire area of interest.



Source: van Wee & Geurs (2011)

Figure 10-1: Lorenz curves and the Gini index

In applying Figure 10-1 to accessibility, the vertical axis becomes the cumulative share of aggregated accessibility values, while the horizontal axis will represent the cumulative proportion of the population from those with low levels of potential accessibility to those with higher level of potential accessibility.

Along the curve, if x_i is a point on the x-axis, and y_i a point on the y-axis, then the Gini index can be written as:

$$\text{Gini} = 1 - \sum_{i=1}^{N}(x_i - x_{i-1})(y_i + y_{i-1}) \tag{10-1}$$

When there are *N* equal intervals on the x-axis, Equation (10-1) simplifies to:

$$\text{Gini} = 1 - \frac{1}{N}\sum_{i=1}^{N}(y_i + y_{i-1}) \tag{10-2}$$

The theoretical framework behind inequality measurement including the Lorenz curves and the Gini coefficient are well documented in Cowell (2000). The next two Sections (10.3) and (10.4) present the application of the affordability framework and the Gini approach for evaluating vertical and horizontal equity in accessibility to jobs and schools.

10.3 Equity in Job Accessibility

10.3.1 Vertical Equity based on Accessibility loss indicator

An accessibility loss index is a measure of the difference between travel time-constrained potential accessibility and a monetary cost-constrained potential accessibility. Time-constrained accessibility reflects the potential opportunities reachable within a specific 'reasonable' travel time threshold without any budget restriction, while money-constrained accessibility reflects the potential opportunities reachable under a specific monetary travel cost budget within the same time threshold. The first relates to answering the question, '*what opportunities can be reached within, say, 60 minutes travel by bus?*' while the second is about the question, '*what opportunities can be reached with x amount of budget money within the 60 minutes of travel threshold?*' The positive difference between these two quantities reflects the potential loss of accessibility. It is a function of the household income of the traveller, and as such, can be considered a suitable measure of vertical equity. The effect of budget restriction on accessibility was earlier presented in an aggregated form in Chapter 8 (Section 8.4), which showed a comparison of accessibility at a maximum travel time threshold of 120 minutes with accessibility achievable with 10%, 15% and 20% of maximum earnable low-income wage as travel budget.

The accessibility loss is a spatial indicator measured for a specific population group based on a predefined threshold of 'reasonable' travel time, and the available monetary budget for travel, given as the percentage of income. The level of equity is therefore reflected by the extent to which each person group suffers potential loss of accessibility across space, as a result of budget limitation.

The potential accessibility loss index, as recalled from Chapter 5 (Equation 5-7), is formulated as;

$$ACC_{L(ik)}^{m,t_{max}} = \frac{\left[\sum_{j=1}^{n} O_{jk}.f\left(C_{ij}\right)^{m}\right] - \left[\sum_{j=1}^{n} O_{jk}.f\left(C_{ij}\right)^{m}.\alpha_k\right]}{\left[\sum_{j=1}^{n} O_{jk}.f\left(C_{ij}\right)^{m}\right]} \qquad (10\text{-}3)$$

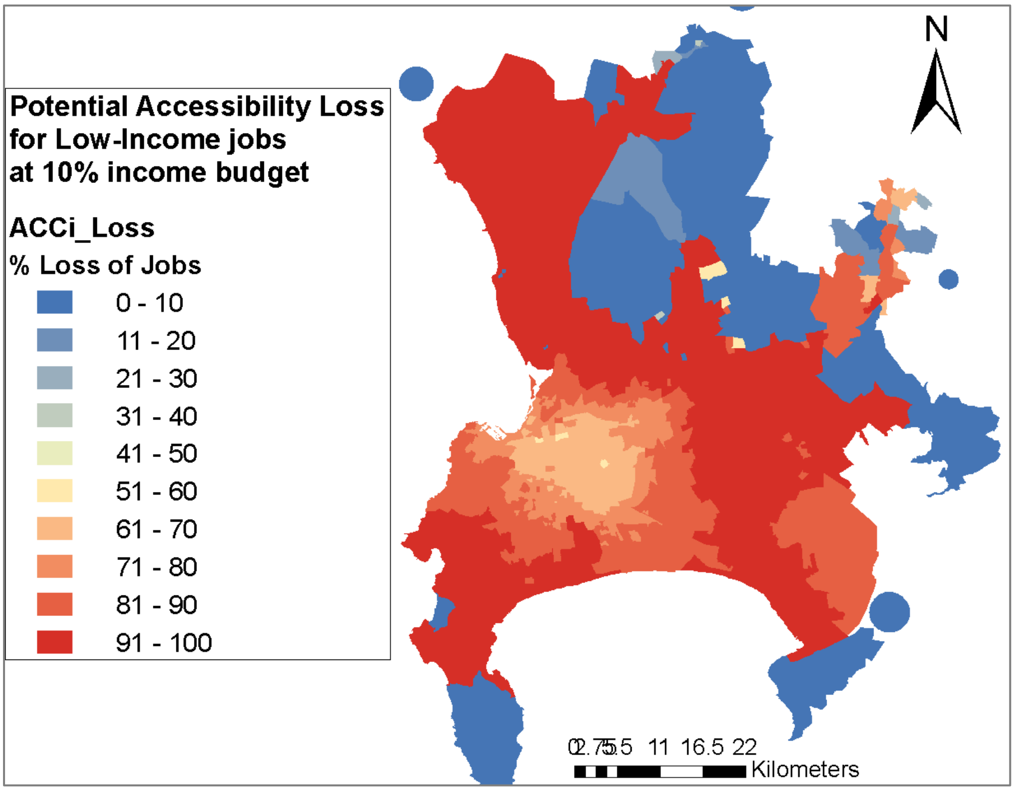
which can also be written as;

$$ACC_{L(ik)}^{m,t_{max}} = \frac{\left[ACC_{ik}^{m,t_{max}}\right] - \left[ACC_{A(ik)|\alpha_k}^{m,t_{max}}\right]}{\left[ACC_{ik}^{m,t_{max}}\right]} \qquad (10\text{-}4)$$

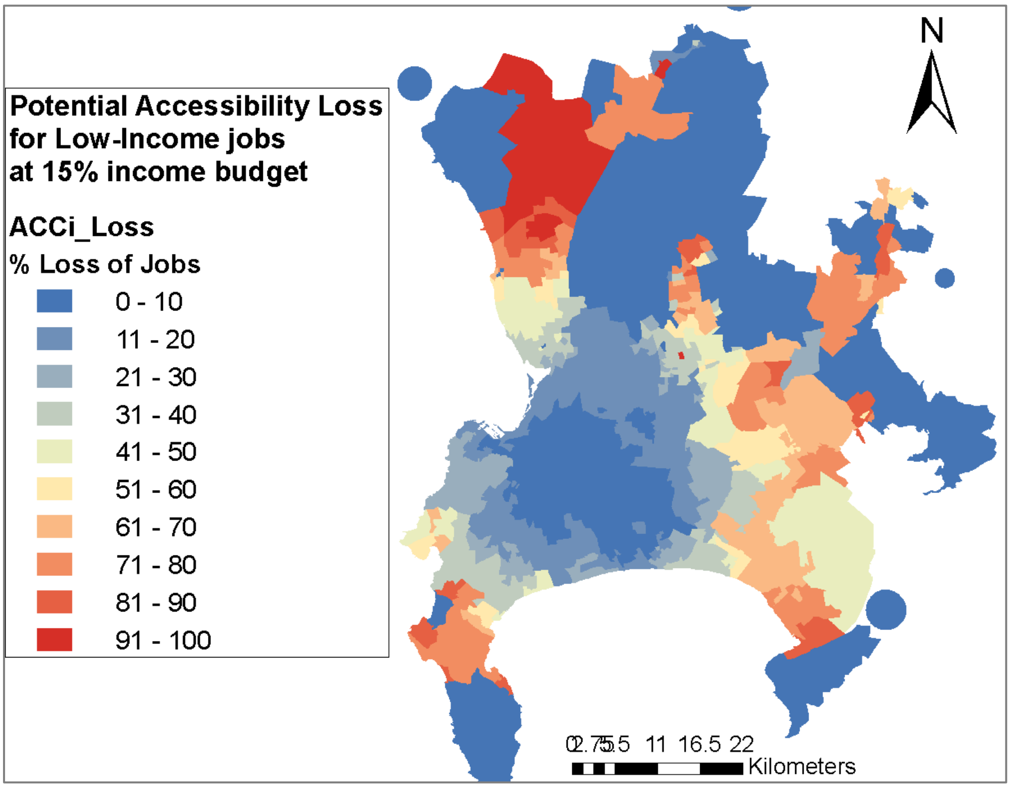
where; $ACC_{L(ik)}^{m,t_{max}}$ is the potential accessibility loss index at zone i attributable to person group k for travel by mode m; $ACC_{ik}^{m,t_{max}}$ is the potential accessibility of zone i using mode m for predefined 'reasonable' maximum travel time t^{max}; $ACC_{A(ik)|\alpha_k}^{m,t_{max}}$ is the affordable potential accessibility index for individual/group k in zone i, for a maximum travel time t_{max} by mode m; α_k is the applied percentage of income defined as travel monetary budget (TMB) for person group k (see also, Section 5.5.3).

In evaluating equity across income groups, a common α_k is specified across the various income groups. For this study, the loss index is applied for accessibility to low-income jobs for a typical low-income household with one source of income, using various percentages of income as travel budget. The percentages applied are 10%, 15% and 20%. These values are guided by the definition of public transport affordability in South Africa which specifies a travel expenditure limit of10% of household income as a planning benchmark.

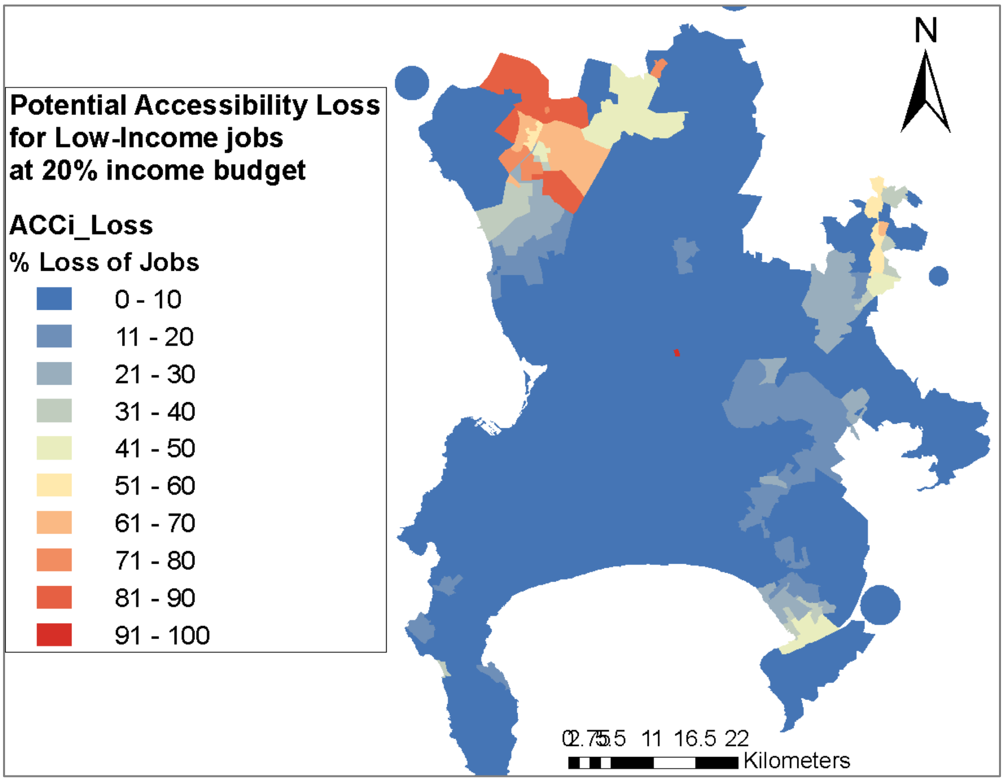
The potential accessibility loss calculated using Equation (10-4) above is presented in Figures 10 – 2 (a) – (c).


Potential Accessibility Loss
for Low-Income jobs
at 10% income budget
ACCi_Loss
% Loss of Jobs
0 - 10
11 - 20
21 - 30
31 - 40
41 - 50
51 - 60
61 - 70
71 - 80
81 - 90
91 - 100
N
Kilometers

(a)


Potential Accessibility Loss
for Low-Income jobs
at 15% income budget
ACCi_Loss
% Loss of Jobs
0 - 10
11 - 20
21 - 30
31 - 40
41 - 50
51 - 60
61 - 70
71 - 80
81 - 90
91 - 100
N
Kilometers

(b)



(c)

Figure 10-2: Potential accessibility loss for the low-income group bounded by (a) 10% (b) 15% and (c) 20% of income as travel budget:

Figures 10-2 (a) – (c) can be interpreted as the percentage change (loss) in potential accessibility for a travel time within 120 minutes with no restriction on budget versus travel within same time frame with budget restrictions of 10%, 15%, and 20% of the maximum income for a low income wage range. That is the loss in opportunities one can ideally reach within 120 minutes and the opportunities reachable where there is a restriction of budget. The opportunities, in this case, being low-income jobs.

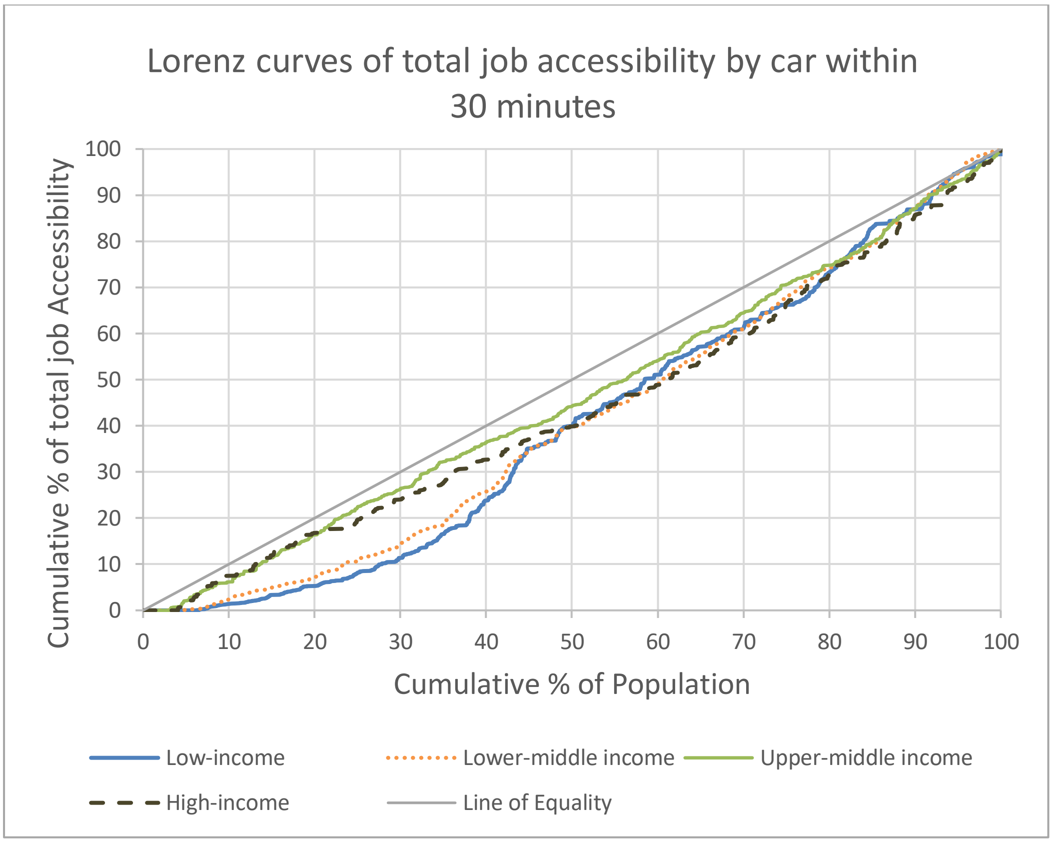
From the Figure, it is evident that travel cost and budget can have a significant implication on the amount of opportunities reachable. As expected, the potential loss of opportunities reduces with a higher travel budget. The difference in accessibility loss between a 10% income budget and 20% income budget is seen to be quite significant. For a 20% income budget, potential loss of accessibility is quite minimal as revealed in Figure 10-2 (c), where most part of the study area only have a 0-10% loss. The minimal loss of accessibility at 20% of income also seems to explain the reality in Cape Town, where the average percentage of income spent on travel to work was estimated (based on empirical observation) to be about 27% of income (see Section 4.6, Figure 4-14).

It can thus be concluded from the evaluation in this particular case that the minimum budget required to reach the potential accessibility enabled by the public transport system of Cape Town within a travel time of 120 minutes, is in the region of 20% of income. By looking at the median income value of the middle- and high-income category, it can be said that affordability is mainly a problem for the poorest group, that is, those who earn a maximum of ZAR3200 per month (for this particular case study). A travel budget of, say, 10% of the median value of the lower-middle-income wage range will still be higher than a 20% of the upper limit of a low-income wage range. Thus, with a 10% of income, the average lower-middle-income person would still have enough travel budget to reach all possible opportunities, compared to a low-income person. The same goes for the upper-middle and high-income categories. It must, however, be emphasized that the analysis is based on one worker and a single source of income per household. The analysis can also be replicated for other travel time threshold and cost budget.

10.3.2 Horizontal Equity based on Lorenz curves and Gini coefficients

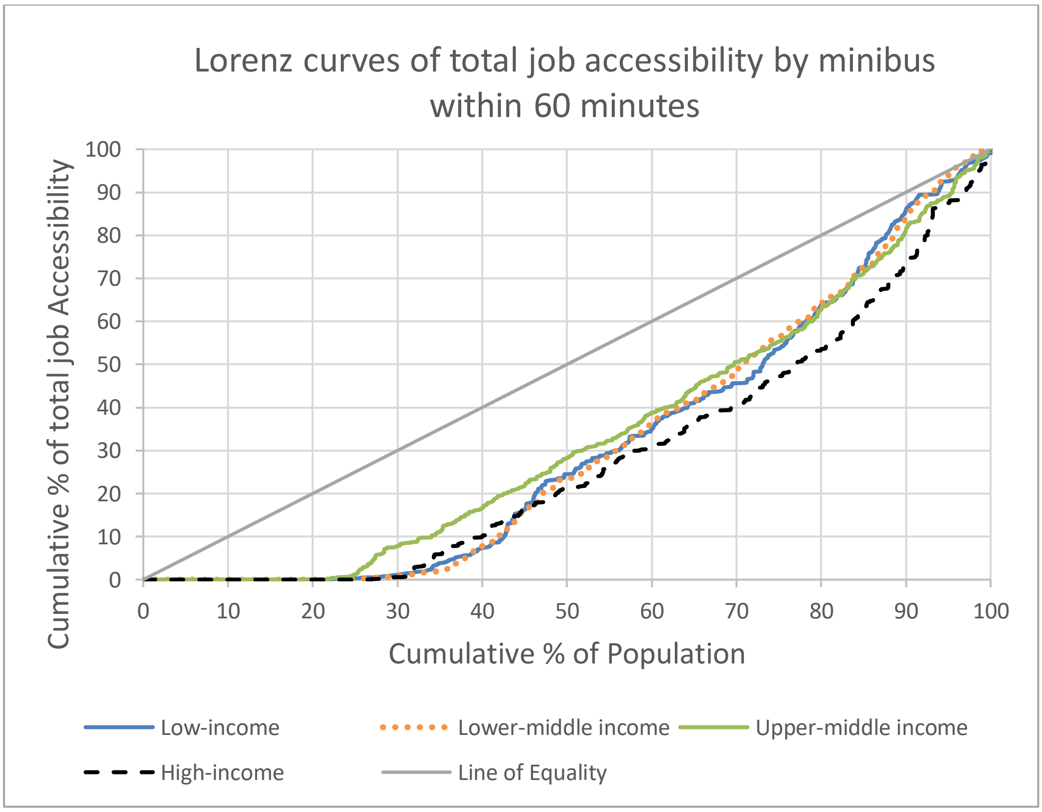
Horizontal equity deals with fairness in the distribution of benefits within similar population group. As mentioned in Section 10.2.2, the Gini measures (Lorenz curves and Gini coefficients) as applied to accessibility, evaluate the fairness in the distribution of accessibility benefit within various population groups. In this study, Lorenz curves and Gini coefficient are computed for total job accessibility for the various population groups by various modes of travel. In other words, equity in accessibility is evaluated across modes for the various population groups. This considers the high accessibility case of car travel within 30 minutes, and for travel by various public transport modes. The public transport modes considered are the minibus, train, and BRT. Among all the public transport modes, the minibus provides the highest level of accessibility, while the BRT provides the lowest level of accessibility. These two modes are also predominantly utilised by the low-income and the middle-income groups respectively, and thus, they are considered suitable for this equity evaluation. Although accessibility has been measured for the various categories of jobs (low income to high-income jobs) as presented in Chapter 8, the consideration of total jobs accessibility here allows for a fair comparison of the equity in accessibility distribution for all population (income) groups.

Presented in Figures 10-3 (a) – (d) below, are the Lorenz curves for the various population groups according to travel mode considered.



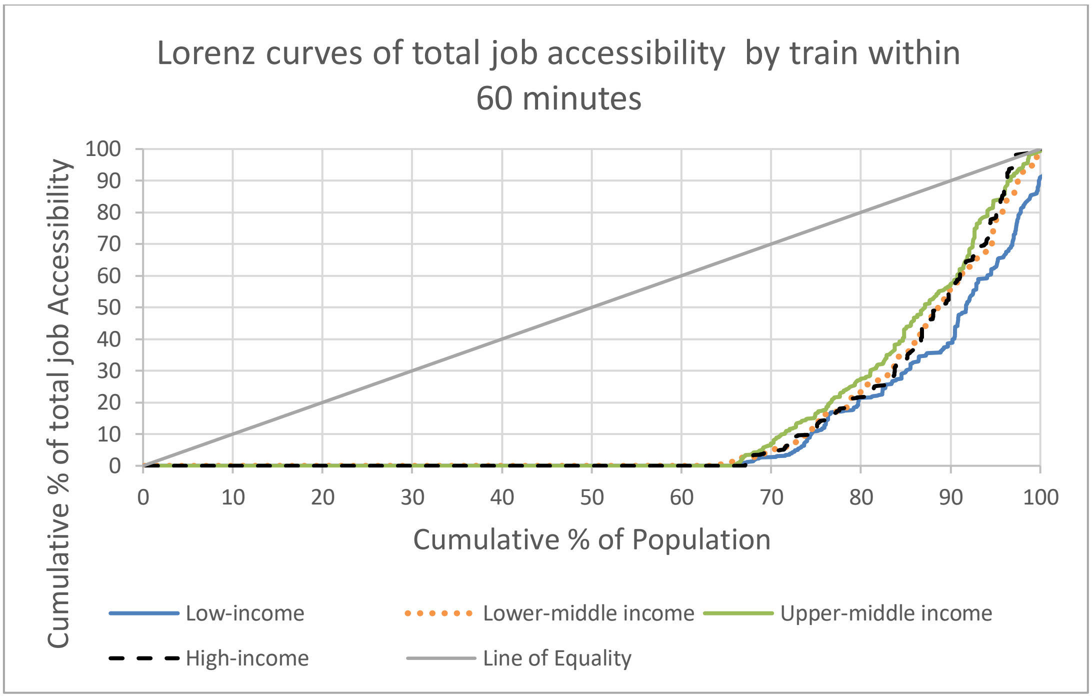
Lorenz curves of total job accessibility by car within 30 minutes
Cumulative % of total job Accessibility
Cumulative % of Population
0
10
20
30
40
50
60
70
80
90
100
Low-income
Lower-middle income
Upper-middle income
High-income
Line of Equality

(a)

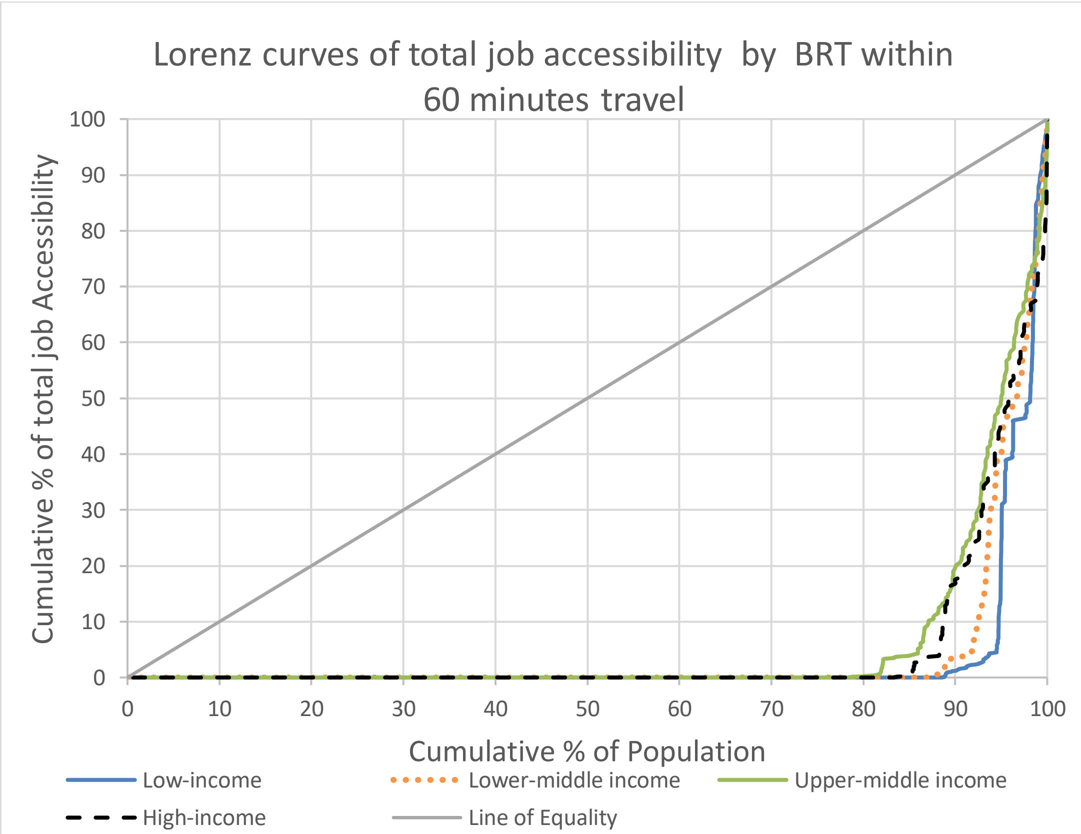


Lorenz curves of total job accessibility by minibus within 60 minutes
Cumulative % of total job Accessibility
Cumulative % of Population
0
10
20
30
40
50
60
70
80
90
100
Low-income
Lower-middle income
Upper-middle income
High-income
Line of Equality

(b)



(c)



(d)

Figure 10-3: Lorenz curves of total job Accessibility by (a) car (b) minibus (c) train (d) BRT

From Figure 10-3 (a) – (d), it is seen that the pattern of inequality varies across modes of travel for the various population groups. For the case of car travel, it can be seen that the inequality in the distribution of total accessibility is higher for the lowest income groups, up to the 50% cumulative population mark. The curves for the low-income and lower-middle-income population show that about 30% of their population only have a share of about 10% and 15% of the total accessibility respectively. For the same proportion of population for the upper-middle- and high-income categories, it is about 25% share of total accessibility. However, beyond 50% of the cumulative population across all income groups, there is not so much disparity in share of total accessibility across these groups. For travel by minibus, on the other hand, there is much higher level of inequality in distribution of accessibility compared to that of car. For this mode, about 25-30% of the population across all groups is seen to have zero cumulative accessibility. This is however worse for the case of train and BRT where about 65% and 80% respectively of all population groups have zero cumulative accessibility.

The calculated Gini coefficients associated with the Lorenz curves above, are shown in Table 10.1 below.

Table 10-1: Gini coefficients of job accessibility by income group

Income Group	Gini coefficient for job accessibility by mode of travel			
	Car_30mins	Minibus_60mins	Train_60mins	BRT_60mins
Low	0.1361	0.3241	0.7374	0.9519
Lower-middle	0.1759	0.3741	0.7446	0.9207
Upper-Middle	0.0811	0.3372	0.7154	0.8860
High	0.1308	0.4395	0.7410	0.9030

The Table shows that travel by car has lesser Gini coefficients across all population groups compared to the public transport modes. This implies a more equitable distribution of accessibility for travel by car. This is as expected, considering that the car provides the highest level of accessibility. What this also implies is that, if every individual in the various population groups has access to the car, there would be relatively higher level of equity in the distribution of accessibility. However, this would not be the case in reality, as the majority of the lower-income population relies more on public transport. Inequality in accessibility is more evident across the public transport modes, with the BRT having the highest level and the minibus providing the lowest level of inequality.

It must further be emphasised that the Gini indicators above analyse equity horizontally, that is, within each income group. Therefore, a relative comparison of values cannot be made between the various income groups, since the opportunities (jobs) are segregated, and the Gini measurement approach relates the population of a particular income group to the job accessibility of that same income group. However, vertical comparison would be possible for a situation where accessibility is measured for the total jobs (without job segregation). In which case, the population of each income group benefiting from the aggregated job accessibility can be established, and relatively compared with the Gini indicators.

10.4 Equity in School Accessibility

10.4.1 Vertical equity based on travel cost for public transport

This approach to equity evaluation seeks to show how potential accessibility to school can vary for persons of the various income categories based on out-of-pocket travel cost of accessing destinations (schools), with an assumption of a travel budget constraint given as a percentage of income. In other words, it assumes that persons of the various income categories will logically have different affordability levels and different budget outlays for school travel. This is significant for the case of Cape Town where there is considerable disparity in income across the population (see Table 10-2) and where public transport is generally priced by distance travelled. The implication is that the space of 'reachability' can be constrained by monetary travel cost budget. Table (10-2) also shows that quite a large proportion of the population falls within the low-income category. This group is considered the most vulnerable from a travel cost perspective, as they would either be constrained by the amount of opportunity they can potentially reach or, spend more, in terms of percentage of income, to attain the same number of opportunities that can be reached by the higher income earners.

Table 10-2: Population by income level in Cape Town

Income Level	Monthly Income range [ZAR]	Population
Low	0 – 3,200	1,423,169
Lower-Middle	3,201 – 25,600	2,249,294
Upper-Middle	25,601 – 51,200	289,995
High	51,201 or more	142,536

In the methodology for calculating accessibility as discussed in Chapter 5, the monetary cost of travel is estimated for every origin-destination pair (zone centroids to schools) using linear fare-distance functions which have been estimated from actual surveys of trip fares by distance across various public transport modes in Cape Town. Cumulative frequency distribution of the monetary cost per origin-destination pair is then plotted for each mode as shown in Figure (10-4).

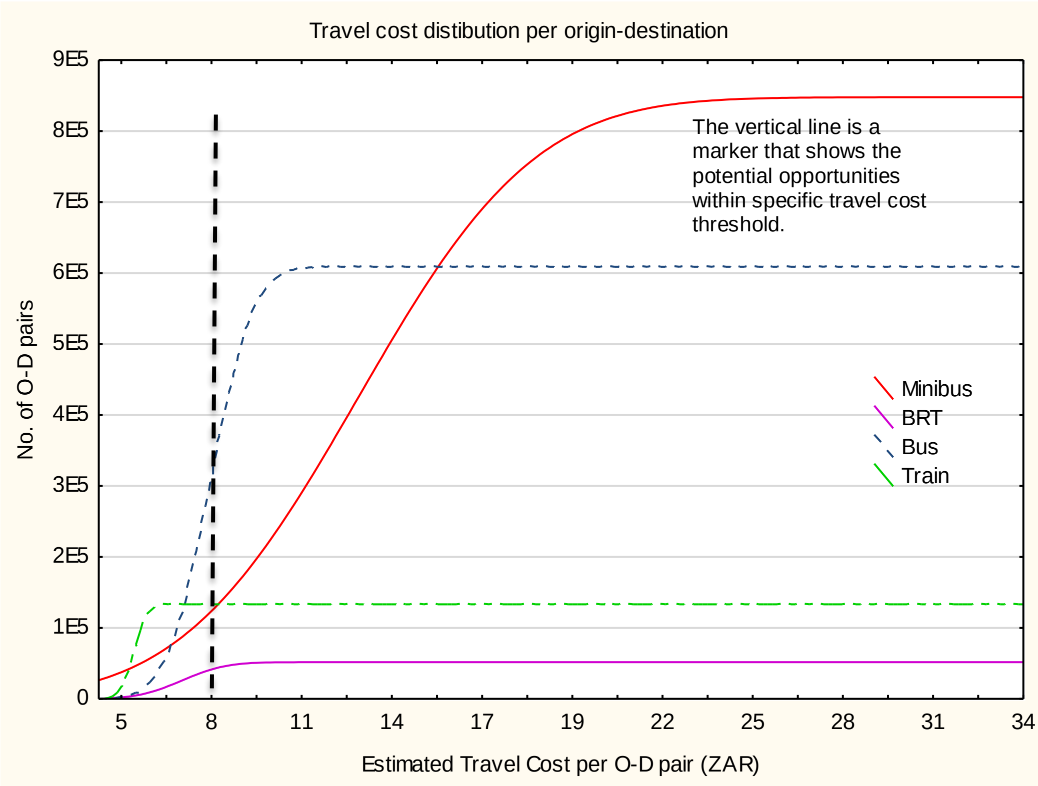


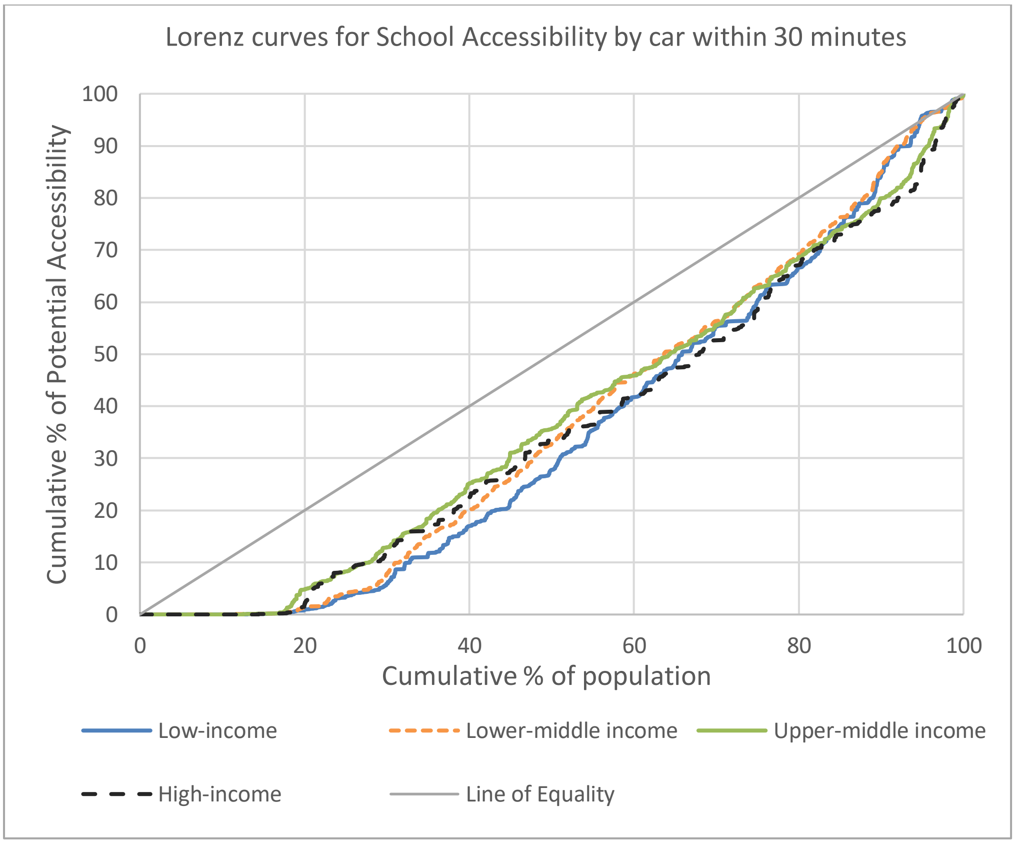
Figure 10-4: Distribution of OD pairs by monetary travel cost

The potential impact of budget constraint on the level of accessibility is revealed by the number of O-D pairs (an indication of the aggregated potential opportunities) within various monetary cost thresholds. The curves can also be displayed as cumulative percentage frequencies, rather than as cumulative frequencies of O-D pairs. Plotting the absolute numbers allows a comparison of the total amount of potential opportunities reachable across the various modes. The point at which each of the curves starts to flatten, gives an indication of the monetary budget associated with 100% of the possible zone-to-school connections for that mode. Since households within the low-income category will invariably have a lesser budget for travel to school (assuming a constant percentage of income), the potential opportunities for such group will also be lesser, compared to higher-income households. The curves in Figure 10-4 can be regarded as curves of aggregated potential accessibility to schools, where the ‘potential’ is reflected by the number of possible zone-to-school connections that can be made under a given travel budget.

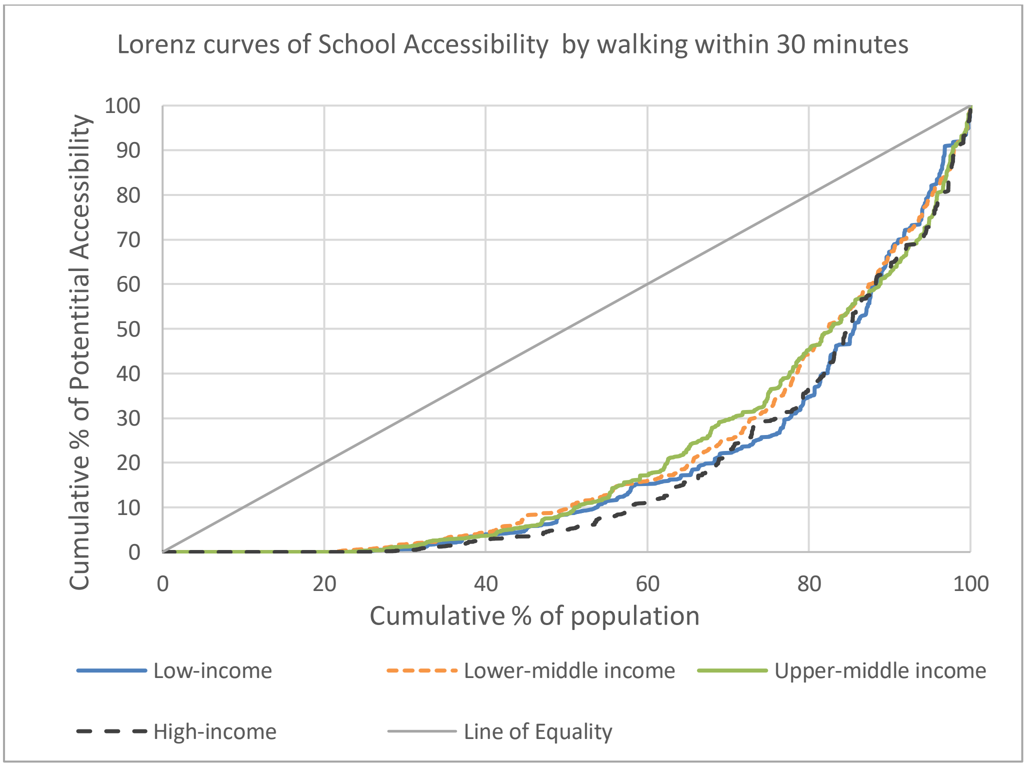
With a logical assumption that higher income will translate to a higher budget outlay for a school trip, any vertical line across the curves will point to the aggregated potential achievable within specific travel cost budget for any mode of public transport. In Figure 10-4, for example, the vertical dashed line drawn across a cost budget of ZAR8 shows that for travel by bus within 60 minutes, only about 50% (that is, 3×10^5 O-Ds) of the total possible connections (about 6×10^5 O-D pairs), can be achieved within that budget. For the more expensive paratransit mode, only 14% of the total possible connection can be achieved with that travel budget. From the figure, the train is seen to be the cheapest option of travel as 100% of the possible connections can be achieved with less than ZAR8. By relating the chart to the income level and affordability of trips for households, one could see a picture of the possible extent to which budget restriction can limit the options of opportunities for households, thus revealing the inequalities of potentials across income groups.

10.4.2 Horizontal Equity based on Lorenz curves and Gini coefficient

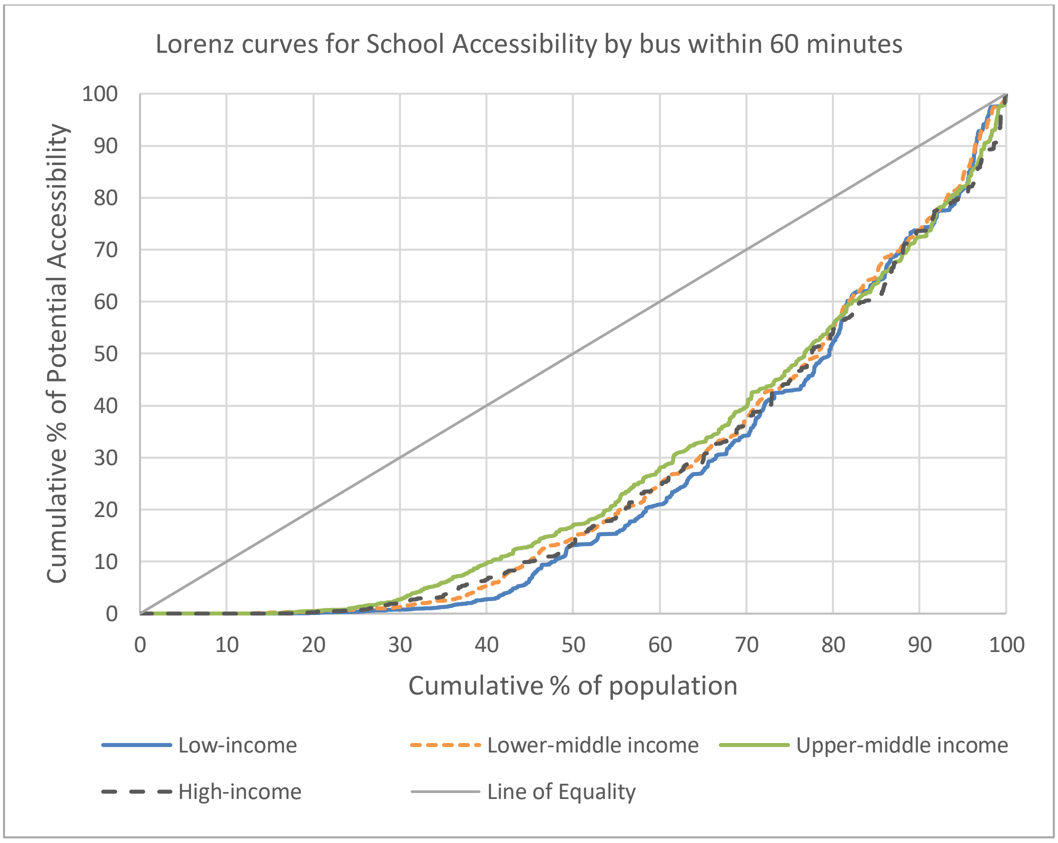
As for job accessibility, Lorenz curves and Gini coefficients are also estimated for school accessibility for the following cases: (1) car travel within 30minutes (2) walking within 30minutes and (3) public transport (bus, minibus taxi and train) travel within 60 minutes. The Lorenz curves for the various population groups for the four travel modes are shown in Figures 10-5 (a)-(d) below.


Lorenz curves for School Accessibility by car within 30 minutes
Cumulative % of Potential Accessibility
100
90
80
70
60
50
40
30
20
10
0
0
20
40
60
80
100
Cumulative % of population
Low-income
Lower-middle income
Upper-middle income
High-income
Line of Equality

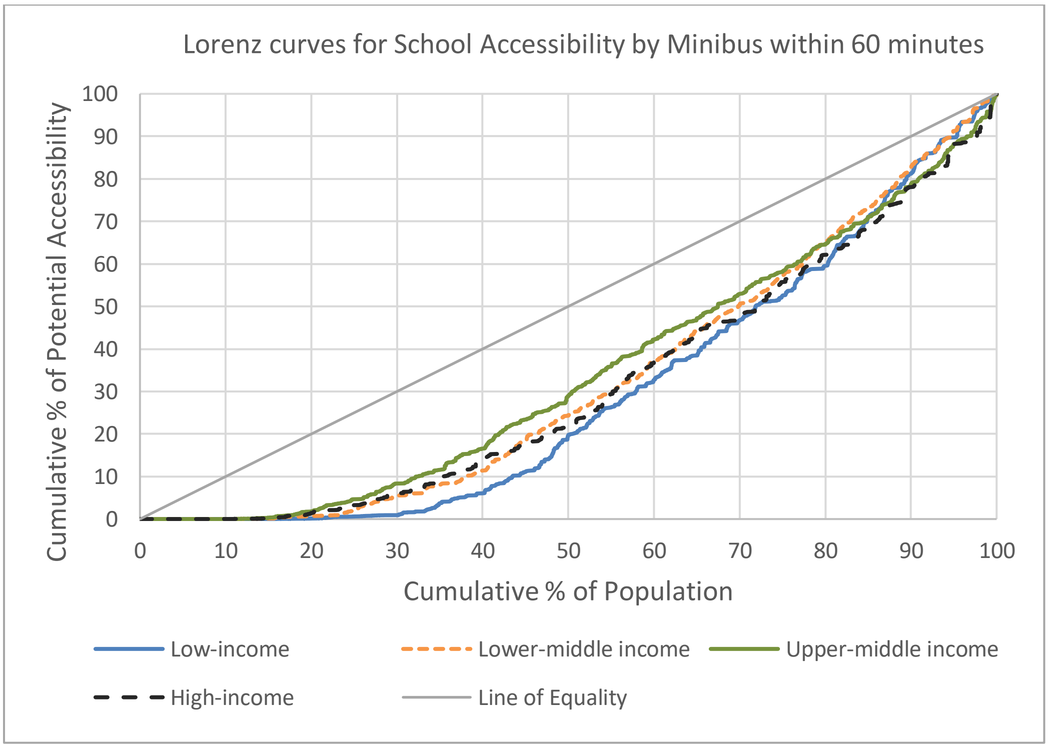
(a)


Lorenz curves of School Accessibility by walking within 30 minutes
Cumulative % of Potentitial Accessibility
100
90
80
70
60
50
40
30
20
10
0
0
20
40
60
80
100
Cumulative % of population
Low-income
Lower-middle income
Upper-middle income
High-income
Line of Equality

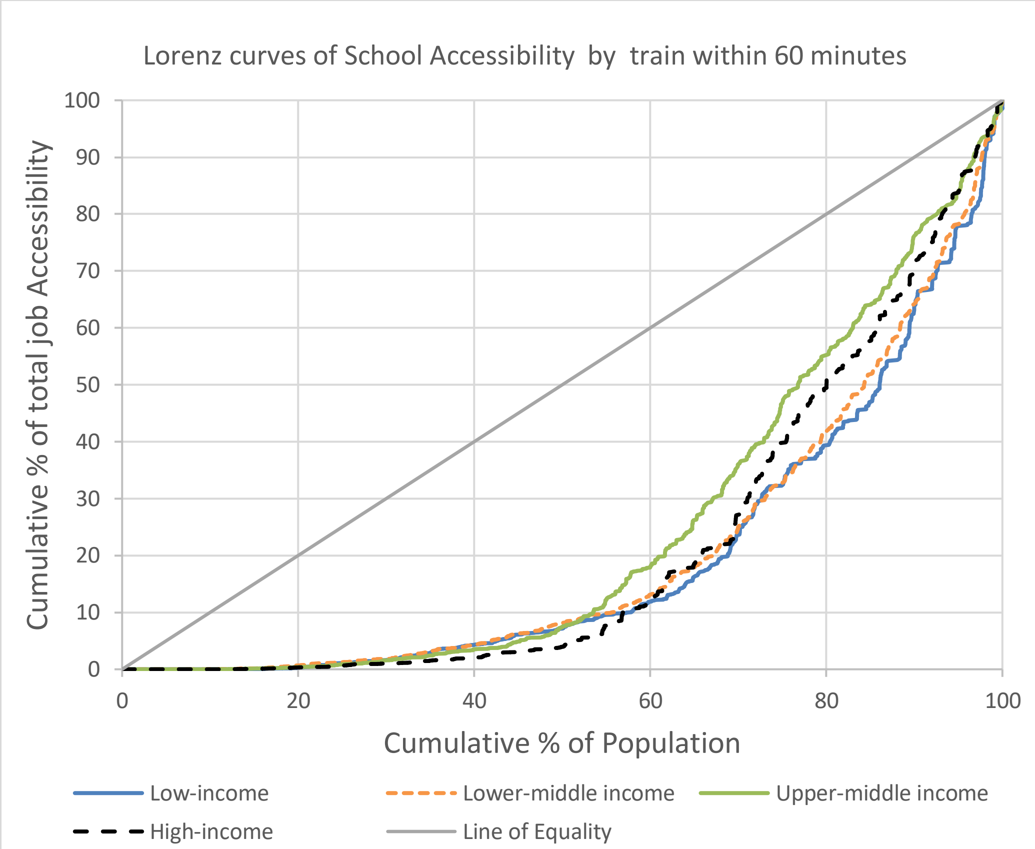
(b)


Lorenz curves for School Accessibility by bus within 60 minutes
Cumulative % of Potential Accessibility
100
90
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
100
Cumulative % of population
Low-income
Lower-middle income
Upper-middle income
High-income
Line of Equality

(c)


Lorenz curves for School Accessibility by Minibus within 60 minutes
Cumulative % of Potential Accessibility
100
90
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
100
Cumulative % of Population
Low-income
Lower-middle income
Upper-middle income
High-income
Line of Equality

(d)



(e)

Figure 10-5: Lorenz curves by population group for school accessibility for travel by (a) car (b)walking (c) Bus (d) minibus (e) train

Interpreting the sum aggregate of potential accessibility across zones as the collective potential wealth, the Lorenz curves in Figure 10-5 show the proportion of the population within each income category benefitting from accessibility. Figure 10-5 (a), for example, shows that 60% of the low-income population enjoys about 40% of the aggregated potential accessibility to schools by car. For the upper-middle-income category, it is marginally higher at 45% of accessibility, for that same proportion (60%) of the population. The estimated Gini coefficients associated with the Lorenz curves above are shown in Table 10-3 below.

Table 10-3: Gini coefficients of school accessibility by income group

Income Group	Mode of travel				
	Car	Walk	Bus	Minibus	Train
Low	0.3024	0.6111	0.5087	0.406488	0.609
Lower-middle	0.2628	0.5757	0.4794	0.350499	0.5910
Upper-Middle	0.2498	0.5755	0.4573	0.316858	0.5147
High	0.2863	0.6308	0.4898	0.372973	0.5699

Across modes, the Gini coefficients reveal a generally higher level of inequality in the distribution of accessibility by walking across all population groups, when compared to the other modes of travel. For the motorised modes, inequality in accessibility is highest for the train. Relating the Gini coefficients of these modes to the accessibility map of these modes (presented in Chapter 8, Section 8.5), it follows that the modes associated with the highest level of accessibility also show a lower level of inequality in the overall distribution of accessibility. It is also seen that Gini coefficients for walking are almost twice that of the car, indicating that inequality in the distribution of accessibility is far higher for walking than for the car. This means that a lower proportion of persons within each income group have access to schools within walking distance, compared to travel by car. Evaluating equity within the income groups, it is seen that inequality of accessibility is higher for the low and high-income population groups compared to lower-middle and upper-middle-income population, across all the modes. One explanation for this would be that schools are more evenly spread across the areas with a high concentration of the middle-income population compared to the low and high-income population.

10.5 Chapter Conclusion

This chapter presented an equity evaluation based on two approaches; a travel cost affordability framework and the Gini approach. A cost-based analysis provides a useful framework for understanding the potential impact of transport affordability on accessibility outcome, and the variability of such outcome for the various population groups. By considering actual monetary cost in the accessibility measurement, opportunities that can be considered reachable will, therefore, be a function of the associated out-of-pocket cost of accessing those opportunities. As such, potential accessibility values of any location will become relative values attributed to persons, rather than fixed values attributed to space, as it will be dependent on the income and available travel budget of individuals or households. This is particularly relevant in the context of developing cities with a considerable proportion of low-income earners.

Although this approach to equity evaluation assumes a defined percentage of income as the budget for travel across all income categories, it is recognised that the proportion of income that households are willing to spend on travel to school might vary, also within the same income group. Other household expenditure such as housing, is expected to impact on the budget available for travel. A cost-based vertical equity evaluation can, however, find relevance for planning strategies targeted at addressing the issue of transport affordability for the poor and could further serve as a tool to inform or guide public transport subsidies across the various modes. Based on the analysis presented in Section 10.3.1, which revealed the potential loss of accessibility for the low-income group as a result of limitations in budget, transport policies must, therefore, be targeted at improving affordability for those in the lower-income class, say, through localized discounts or subsidies. Other innovative pricing mechanisms could also be applied to reduce the distance effect on monetary cost of travel for the poor.

The Gini-based framework further adds a strong dimension to evaluating horizontal equity within each population group according to travel mode. The calculated Gini coefficients show how inequality is generally higher for public transport compared to the car, for both cases of job and school accessibility considered in the analyses. The Gini coefficients and Lorenz curves also serve as powerful communicative tools for comparing and visualising the differences in inequalities within the various income groups.

Chapter 11

Conclusions and Implications for Policy

"I cannot say whether things will get better if we change; what I can say is that they must change if they are to get better." — Georg Christoph Lichtenberg

11.1 Introduction

This chapter presents the overall conclusions of this dissertation, highlighting the key findings of the research in relation to the predefined objectives presented in the introductory chapter. It also presents the implications of these findings for policy in land-use and transport planning, as well as public transport operational decisions particularly for Cape Town, South Africa.

The remaining parts of this chapter are structured as follows: Section (11.2) recaps the main objectives of the research and the methods employed in addressing those objectives. In Section (11.3), the research innovations are highlighted. Section (11.4) summarises the major research findings. This include findings based on the accessibility indicators, as well as finding from the evaluation of equity. Section (11.5) presents some planning policy considerations based on the research findings. Section (11.6) reflects on some limitations of the research and recommendations for future improvement. Section (11.7) presents the concluding remark.

11.2 Revisiting the research objectives and methods

This study has been inspired on the one hand by some of the major urban development issues most developing cities (in Africa) face, and on the other hand, by the vast body of literature about accessibility. Some of these issues, as discussed in Chapters 1 and 2, include; urban poverty, social exclusion, inequality, economic segregation, amongst others. As pointed out in Section (2.2), transport forms a core dimension in most of these urban issues. Based on this, a research theme encompassing two broad objectives was presented.

The first objective was to develop indicators of accessibility to vital socioeconomic opportunities such as; jobs, healthcare and education. In subsequent Chapters (5) – (8), the development of the measures, as well as the accessibility results for Cape Town, were discussed. The computation of accessibility also required the development of a network model of the existing transport system comprising all modes of public transport, car and walking. The accessibility maps presented in Chapter 8 employed various measures to show areas of low and high levels of accessibility for the different opportunities considered.

The measurement of accessibility considered the ‘potential’ for destination reachability in terms of time, as well as the out-of-pocket cost of overcoming distance between origin and destination. The monetary costs have been determined using linear price-distance functions, which were derived from actual fare data from public transport passenger trips surveys. The job accessibility metric does not incorporate nor address qualitative differences among destinations, and therefore, does not capture travellers’ choice response to destinations because of these qualitative differences.

Although all destinations have been weighted differently by the quantity of available opportunities (for example, number of jobs), such opportunities have been equally valued in terms of potential for reachability. In other words, every zone with opportunities is considered as a potential destination from every origin zone. Other qualitative attributes such as neighbourhood safety for walking, availability of shopping or leisure opportunities, store opening hours, etc., have not been considered. For example, there is a possibility that a traveller might value a 20km journey to the CBD (with safe walking environment) more than a 10km journey to a local neighbourhood that might be considered relatively unsafe. A zone that has a combination of other activities or offers the potential for activity-chaining for trip makers, might also be valued more than that without such potential. While these aspects could be considered vital for a more holistic accessibility analysis, there are, however, methodological challenges posed by data limitations for such complex analyses. Thus, the analysis presented in this study is only based on weighted opportunities, defined by the degree of spatial separation and the cost of accessing destinations. Ease of communication/implementation is also a factor considered in the choice of indicators developed in this research.

While the first objective involves developing the indicators of accessibility, a sub-objective was to understand the relationship of accessibility with the socioeconomic and built environment features of the study area. This was further developed in Chapter 9, where exploratory OLS regression technique was employed to model the relationship between job accessibility (by car and public transport) and a combination of socioeconomic and built environment variables.

The second major objective of the research was to evaluate the level of equity that exists in the distribution of accessibility across zones occupied by individuals of the various income classes. As discussed in Chapter 10 (Section 10.1), equity can take on numerous dimensions, and thus, can be evaluated using several approaches. For this study, the focus was on equity across various population groups and within each population group, otherwise considered as vertical equity and horizontal equity respectively.

Two approaches were developed and applied in evaluating equity; an affordability-based framework for vertical equity, and a Gini-based framework for horizontal equity. The affordability framework evaluates potential accessibility by considering the potential implication of low income and limited monetary travel budget on the potential reachability of destinations. Under this framework, two indicators were developed and proposed as measures of vertical equity; an 'Affordable potential accessibility indicator', and the associated 'Accessibility loss indicator'. Both indicators employ a pre-established benchmark of transport affordability (given as a percentage of monthly income) and present a picture of what accessibility looks like for the low-income population, who are considered the most vulnerable group with limited monetary budget for travel. An additional measure employed for horizontal equity evaluation was the Gini measure, which evaluates the accessibility benefit for each population group across various modes of travel. Details of these measures are further summarised in the next section, which highlights the innovations of the research.

11.3 Innovations of the Research

The key innovations of this research are summarised in the points below:

- Development of a network-based model of the multimodal transportation system of Cape Town using GIS
  Every accessibility analysis is reliant on a model of the transport system and mode(s) of interest. For this research, network models of the transport system were developed from scratch using lines and points shapefiles of the transport network for multiple modes of travel. Both unimodal and multimodal public transport network models have been developed and applied for the various accessibility cases.

- Development of the ‘Affordable potential accessibility indicator’ (Sections 5.5.2 and 8.4) as an enhancement/modification of the Hansen’s potential measure, to enable accessibility evaluation for the low-income population, who are most likely to be affected by high monetary cost of travel and limited travel budget.

- Development of an Accessibility loss indicator as a measure of vertical equity. The Accessibility Loss Index is one of the ‘context-sensitive’ measures developed and applied as a measure of vertical equity in this research. This index is considered suitable for public transport accessibility evaluation, especially for a system that operates a distance-based pricing structure, such as Cape Town, whereby the distance between residents and the opportunities impacts directly on the monetary cost of overcoming such separation. The critical feature of the indicator is that it takes affordability of transport by the low-income group into consideration.

- Development of Gini-indicators across all income groups for various modes of travel.
  In this study, Lorenz curves and associated Gini indicators have been utilised as indicators of horizontal equity in accessibility. They summarise the accessibility (analogous to commonwealth) measured across the study area and show the proportions of the population within the respective income groups benefiting from accessibility.

11.4 Summary of Major Research Findings

The major findings of this research are summarized into these categories: (1) findings based on the indicators of network access (2) findings based on the indicators of accessibility to opportunities and (3) findings from equity evaluation.

11.4.1 Findings from the Network Access Indicator

From the public transport network access indicators presented in Section (8.2), the following are noted:

- From a spatial equity perspective, in terms of spatial access to the public transport network, it is found that residents in predominantly low-income residential areas do not suffer lack of access, as the network well covers most of the zones falling within these low-income areas. In other words, from an access point of view, the vulnerable social groups are not necessarily as disadvantaged as generally perceived. Although access coverage varies widely across modes.

- The minibus taxi provides the widest coverage among the various public transport modes. This can be attributed to the relatively higher network density of this mode compared to the other modes.
- The regular bus system is also seen to provide a wide access coverage of the low-income zones.
- Access coverage of the BRT (MyCiTi) system is found to be the lowest among the four modes. The majority of the low-income residential zones are not within the coverage of the BRT.

It must, however, be emphasized that the indicator of access coverage, as presented in Section(8.2) is purely network-based and has not considered individuals' perception of the public transport system in terms of availability, safety or reliability. It is recognised that such qualitative attributes of the system, whether perceived or revealed, can impact on the experience level of access. These have been highlighted in the recommendations for future improvement of this research in Section (11.6).

11.4.2 Findings from the indicators of accessibility to opportunities

Based on the indicators of accessibility presented in Section (8.3) – (8.7), the following are noted:

- There is considerable disparity in job accessibility achievable by car, compared to public transport, with the car providing relatively higher level of accessibility.
- On the average, about 30% of the jobs (all income categories) are potentially accessible from a zone, for travel by public transport within 60 minutes. For travel by car, the average is seen to be higher at about 40% within the same time threshold.
- When the monetary cost of travel is taken into consideration in evaluating accessibility, the opportunity space available for the low-income individual/household further shrinks drastically.
- The Affordable potential accessibility indicator shows that for an affordability benchmark of 10% of income as travel budget, there is about 80% loss in potential accessibility to jobs for the low-income individual/household, for travel by public transport. Over 20% of income is required to reach all potential opportunities reachable within 120 minutes travel.

- In terms of school accessibility, the average number of schools reachable within 30 minutes of walking is 3, compared to over 250 for travel by car within the same time threshold.
- Healthcare accessibility indicator (Section 8.6) shows that the low-income zones also have a relatively low level of accessibility to public hospital facilities compared to the majority of the higher income zones.
- From the OLS regression models presented in Chapter 9 (Section 9.4), proximity to the major urban nodes of Cape Town, comprising the Central business district as well as the Northern and Southern Suburbs business districts, all show a strong relationship with job accessibility of zones.
- Certain socioeconomic variables such as number of retail and manufacturing jobs, population of full-time workers, were also found have a strong correlation with zonal accessibility. Among the nine socioeconomic variables considered for the eight model cases (see Table 9-1), these three variables were found to be the most significant.

11.4.3 Findings from the evaluation of equity

- The affordability-based framework is a powerful and intuitive approach for evaluating vertical equity in accessibility across population groups.
- Gini indicators for both jobs and school accessibility reveal that inequality in accessibility is generally higher for travel by public transport compared to the car (see Section (10.3.2) and (10.4.2)).
- In terms of school accessibility, there is a higher level of inequality in accessibility for travel by walking, compared to travel by public transport or by car.
- About 60% of the low-income population enjoys about 40% of the aggregated potential accessibility to schools by car. For the upper-middle-income category, it is marginally higher at 45% of aggregate accessibility, for that same proportion (60%) of the population.

11.5 Planning Policy Considerations

11.5.1 Towards Affordable Accessibility

This study presented, among other things, a pragmatic approach to measuring accessibility under an affordability constraint, demonstrating how limitations of travel budget could potentially reduce the ability to overcome spatial separation and thus, level of accessibility of opportunities especially considering the low-income earners.

A key proposition in this study is that, for evaluation of accessibility for different person-groups, their socioeconomic characteristics (such as income and affordability of public transport fares) should be taken into consideration. Such an approach would introduce some fairness in the analysis of accessibility. If equity issues around transport for the poor population are to be addressed, then affordable accessibility should be a significant concern for the planners involved. Equitable access would be considered here as ‘affordable access’. The underlying policy questions, would then be; *how do we define the parameters of affordable access? What proportion of income should be used to define an affordable system considering that people usually exhibit varying degrees of willingness to pay? How do we facilitate equitable and affordable access for the poor? What are the key policy measures to be taken?* Again, these are very context-sensitive and quite complex questions. While the objective of this study is not to propose a defined and specific policy response measure, it, however, poses these questions as issues that need to be dealt in defining or implementing strategies for promoting equitable access.

11.5.2 Rethinking distance-based pricing of public transport

One of the key policy aspects that this research has challenged, is the fare policy of public transport in Cape Town, which utilises a distance-based pricing model for all modes. From the analyses presented in the previous chapters, it is evident that distance-based pricing can lead to reduction in potential accessibility especially for the poor.

Although distance-based pricing has been regarded as economically efficient and utilised by numerous agencies around the world, it could be argued that such approach to pricing in the context of Cape Town has some social and equity implications for the majority of the poor population, especially those who happened to find themselves residing on the outskirts of the city, not as a matter of their own choice but of the legacy of the apartheid planning system. The question would then be; *of what justification is the distance-based pricing to the welfare of the poor who have been confined to a situation where they have to travel a longer distance to access opportunities? Is it justifiable from an equity perspective for a system that has (over the years) created the spatial dislocation in the first place, implement a pricing system that would further disadvantage the already-disadvantaged in terms of accessibility?* These are a few of the questions that need to be interrogated at a much deeper level. Although this study has viewed the issue of inequality from a transport perspective, a holistic evaluation of equity and social inclusiveness will require more analyses incorporating many other dimensions (for example, housing) that contribute to the overall social well-being of inhabitants.

11.5.3 Rethinking subsidy distribution

The analyses presented in this study has revealed that opportunity space and thus, the amount of accessibility can diminish to a large extent when travel cost is considerably high and beyond the affordability threshold of the low-income population. One of the ways in which cities have eased the burden of transport for low-income earners is through subsidies for public transport. For the case of Cape Town, most of the public transport modes (other than the minibus taxi) enjoy various degrees of subsidy. However, considering that majority of the low-income households are still spending a sizable portion (up to 27%) of their income on transport to work, as shown by the analysis of the 2013 Cape Town Household Travel Survey, there is a need to revisit the issue of subsidy with a view to optimising the distribution such that it impacts directly on those who need it the most.

Serebrisky et al. (2009) raised two vital issues concerning transport subsidies and noted that the majority of research in this field only focus on the allocative efficiency of subsidies, with very little focusing on the distributional incidence. The distributional incidence of subsidy as pointed out by Serebrisky et al. (2009), are seldom evaluated in both developed and developing economies, making it impossible to determine the real impact of these subsidies on the welfare of the poor.

This research aligns with the distributional incidence of subsidy. One way in which the distributional impact can be evaluated is through the measures of potential accessibility. An assessment of the percentage of income spent on travel following subsidy implementation can also be one way of evaluating such impact. From an accessibility perspective, the impact of subsidy can be evaluated using the affordable potential accessibility indicator developed in this study. Based on the indicators presented for the Cape Town case, achieving equity in accessibility for the low-income population, would require that existing subsidies be reallocated or redistributed such that it impacts on the overall welfare of these population groups. A possible way of achieving such subsidy redistribution would be through a localised subsidisation scheme, whereby the public transport trips originating or terminating at the low-income residential zones enjoy a higher proportion of subsidy compared to that enjoyed by the higher income zones.

Transport subsidy could also be implemented at the person level, whereby public transport users enjoy subsidy based on need, as measured, for example, through income level and other household expenditure. The availability of smart card technologies, for example, makes it possible to capture a wide array of information regarding every traveller. Such information can be harnessed in designing a person-based subsidisation scheme. The amount of subsidy required will be a function of the desired level of accessibility. Thus, an equity standard would need to be established.

11.5.4 Setting Standards of Equity

Setting an equity standard for accessibility will require establishing (1) the level of accessibility that can be considered 'sufficient' (2) the minimum resources in terms of the proportion of income required to achieve such sufficiency in accessibility. Sufficiency in accessibility can be established in terms of a benchmark travel time. That is, setting a standard on what travel time can be considered 'reasonable' or 'excessive'. In Section 4.6, a travel time threshold of 120 minutes was applied in establishing accessibility loss. In terms of setting equity standard, a much lesser travel time of say 60 minutes or 45 minutes can be adopted, depending on the existing characteristics of the area. This should, however, be at the discretion of the land use or transport planning professional and should be judged from observed average travel time in travel surveys.

The second aspect of setting an equity standard will involve determining the average monetary cost of travel within the stipulated travel time threshold across various public transport modes or combination of modes. The average cost of travel should be within the pre-established benchmark of affordability (maximum share of income) for the low-income group and thus, should guide the pricing system of public transport. In essence, a fair pricing system to achieve equity standard of accessibility would be such that public transport within the benchmark travel time, cost no more than the benchmark threshold of affordability (maximum share of household income) for the low-income group. In other words, fair pricing would not lead to a loss of accessibility, as it would be possible to reach all destinations that can be reached within reasonable travel time with a reasonable monetary budget.

The Accessibility Loss index which is a measure of equity can be applied to establish the minimum acceptable percentage loss of accessibility for the lower-income population groups or those likely to face budget constraints. It must be recognised, however, that this index is only prescriptive in nature, considering that it is based on pre-established reasonable expenditure on transport as captured by percentage of income. It does not capture the actual willingness to pay of individuals or households. Thus, its application in the judgement of equity standards is also very subjective. It nevertheless, can supplement other planning indicators in establishing equity standards.

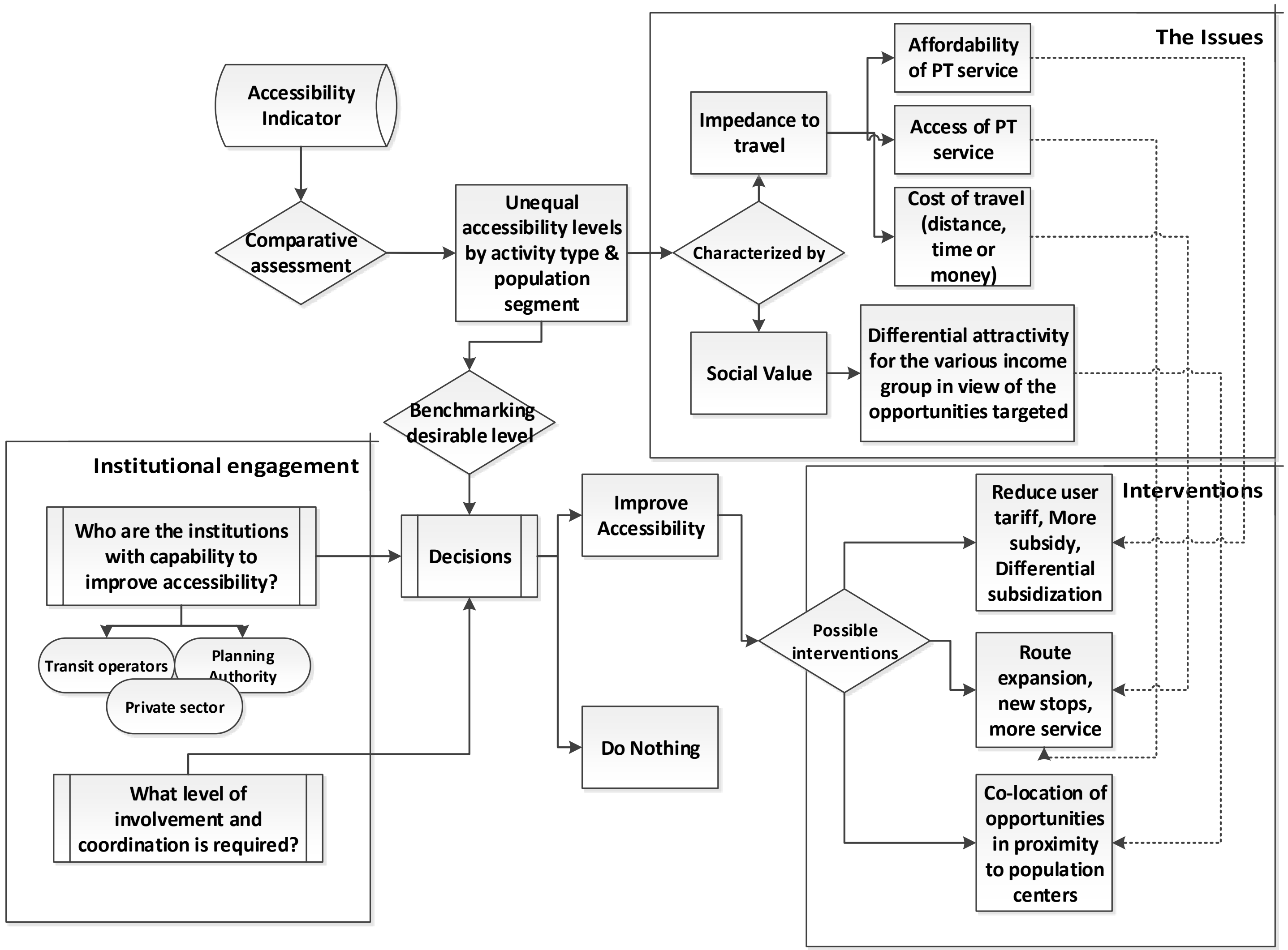
11.5.5 Land Use Interventions

Sections (11.5.1) – (11.5.4) have highlighted possible planning policy considerations for improving accessibility and equity from the transport side of the accessibility equation. Just as transport forms a core part of accessibility, the intensity and spatial distribution pattern of the available opportunities also determines the level of accessibility across zones. Therefore, improvement of accessibility can also be achieved through land-use planning policies and patterns of activity or residential development. The exploratory regression analyses of potential factors affecting accessibility presented in Chapter (9) reveal that the city spatial structure has an impact on accessibility. Distances from residential zones to the major urban nodes such as the central business district (CBD) and the northern suburb business district (NBD) were found to have a direct relationship with accessibility as presented in Section (9.4). Considering that these nodes are the major hubs of economic activities for the various income categories, it, therefore, suggests that some level of decentralisation of either the activities/opportunities or the residential locations can improve accessibility for individuals.

Decentralisation can be achieved through the development of more economic nodes at strategic locations such that travel distance and hence the monetary cost of travel are minimised for the majority of the low-income population who either walk or rely on public transport as their mobility options. With such decentralisation, other parameters of mobility, such as trip length and travel time can be significantly influenced. A reduction in trip length, for example, would further positively influence other parameters. For example, disposable income or budget would be positively influenced by a shorter trip length which reduces the transportation costs especially in situations where distance-based pricing is prevalent. Reduction in trip length will also mean that the need for transportation infrastructure will be reduced. Thus, a substantial impact can be made on the level of mobility through effective land-use planning mechanisms and decentralisation strategies.

Although, decentralisation of opportunities such as jobs can theoretically reduce trip length and improve accessibility by bringing the opportunities closer to the individuals, achieving such decentralisation in reality, is not expected to be an easy endeavour, considering that private sector participation largely drives job creation, and growth in opportunities usually follow along the existing locational trends. An alternative land use planning strategy for achieving a similar goal would be through the centralisation of residential areas, whereby residential developments are located close to the activity locations. By settling along the periphery of the city, the poorer households often trade off low land/housing costs for higher transport costs to opportunities. Centralisation, however, gives the poor households an opportunity to settle in relatively more expensive, but centrally located land/housing close to opportunities, thereby trading off higher land/housing costs against lower transport costs. In terms of social benefit provision, a key planning question would then be to establish what option needs to be subsidized between land/housing and transport.

A conceptual decision mechanism for operationalising accessibility indicators, and which summarises the various planning policy considerations, is depicted in Figure 11-1 on the next page.



Source: Author

Figure 11-1: Conceptual representation of a decision mechanism for operationalising accessibility indicators

Figure 11-1 shows the inter-relationship between the various identified components that make up the decision process. The representation comprises four key aspects: the indicator; the institutional engagement; the issues and the possible interventions. The indicator shows locations of low/high accessibility, which is a function of the cost of travel and affordability for households, as well as the spatial distribution of opportunities. Institutional engagement looks at the potential stakeholders with the capacity for improving accessibility. These have been identified broadly as; the planning authority, the transit operators and the private sector. The level of involvement of the stakeholders is dependent on the kind of issues to be addressed as well as the proposed interventions. For example, on the issue of affordability of transport, interventions say, through transport pricing mechanisms, would involve engagement of both the transit authority and the transit operators as the primary stakeholders responsible for tariff setting and regulation. However, the interest of other stakeholders, such as individuals, communities or social groups would ideally be represented in the decision-making process as well. For land-use interventions, on the other hand, such as decentralisation of opportunities or centralisation of residential developments, the primary decision-makers would comprise the planning authority and private sector organisations, including funding agencies and real estate developers. Land use interventions are also expected to be shaped by the socio-political environment and the existing legislative frameworks.

In addition to the various aspects of operationalisation of accessibility metrics described above, there is also the need for an in-depth understanding of user decisions and preferences on several aspects of the land use and transport system. For example, understanding households residential location choice decisions and factors that drive transport choices can all be considered within a more robust accessibility measure. This will, however, further require strong theoretical framework to be developed, which is beyond the scope of this research.

11.6 Limitations and Recommendations for Further Research

The accessibility models developed in this research have employed the theoretical framework of spatial interaction modelling in line with reasonable assumptions regarding the land use and transport systems. The models reveal the potentials based on the distribution of opportunities and the availability of transport infrastructure. There is, however, rooms for improvement of these models. The most significant areas for further investigation are as follows:

- The public transport network access model for example, only takes into account infrastructure supply, without consideration of actual service frequencies and reliability. With the availability of more comprehensive data on public transport services, the measures can be further developed to accommodate such service attributes. Nevertheless, the access measure proposed in this study can be applied for strategic level evaluation of public transport infrastructure coverage.
- An investigation of trip makers' preferences and perceptions of the public transport system can further complement the network-based access measure. While the access indicator is only reflective of potential access based on network infrastructure supply, an understanding of the revealed or perceived access level by users or potential users of the public transport system can further validate the network-based indicator.
- The accessibility indicators presented are static indicators which reveal the weighted sum of potential opportunities, based on the travel impedance. With the availability of comprehensive schedule data for all modes of public transport, a temporal dimension can be incorporated into the accessibility model to understand how potential opportunities may vary across time of day, such as during peak/off-peak travel conditions. Although temporal analysis was demonstrated for the BRT mode using GTFS data, such analysis can be replicated for other modes provided there is data available.
- In line with the available data and the limited processing capacity of the utilised hardware, this study has been carried out at the level of Traffic Analysis Zone (TAZ), with a total of 1787 TAZs defined for the entire study area. Although the TAZ level is considered sufficient for a city-wide analysis of potential accessibility such as this case study, there is nevertheless, room for a more refined level of analysis, say, for example, at a land parcel level. However, for an area like Cape Town, with over 700,000 defined land parcels, a parcel-level analysis would require high processing capacity machine with multiple cores run using parallel processing.
- This study has identified potential policy considerations that could improve accessibility and lessen the burden of transport for the poor. A conceptual representation of a decision framework has also been developed as shown in Figure 11-1. There is, however, room for additional research towards refining the policy measures and implementation strategies. A key example would be a study on alternative pricing structure and subsidisation approaches for

public transport in Cape Town, and the potential impact on accessibility and overall welfare of the poor households. This aspect is beyond the scope of this research but worth investigating in the future.

11.7 Concluding Remarks

Transportation and land use plans and projects are in practice evaluated by different measures which are typically based on the goals and objectives, as well as the concerns of the decision-makers and planners. Accessibility is one of the measures that can be used to evaluate systems and plans. While indicators of accessibility may not be an end-in-itself decision indicator, it holds the capacity to supplement other decision criteria considering that numerous factors ranging from social, economic to political, come into play in infrastructure decision-making in practice. Evaluating a transport system from an accessibility perspective could help in identifying how well the transport system is serving its primary objective, which is, providing access to desired activities and opportunities. As Cervero (2005) has put it, such accessibility evaluation provides a 'balanced and more holistic approach' to transportation analysis and planning.

Considering that the accessibility modelling approach presented in this study encompasses components defining the opportunities, the transport infrastructure, and user ability to pay, such accessibility indicators would find a useful role in decisions concerning investments in transport infrastructure, land use development, social infrastructure location or transport service pricing. For instance, a residential zone identified to have low accessibility to jobs should incite decisions as to options of either locating opportunities closer to the population or rather improving transport service and level of connectivity to the already available opportunities. Hence accessibility-based analyses provide the opportunity for consideration of possible interventions that could be considered to achieve desired outcomes.

Further, the affordability framework developed for the measurement of accessibility enables the evaluation of the sensitivity of accessibility to varied user tariffs of public transport services. As such, it would be possible to investigate, for example, the level of transport subsidy required to achieve desirable or benchmarked level of accessibility, or how limited subsidy could be efficiently utilised, such that accessibility benefit is optimised for the more impoverished population who are likely facing budget constraints. The issue of tariff restructuring and subsidy implementation are, however, beyond the scope of this study, and would, therefore, require additional research.

The affordability framework can further be improved by incorporating individuals' behaviour and preferences, including willingness to pay for transport services.

Finally, in terms of applicability, the indicators developed in this study find strength in their intuitiveness and relative ease of interpretation. The measures have been developed from the essential elements of spatial interaction theory, with modifications to suit the context of Cape Town. Although the study has been targeted at Cape Town, the approach can be replicated in other developing cities characterised by low income, urban poverty, inadequate transport infrastructure and unaffordable cost of public transport for the poor.

REFERENCES

Annis, D. S., Mosher, D. F. and Roberts, D. D. (2012) 'Walking Distance by Trip Purpose and Population Subgroups', *American Journal of Preventive Medicine*, 1(43), pp. 11–19.

Arce-ruiz, R., Calderón, E., Condeço-melhorado, A. and Ortega, E. (2012) 'Isochrone Maps to Facilities . Shopping Centres in the Metrosur Influence Area (IMaFa)', in Hull, A., Silva, C., and Bertolini, L. (eds) *Accessibility Instruments for Planning Practice*. COST Office, pp. 167–172.

Armstrong-Wright, A. and Thiriez, S. (1987) *Bus Services - Reducing Costs, Raising Standards*, *World Bank Technical Paper*. 68. Washington DC, USA

Baharoglu, D. and Kessides, C. (2002) 'Urban Poverty', in Klugman, J. (ed.) *A Sourcebook for Poverty Reduction Strategies - Core Techniques and Cross-Cutting Issues*. The World Bank, pp. 123–159.

Batty, M. (2007) 'Spatial Interaction', *Encyclopedia of Geographic Information Science*. SAGE Publications, Inc.

Behrens, R. (2005) 'Accommodating walking as a travel mode in South African cities: Towards improved neighbourhood movement network design practices', *Planning Practice and Research*, 20(2), pp. 163–182.

Behrens, R., McCormick, D. and Mfinanga, D. (2015) *Paratransit in African cities: Operations, regulation and reform*, *Paratransit in African Cities: Operations, Regulation and Reform*. Routledge Publishers

Ben-akiva, M. and Bierlaire, M. (2003) 'Discrete Choice Methods & Their Applications to Short Term Travel Decisions', in Hall, R. (ed.) *Handbook of Transportation science*. Springer USA, p. 29.

Ben-Akiva, M. and Lerman, S. (1979) 'Disaggregate travel and mobility choice models and measures of accessibility', *Behavioural Travel Modelling*. Croom Helm, pp. 654–679.

Bertolini, L. and Clercq, F. le (2003) 'Urban development without more mobility by car? Lessons from Amsterdam, a multimodal urban region', *Environment and Planning A*. Pion Ltd., 35(4), pp. 575–589.

Betti, G. and Lemmi, A. (2008) *Advances on Income Inequality and Concentration*

Measures. United Kingdom: Routledge, Taylor and Francis Group

Beukes, E. A., Vanderschuren, M. J. W. A. and Zuidgeest, M. H. P. (2011) 'Context sensitive multimodal road planning: A case study in Cape Town, South Africa', *Journal of Transport Geography*. Pergamon, 19(3), pp. 452–460.

Bhat, C., Handy, S., Kockelman, K., Mahmassani, H., Chen, Q. and Weston, L. (2002) *Development of an urban accessibility index: literature review*. Austin, Texas

Bhat, C., Handy, S., Kockelman, K., Mahmassani, H., Gopal, A., Srour, I. and Weston, L. (2002a) *Development of an Urban Accessibility Index: Formulations, Aggregation and Applications*. Florida, USA

Bhat, C., Handy, S., Kockelman, K., Mahmassani, H., Gopal, A., Srour, I. and Weston, L. (2002b) *Development of an Urban Accessibility Index: Formulations, Aggregations and Application*

Bhat, C. R., Guo, J. Y., Sen, S. and Weston, L. (2005) *Measuring Access to Public Transportation Services: Review of Customer-Oriented Transit Performance Measures and Methods of Transit Submarket Identification*

Bocarejo, J. . and Oviedo, D. . (2012) 'Transport accessibility and social inequities: a tool for identification of mobility needs and evaluation of transport investments', *Journal of transport geography*. Elsevier Ltd, 24, pp. 142–154.

Bocarejo, J. P., Escobar, D., Hernandez, D. O. and Galarza, D. (2014) 'Accessibility Analysis of the Integrated Transit System of Bogota', *International Journal of Sustainable Transportation*, 24(December), pp. 142–154.

Booth, D., Hanmer, L. and Lovell, E. (2000) *Poverty and Transport*. Washington DC, USA

Bradshaw, J., Kemp, P., Baldwin, S. and Rowe, A. (2004) *The drivers of social exclusion*. London: ODPM Publications

Te Brömmelstroet, M., Silva, C. and Bertolini, L. (2014) *COST Action TU1002 - Assessing Usability of Accessibility Instruments*. Netherlands: COST office

Bt Omar, D. (2006) 'Urban planning and the quality of life in Putrajaya, Malaysia', *WIT Transactions on the Built Environment*, 86(June 2006), pp. 83–90.

Burns, L. D. (1979) *Transportation, temporal, and spatial components of accessibility*. USA: Lexington Books

Cascetta, E., Cartenì, A. and Montanino, M. (2016) 'A behavioral model of accessibility based on the number of available opportunities', *Journal of Transport Geography*. Elsevier B.V., 51, pp. 45–58.

Cerdá, A. (2009) *Accessibility : a performance measure for land-use and transportation planning in the Montréal Metropolitan Region*. McGill University Canada

Cervero, R. (2005) *Accessible Cities and Regions : A Framework for Sustainable Transport and Urbanism in the 21st Century*. California, USA

Cervero, R., Rood, T. and Appleyard, B. (1995) *Job Accessibility as a Performance Indicator : An Analysis of Trends and Their Social Policy Implications in the San Francisco Bay Area Robert Cervero*. California, USA

Cheng, J. and Bertolini, L. (2013) 'Measuring urban job accessibility with distance decay, competition and diversity', *Journal of Transport Geography*. Elsevier Ltd, 30(JUNE 2013), pp. 100–109.

Chin, H. C. and Foong, K. W. (2006) 'Influence of School Accessibility on Housing Values', *Journal of Urban Planning and Development*, 132(September), pp. 120–129.

Christopher, A. J. (1987) 'Apartheid Planning in South Africa : The Case of Port Elizabeth', *The Geographical Journal*. The Royal Geographical Society (with the Institute of British Geographers), 153(2), pp. 195–204.

City of Cape town (2017) *Cape Town Municipal Spatial Development Framework (MSDF) 2017-2022*. Cape Town, South Africa

City of Cape Town (2009) *Integrated Transport Plan for the City of Cape Town 2006 To 2011- Review & Update 2009*. Cape Town, South Africa

City of Cape Town (2010a) *Business Plan: Phase 1A of Cape Town's MyCiTi Integrated Rapid Transit system*. Cape Town, South Africa

City of Cape Town (2010b) *Cape Town spatial development framework: Technical Report*. Cape Town, South Africa

City of Cape Town (2013a) *2013 – 2018 Comprehensive Integrated Transport Plan*. Cape Town, South Africa

City of Cape Town (2013b) *Development of a city wide integrated public transport network (IPTN) and the concept design and operational plan for the IRT component of the Lansdowne · Wetton corridor. Household Survey Report*

Final Draft. Cape Town, South Africa

City of Cape Town (2013c) *Integrated Development Plan- Draft 2013/14 Review*. Cape Town, South Africa

City of Cape Town (2013d) *Integrated Development Plan, 2012 - 2017*. Cape Town, South Africa

City of Cape Town (2013e) *Integrated Transport Plan Draft 2013 - 2018*. Cape Town, South Africa.

City of Cape Town (2015a) *Municipal Planning By-law 2015*. Cape Town, South Africa

City of Cape Town (2015b) *The City of Cape Town's Development Management Scheme*. http://www.capetown.gov.za/Work and business/Planning-portal/Regulations-and-legislations/The-city-of-cape-towns-development-management-scheme (Accessed: 24 August 2018).

City of Cape Town (2017) *Comprehensive Integrated Transport Plan 2017 – 2022*. Cape Town, South Africa.

Cowell, F. A. (2000) 'Measurement of Inequality', in Atkinson, A. B. and Bourguignon, F. (eds) *Handbook of Income Distribution, Volume 1*. Elsevier Science B.V, pp. 23–42.

CSIR (2000) *Guidelines for Human Settlement Planning and Design*. Pretoria: Council for Scientific and Industrial Research

Dalvi, M. Q. and Martin, K. M. (1976) 'The measurement of accessibility: Some preliminary results', *Transportation*, 5(1), pp. 17–42.

Department of Transport (1996) *White Paper on National Transport Policy*. Pretoria, South Africa

Department of Transport (1998) *Moving South Africa*. Pretoria, South Africa: National Department of Transport

Department of Transport (2015) *National Learner Transport Policy 2015*. Pretoria, South Africa: National Department of Transport

Department of Transport (2017a) *Draft Revised White Paper on National Transport Policy 2017*. Pretoria, South Africa

Department of Transport (2017b) *Revised Strategic Plan 2015 - 2020*. Pretoria, South Africa: National Department of Transport

Donaldson, R. (2001) 'A Model for South African Urban Development in the 21st Century?', in *20th South African Transport Conference 'Meeting the Transport Challenges in Southern Africa'*, pp. 1–13.

Dong, X., Ben-Akiva, M. E., Bowman, J. L. and Walker, J. L. (2006) 'Moving from trip-based to activity-based measures of accessibility', *Transportation Research Part A: Policy and Practice*, 40(2), pp. 163–180.

Draper, N. R. and Smith, H. (1998) *Applied regression analysis*. USA: John wiley & Sons

El-Geneidy, A. M. and Levinson, D. M. (2006) *Access to Destinations : Development of Accessibility Measures*, *Minnesota Department of Transportation Research Services Section*

ESRI (2006) *ArcGIS Schematics : Dealing with Connectivity*. New York, USA: ESRI

ESRI (2018) *How Exploratory Regression works- ArcGIS Desktop*. http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/how-exploratory-regression-works.htm#ESRI_SECTION1_F404115DA26C46BDA0C013824309EFD6 (Accessed: 1 November 2018).

Fan, Y. and Huang, A. (2011) *How Affordable is Transportation? A Context-Sensitive Framework*. Minnesota, USA

Farber, S. and Fu, L. (2017) 'Dynamic public transit accessibility using travel time cubes: Comparing the effects of infrastructure (dis)investments over time', *Computers, Environment and Urban Systems*. Elsevier Ltd, 62, pp. 30–40.

Farber, S., Morang, M. Z. and Widener, M. J. (2014) 'Temporal variability in transit-based accessibility to supermarkets', *Applied Geography*. Elsevier Ltd, 53, pp. 149–159.

Fayyaz, S. K., Liu, X. C. and Porter, R. J. (2017) 'Dynamic transit accessibility and transit gap causality analysis', *Journal of Transport Geography*. Elsevier Ltd, 59, pp. 27–39.

Flowerdew, R. and Aitkin, M. (1982) 'A method of fitting the gravity model based on the poisson distribution', *Journal of Regional Science*. Blackwell Publishing Ltd, 22(2), pp. 191–202.

Foda, M. A. and Osman, A. O. (2010) 'Using GIS for Measuring Transit Stop Accessibility Considering Actual Pedestrian Road Network', *Journal of Public*

Transportation, 13(4), pp. 23–40.

Ford, A., Barr, S., Dawson, R. and James, P. (2015) 'Transport Accessibility Analysis Using GIS: Assessing Sustainable Transport in London', *ISPRS International Journal of Geo-Information*, 4(1), pp. 124–149.

Foth, N., Manaugh, K. and El-geneidy, A. M. (2013) 'Towards equitable transit : examining transit accessibility and social need in Toronto , Canada , 1996 – 2006', *Journal of Transport Geography*. Elsevier, 29, pp. 1–10.

Fotheringham, A. S. (1981) 'Spatial Structure and Distance-Decay Parameters', *Annals of the Association of American Geographers*, 71(3), pp. 425–436.

GABS (2017) *Golden Arrow Bus Services - Background*. https://www.gabs.co.za/our-company/ (Accessed: 31 October 2018).

Gadzinski, J. and Beim, M. (2010) 'Public Transport Accessibility in Poznan', in *Real Corp 2010: Cities for Everyone*, pp. 18–20.

Geurs, K. T., Dentinho, T. P. and Patuelli, R. (2009) 'Accessibility, equity and efficiency', in Geurs, K. T., Patuelli, R., and Dentinho, T. P. (eds) *Accessibility, Equity and Efficiency - Challenges for Transport and Public Services*. UK: Edward Elgar Publishing Inc., pp. 3–8.

Geurs, K. T. and Ritsema van Eck, J. R. (2001) *Accessibility measures: review and applications. Evaluation of accessibility impacts of land-use transportation scenarios, and related social and economic impact*, *RIVM Report*. Rijksinstituut voor Volksgezondheid en Milieu RIVM

Geurs, K. T. and van Wee, B. (2004) 'Accessibility evaluation of land-use and transport strategies : review and research directions', *Journal of Transport Geography*, 12(2), pp. 127–140.

Geurs, K., Zondag, B., de Jong, G. and de Bok, M. (2010) 'Accessibility appraisal of land-use/transport policy strategies: More than just adding up travel-time savings', *Transportation Research Part D: Transport and Environment*, 15(7), pp. 382–393.

Gómez-Lobo, A. (2011) 'Affordability of public transport: a methodological clarification', *Journal of Transport Economics and Policy*, 45(3), pp. 437–456.

Google (2012) *General Transit Feed Specification*. General Transit Feed Specification:

https://www.transitwiki.org/TransitWiki/index.php/General_Transit_Feed_Specification (Accessed: 1 March 2018).

Google Developers (2016) *GTFS Static Overview | Static Transit | Google Developers*. https://developers.google.com/transit/gtfs/ (Accessed: 1 March 2018).

Gould, P. R. (1969) 'Spatial Diffusion, Resource paper No. 4', in. Washington DC: Association of American Geographers, Washington DC

Grengs, J. (2010) 'Job accessibility and the modal mismatch in Detroit', *Journal of Transport Geography*. Elsevier Ltd, 18(1), pp. 42–54.

Grengs, J. (2015) 'Nonwork Accessibility as a Social Equity Indicator', *International Journal of Sustainable Transportation*, 9(1), pp. 1–14.

Griffith, D. A. and Fischer, M. M. (2013) 'Constrained variants of the gravity model and spatial dependence: Model specification and estimation issues', *Journal of Geographical Systems*. Springer-Verlag, 15(3), pp. 291–317.

Gulhan, G., Ceylan, H. H., Baskan, O. and Ceylan, H. H. (2014) 'Using Potential Accessibility Measure for Urban Public Transportation Planning : a Case Study of Denizli , Turkey', *Traffic and Transportation*, 26(2), pp. 129–137.

Guo, Z. (2008) *Transfers and Path Choice in Urban Public Transport Systems*, *PhD Thesis*. Massachusetts Institute of Technology

Gutiérrez, J., Cardozo, O. D. and García-Palomares, J. C. (2011) 'Transit ridership forecasting at station level: An approach based on distance-decay weighted regression', *Journal of Transport Geography*, 19(6), pp. 1081–1092.

Guzman, L. A., Oviedo, D. and Rivera, C. (2017) 'Assessing equity in transport accessibility to work and study: The Bogotá region', *Journal of Transport Geography*. Elsevier Ltd, 58, pp. 236–246.

Ha, P. T. H., van den Bosch, F., Quang, N. N. and Zuidgeest, M. (2011) 'Urban Form and Accessibility to Jobs: A Comparison of Hanoi and Randstad Metropolitan Areas', *Environment and Urbanization Asia*, 2(2), pp. 265–285.

Hägerstrand, T. (1970) 'What about people in Regional Science?', *Papers of the Regional Science Association*, 24(1), pp. 6–21.

Halden, D., Jones, P. and Wixey, S. (2005) *Measuring Accessibility as Experienced by Different Socially Disadvantaged Groups*. United Kingdom

Hall, P. D. (1975) *An Assessment of the Calibration of Spatial Interaction Models*, *MA Thesis*. McMaster University

Handy, S. (2002) *Accessibility VS Mobility - Enhancing Strategies for Addressing Automobile Dependence in the US*. California, USA

Handy, S. L., Niemeier, D. A., Handy, S. L. and Niemeier, D. A. (1997) 'Measuring accessibility: an exploration of issues and alternatives', *Environment and Planning A*. Pion Ltd., 29(7), pp. 1175–1194.

Hansen, W. G. (1959) 'How Accessibility Shapes Land Use', *Journal of the American Institute of Planners*, 25(2), pp. 73–76.

Hanson, S. and Schwab, M. (1987) 'Accessibility and intraurban travel', *Environment and Planning A*. Pion Ltd., 19(6), pp. 735–748.

Hardcastle, D. and Cleve, I. (1995) 'Accessibility Modelling using GIS', in *Geographic Information Systems. Proceedings of Seminar N, 23rd European Transport Forum, University of Warwick, England, September 11-15, 1995. Volume P400*

Harrell, F. E. (2001) *Regression Modelling Strategies - With Applications to Linear Models, Logistic Regression and Survival Analysis*, *Springer Series in Statistics*. Springer Science

Haynes, K. and Fotheringham, A. (1984) *Gravity and spatial interaction models*. USA: Beverly Hills Sage

Hensher, D. a., Truong, T. P., Mulley, C. and Ellison, R. (2012) 'Assessing the wider economy impacts of transport infrastructure investment with an illustrative application to the North-West Rail Link project in Sydney, Australia', *Journal of Transport Geography*. Elsevier Ltd, 24, pp. 292–305.

Herijanto, W. and Thorpe, N. (2005) 'Developing the Singly Constrained Gravity Model for Application in Developing Countries', *Eastern Asia Society for Transportation Studies*, 6, pp. 1708–1723.

Hilbers, H. D. and Verroen, E. J. (1993) 'Measuring accessibility, a key factor for successful transport and land-use planning strategies', in *21st PTRC Summer Annual Meeting 1993*. United Kingdom

Hillman, R. and Pool, R. (1997) 'GIS-Based Innovations for Modelling Public Transport Accessibility.', *Traffic Engineering & Control*

Holst, O. (1979) 'Accessibility as the objective of public transportation planning: an integrated transportation and land use model', *European Journal of Operational Research*, 3(4), pp. 267–282.

Hu, L. (2017) 'Job accessibility and employment outcomes: which income groups benefit the most?', *Transportation*. Springer US, 44(6), pp. 1421–1443.

Huff, D. L. (1963) 'A Probabilistic Analysis of Shopping Center Trade Areas', *Land Economics*, 39(1), pp. 81–90.

Hull, A., Papa, E., Silva, C., Bertolini, L. and Joutsiniemi, A. (2012) 'Accessibility Instruments Survey', in Hull, A., Silva, C., and Bertolini, L. (eds) *Accessibility Instruments for Planning Practice*, pp. 205–238.

Hull, A., Silva, C. and Bertolini, L. (2012) *Accessibility Instruments for Planning Practice - TU1002 COST Action*. Brussels, Belgium: COST office

Iacono, M., Krizek, K. J. and El-Geneidy, A. (2008) *Access to Destinations: How Close is Close Enough? Estimating Accurate Distance Decay Functions for Multiple Modes and Different Purposes*, *Minnesota Department of Transportation Research Services Section*. Minnesota

Jadraque, D. E., De Caceras, A. M., Pinto, C. C. and Duque, D. M. (1996) 'Accessibility Levels Conferred by Public Transport in Madrid Metropolitan Area', in *Transportation Planning Methods. Proceedings of Seminar E Held at the PTRC European Transport Forum, Brunel University, England 2-6 September. Volume P404-2*

Jara-Díaz, S. (1997) 'Time and income in travel demand: towards a microeconomic activity framework', in Garling, T., Laitia, T., and Westin, K. (eds) *Theoretical Foundations of Travel Choice Modelling*. Chile: Elsevier

Jelinski, D. E. and Wu, J. (1996) 'The modifiable areal unit problem and implications for landscape ecology', *Landscape Ecology*, 11(3), pp. 129–140.

Jin, X., Beimborn, E. and Greenwald, M. (2005) *Impacts of Accessibility, Connectivity and Mode Captivity on Transit Choice*. USA: Federal Transit Administration

Jones, S. R. (1981) *Accessibility Measures: A Literature Review*. Berkshire, United Kingdom

Kaltheier, R. M. (2002) 'Urban Transport and Poverty in Developing Countries : Analysis and Options for Transport Policy and Planning', *Deutsche Gesellschaft für Technische Zusammenarbeit (GTZ) GmbH, Eschborn.*

Kanuganti, S., Sarkar, A. K. and Singh, A. P. (2016) 'Quantifying Accessibility to Health Care Using Two-step Floating Catchment Area Method (2SFCA): A Case Study in Rajasthan', *Transportation Research Procedia*. Elsevier B.V., 17(December 2014), pp. 391–399.

Karner, A. (2018) 'Assessing public transit service equity using route-level accessibility measures and public data', *Journal of Transport Geography*. Pergamon, 67, pp. 24–32.

Karou, S. and Hull, A. (2012) 'Accessibility Measures and Instruments', in Hull, A., Silva, C., and Bertolini, L. (eds) *Accessibility Instruments for Planning Practice*. COST Office, pp. 1–19.

Khan, A. A. (1992) 'An Integrated Approach to Measuring Potential Spatial Access to Health Care Services', *Socio-Economic Planning Sciences*, 26(4).

Kittelson & Associates, KFH Group, Parsons Brinckerhoff Quade & Douglass and Hunter-Zaworski, K. (2003) *Transit Capacity and Quality of Service Manual (TCRP Report 100)*, *TCRP Report 100*. USA: Transportation Research Board

Klir, G. J., Yuan, B. and Klir, George J., Yuan, B. (1995) *Fuzzy sets and fuzzy logic, theory and applications*, *Prentice Hail P T R*

Koenig, J. . G. (1980) 'Indicators of urban accessibility: Theory and application', *Transportation*. Kluwer Academic Publishers, 9(2), pp. 145–172.

Koopmans, C., Groot, W., Warffemius, P., Anne, J. and Hoogendoorn-lanser, S. (2013) 'Measuring generalised transport costs as an indicator of accessibility changes over time', *Transport Policy*. Elsevier, 29, pp. 154–159.

Kwan, M.-P. and Weber, J. (2008) 'Scale and accessibility: Implications for the analysis of land use–travel interaction', *Applied Geography*, 28(2), pp. 110–123.

Kwan, M. (1998) 'Space-time and integral measures of individual accessibility: a comparative analysis using a point-based framework', *Geographical analysis*. Wiley Online Library, 30(3), pp. 191–216.

Langford, M., Fry, R. and Higgs, G. (2012) 'Measuring transit system accessibility using a modified two-step floating catchment technique', *International Journal of Geographical Information Science*, 26(2), pp. 193–214.

Lee, B. H.-Y. (2005) 'Parcel-level measure of public transit accessibility to destinations', in Levinson, D. M. and Krizek, K. J. (eds) *Access to Destinations*.

Elsevier Ltd, pp. 215–242.

Lei, T. L. and Church, R. L. (2010) 'Mapping transit-based access: integrating GIS, routes and schedules', *International Journal of Geographical Information Science*, 24(2), pp. 283–304.

Levitas, R., Pantazis, C., Fahmy, E., Gordon, D., Lloyd, E. and Patsios, D. (2007) *The Multi-dimensional Analysis of Social Exclusion*

Linneker, B. J. and Spence, N. A. (1992) 'Accessibility Measures Compared in an Analysis of the Impact of the M25 London Orbital Motorway on Britain', *Environment and Planning A*. SAGE PublicationsSage UK: London, England, 24(8), pp. 1137–1154.

Lionjanga, N. and Venter, C. (2017) 'Time-series Analysis of Accessibility in the city of Johannesburg', *36th Southern Africa Transport Conference (SATC 2017)*, (July), pp. 416–429.

Litman, T. (2003) 'Social inclusion as a transport planning issue in Canada, Contribution to the FIA Foundation G7 Comparison Paper', in *European Transport Conference*. Association for European Transport and Contributors 2003

Litman, T. (2014) 'Evaluating Accessibility for Transportation Planning Measuring People ' s Ability to Reach Desired Goods and Activities'. British Columbia, (January 2008), p. 49.

Litman, T. (2016) *Evaluating Transportation Equity: Guidance for Incorporating Distributional Impacts in Transportation Planning*, *Victoria Transport Policy Institute*

Liu, R., Chen, Y., Wu, J., Xu, T., Gao, L. and Zhao, X. (2018) 'Mapping spatial accessibility of public transportation network in an urban area – A case study of Shanghai Hongqiao Transportation Hub', *Transportation Research Part D: Transport and Environment*. Elsevier, 59(February), pp. 478–495.

Long, J. (2017) 'Modelling Accessibility', in Wilson, J. P. (ed.) *The Geographic Information Science & Technology Body of Knowledge*. Washington DC, US: Association of American Geographers

Lowe, J. C. and Moryadas, S. (1975) *The geography of movement*, *Houghton Mifflin Company*. USA: Houghton Mifflin

Lucas, K. (2004) 'Towards a "social welfare" approach to transport', in Lucas, K. (ed.)

Running on Empty - Transport, social exclusion and environmental justice. Great Britain: The Policy Press, University of Bristol, p. 321.

Lucas, K. (2012) 'Transport and social exclusion: Where are we now?', *Transport Policy*. Elsevier, 20, pp. 105–113.

Lucas, K., van Wee, B. and Maat, K. (2016) 'A method to evaluate equitable accessibility: combining ethical theories and accessibility-based approaches', *Transportation*, 43(3), pp. 473–490.

Luke, R. and Heyns, G. (2013) 'Public transport policy and performance: The results of a South African public opinion poll', *Journal of Transport and Supply Chain Management*, 7(1), pp. 1–8.

Luo, W. and Qi, Y. (2009) 'An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians.', *Health & place*, 15(4), pp. 1100–7.

Luo, W. and Wang, F. (2003) 'Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region', *Environment and Planning B: Planning and Design*, 30(6), pp. 865–884.

Mackett, R. L. and Thoreau, R. (2015) 'Transport, social exclusion and health', *Journal of Transport & Health*. Elsevier, pp. 1–8.

Mahrous, R. F. (2012) *Multimodal Transportation Systems: modelling challenges*, *Msc Thesis*. University of Twente.

Makrí, M. and Folkesson, C. (2000) 'Accessibility Measures for Analyses of Land Use and Travelling with Geographical Information Systems', in *2nd KFB Research Conference*, pp. 251–265.

Malekzadeh, A. (2015) *Measurement of Transit Network Accessibility Based on Access Stop choice Behaviour*. Queensland University of Technology

Mamun, S. A., Lownes, N. E., Osleeb, J. P. and Bertolaccini, K. (2013) 'A method to define public transit opportunity space', *Journal of Transport Geography*, 28, pp. 144–154.

Mamun, S. Al and Lownes, N. E. (2011) 'A Composite Index of Public Transit Accessibility', *Journal of Public Transportation*, 14(2), pp. 69–87.

Manderscheid, K. (2009) 'Unequal Mobilities', in Ohnmacht, T., Maksim, H., and Bergman, M. M. (eds) *Mobilities and Inequality*. Ashgate Publishing Limited

Manout, O., Bonnel, P. and Bouzouina, L. (2018) 'Transit accessibility: A new definition of transit connectors', *Transportation Research Part A: Policy and Practice*, 113(February), pp. 88–100.

Martellato, D. and Nijkamp, P. (1998) 'The Concept of Accessibility Revisited', in Reggiani, A. (ed.) *Accessibility, Trade and Locational Behaviour*. Ashgate Publishing Limited, pp. 17–40.

Martens, K. (2016) *Transport justice : designing fair transportation systems*. Routledge, Taylor and Francis Group

Martinez, L. M. and Viegas, J. M. (2013) 'A new approach to modelling distance-decay functions for accessibility assessment in transport studies', *Journal of Transport Geography*, 26, pp. 87–96.

Mavoa, S., Witten, K., McCreanor, T. and O'Sullivan, D. (2012) 'GIS based destination accessibility via public transit and walking in Auckland, New Zealand', *Journal of Transport Geography*. Elsevier Ltd, 20(1), pp. 15–22.

Mcgrail, M. R. and Humphreys, J. S. (2014) 'Measuring spatial accessibility to primary health care services : Utilising dynamic catchment sizes', *Applied Geography*. Elsevier Ltd, 54, pp. 182–188.

Meiring, T., Kannemeyer, C. and Potgieter, E. (2018) *The gap between rich and poor : South African society ' s biggest divide depends on where you think you fit in*. Cape Town

Melinda, M. (2017) *Add GTFS to a Network Dataset User's Guide*, *Esri*. http://www.transit.melindamorang.com/download_AddGTFStoND.html.

Meyer, J., Becker, H., Bösch, P. M. and Axhausen, K. W. (2017) 'Autonomous vehicles: The next jump in accessibilities?', *Research in Transportation Economics*, 62, pp. 80–91.

Miller, H. J. (1991) 'Modelling accessibility using space-time prism concepts within geographical information systems', *International Journal of Geographical Information Systems*, 5(3), pp. 287–301.

Miller, H. J. (1999) 'Measuring Space-Time Accessibility Benefits within Transportation Networks: Basic Theory and Computational Procedures', *Geographical Analysis*. Blackwell Publishing Ltd, 31(2), pp. 187–212.

Miller, H. J. and Shaw, S.-L. (2001) *Geographic Information Systems for Transportation: Principles and Applications*. Oxford University Press

Miller, H. J. and Wu, Y. (2000) 'GIS Software for Measuring Space-Time Accessibility in Transportation Planning and Analysis', *GeoInformatics*, 4(2), pp. 141–159.

Mokgalaka, H. (2015) *GIS-Based Analysis of Spatial Accessibility: An Approach to Determine Public Primary Healthcare Demand in Metropolitan Areas*, *MSc Thesis*. University of Cape Town

Murray, A. T. (2001) 'Strategic analysis of public transport coverage', *Socio-Economic Planning Sciences*, 35(3), pp. 175–188.

Murray, A. T., Davis, R., Stimson, R. J. and Ferreira, L. (1998) 'Public Transportation Access', *Transportation Research Part D: Transport and Environment*, 3(5), pp. 1–2.

O'Sullivan, D., Morrison, A. and Shearer, J. (2000) 'Using desktop GIS for the investigation of accessibility by public transport: an isochrone approach', *International Journal of Geographical Information Science*, 14(1), pp. 85–104.

ODPM (2004) *The Social Exclusion Unit*, *Office of the Deputy Prime Minister*. London, United Kingdom: Office of the Deputy Prime Minister

Ortuzar, J. de D. and Willumsen, L. G. (2011) *Modelling Transport*. 4th edn. United Kingdom: John wiley & Sons

Páez, A., Scott, D. M. and Morency, C. (2012) 'Measuring accessibility: positive and normative implementations of various accessibility indicators', *Journal of Transport Geography*. Elsevier Ltd, 25, pp. 141–153.

Papa, E. and Coppola, P. (2012) 'Gravity-Based Accessibility Measures for Integrated Transport-Land Use Planning (GraBAM)', in Hull, A., Silva, C., and Bertolini, L. (eds) *Accessibility Instruments for Planning Practice*. Brussels, Belgium: COST Office, pp. 117–124.

Papa, E. and Ferreira, A. (2018) 'Sustainable Accessibility and the Implementation of Automated Vehicles: Identifying Critical Decisions', *Urban Science*, 2(1), p. 5.

Parliament of the Republic of South (1950) *The Group Areas Act, Act No. 41, 1950*, *Parliament of Republic of South Africa*

Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J. M., Wardman, M. R., Shires, J. D. and White, P. (2006) 'The Demand for Public Transport: The Effects of Fares, Quality of Service, Income and Car Ownership', *Transport*

Policy, 13(4), pp. 295–306.

Perry, B. and Gesler, W. (2000) ‘Physical access to primary health care in Andean Bolivia’, *Social Science and Medicine*, 50(9), pp. 1177–1188.

Pirie, G. H. (1979) ‘Measuring Accessibility: A Review and Proposal’, *Environment and Planning A*. SAGE PublicationsSage UK: London, England, 11(3), pp. 299–312.

Pitot, M., Yigitcanlar, T., Sipe, N., Evans, R. and Land, R. (2006) ‘Land Use & Public Transport Accessibility Index (LUPTAI) Tool - The development and pilot application of LUPTAI for the Gold Coast’, in *Australian Transport Research Forum*. Gold Coast, pp. 27–29.

Polzin, S. E., Pendyala, R. M. and Navari, S. (2002) ‘Development of Time-of-day-based Transit Accessibility Analysis Tool’, *Transportation Research Record*, (1799).

Preston, J. and Rajé, F. (2007) ‘Accessibility, mobility and transport-related social exclusion’, *Journal of Transport Geography*, 15(3), pp. 151–160.

Primerano, F. (2004) *Development of Accessibility Measures for Transport and Urban Planning*, *PhD Thesis*. University of South Australia

Rastogi, R. and Krishna Rao, K. V. (2003) ‘Defining transit accessibility with environmental inputs’, *Transportation Research Part D: Transport and Environment*, 8(5), pp. 383–396.

Rawal, N. (2007) ‘Social Inclusion and Exclusion : A Review’, *Dhaulguri Journal of Sociology and Anthropolgy*, 2, pp. 161–180.

Reggiani, A., Bucci, P., Russo, G., Haas, A. and Nijkamp, P. (2011) ‘Regional labour markets and job accessibility in City Network systems in Germany’, *Journal of Transport Geography*. Elsevier Ltd, 19(4), pp. 528–536.

Ritsema van Eck, J. R. and de Jong, T. (1999) ‘Accessibility analysis and spatial competition effects in the context of GIS-supported service location planning’, *Computers, Environment and Urban Systems*, 23, pp. 75–89.

Rosero-bixby, L. (2004) ‘Spatial access to health care in Costa Rica and its equity : a GIS-based study’, *Social Science & Medicine*, 58, pp. 1271–1284.

Roy, J. R. (2004) *Spatial Interaction Modelling - A Regional Science Context*, *Springer*. Springer Berlin Heidelberg

Salze, P. *et al.* (2011) 'Estimating spatial accessibility to facilities on the regional scale : an extended commuting-based interaction potential model', *International Journal of Health Geographics*. BioMed Central Ltd, 10(1), p. 2.

Scheurer, J. and Curtis, C. (2007) *Accessibility Measures: Overview and Practical Applications*, *Impacts of Transit Led Development*. 4

Schwanen, T., Lucas, K., Akyelken, N., Cisternas, D., Carrasco, J. and Neutens, T. (2015) 'Rethinking the links between social exclusion and transport disadvantage through the lens of social capital', *Transportation Research Part A*. Elsevier Ltd, 74, pp. 123–135.

Sen, A. (2000) *Social Exclusion: Concept, Application and Scrutiny*. Manila, Philippines

Sen, A. and Smith, T. E. (1995) *Gravity Models of Spatial Interaction Behavior*. Germany: Springer-Verlag Berlin Heidelberg

Serebrisky, T., Gómez-Lobo, A., Estupiñán, N. and Muñoz-Raskin, R. (2009) 'Affordability and Subsidies in Public Urban Transport: What Do We Mean, What Can Be Done?', *Transport Reviews: A Transnational Transdisciplinary Journal*, 29(December), pp. 715–739.

Silva, C. (2012) 'Structural Accessibility Layer (SAL)', in Hull, A., Silva, C., and Bertolini, L. (eds) *Accessibility Instruments for Planning Practice*. COST Office, pp. 145–151.

Silva, C. (2013) 'Structural accessibility for mobility management', *Progress in Planning*, 81, pp. 1–49.

Silverman, B. W. (1986) 'Density estimation for statistics and data analysis', *Monographs on Statistics and Applied Probability*, 37(1), pp. 1–22.

Simonoff, J. S. (1996) *Smoothing methods in statistics*. New York, USA: Springer New York

Sinha, K. C. and Labi, S. (2007) *Transportation Decision Making - Principles of Project Evaluation and Programming*. New Jersey, USA: John wiley & Sons

Skov-Petersen, H. (2001) 'Estimation of distance-decay parameters-GIS-based indicators of recreational accessibility', *ScanGIS*, pp. 24–27.

Social Exclusion Unit (2003) *Making the Connections: Final Report on Transport and*

Social Exclusion. London, United Kingdom: Social Exclusion Unit

Stanley, J. and Lucas, K. (2008) 'Social exclusion: What can public transport offer?', *Research in Transportation Economics*, 22(1), pp. 36–40.

Statistics South Africa (2014) *National Household Travel Survey 2013 -Statistical release P0320*. Pretoria, South Africa: National Department of Transport

Stewart, A. F. (2017) 'Mapping transit accessibility: Possibilities for public participation', *Transportation Research Part A: Policy and Practice*. Elsevier Ltd, 104, pp. 150–166.

Stewart, J. Q. (1947) 'Suggested Principles of "Social Physics"', *Science*, 106(2748), pp. 179–180.

Stokes, G. (2015) 'Incomes, accessibility and transport poverty', in Hickman, R., Givoni, M., Bonilla, D., and Banister, D. (eds) *Handbook on Transport and Development*. Edward Elgar Publishing Inc., pp. 414–429.

Strydom, M. (2010) *Integrated Rapid Transport : Is the City of Cape Town utilising its full potential?*, *MA Thesis*. North-West University

Talen, E. (1998) 'Visualizing fairness: Equity maps for planners', *Journal of the American Planning Association*, 64(1), pp. 22–38.

Talen, E. (2001) 'An empirical investigation of access to elementary schools in West Virginia', *Annals of the Association of American Geographers*, 91(3), pp. 465–486.

Taylor, P. J. (1975) 'Distance Decay in Spatial Interactions', in *Concepts and Techniques in Modern Geography*

Teunissen, T., Sarmiento, O., Zuidgeest, M. and Brussel, M. (2015) 'Mapping equality in access: The case of Bogotá's sustainable transportation initiatives', *International Journal of Sustainable Transportation*, 9(7), pp. 457–467.

The Presidency Republic of South (2009) *National Land Transport Act, 2009*, *Government Gazette*. The Presidency, Republic of South Africa

Thériault, M., Des Rosiers, F. and Joerin, F. (2005) 'Modelling accessibility to urban services using fuzzy logic', *Journal of Property Investment & Finance*, 23(1), pp. 22–54.

Thomopoulos, N., Grant-Muller, S. and Tight, M. R. (2009) 'Incorporating equity considerations in transport infrastructure evaluation: Current practice and a proposed methodology', *Evaluation and Program Planning*, 32(4), pp. 351–359.

Tilahun, N. and Fan, Y. (2014) 'Transit and job accessibility: an empirical study of access to competitive clusters and regional growth strategies for enhancing transit accessibility', *Transport Policy*. Elsevier, 33, pp. 17–25.

Timmermans, H., Arentze, T. and Joh, C. (2002) 'Analysing space-time behaviour : new approaches to old problems', *Progress in Human Geography*, 2, pp. 175–190.

Tizora, P., Roux, A. Le, Mans, G. and Cooper, A. (2016) *Land Use and Land Cover Change in the Western Cape Province : Quantification of Changes & Understanding of Driving Factors*

Torrens, P. M. (2000) *How Land Use - Transportation Models Work*. 20. London

Transport and Urban Development Authority (2017) *Transport in Cape Town*. https://www.tda.gov.za/en/transport/ (Accessed: 8 March 2019).

Transport for London (2010) *Measuring Public Transport Accessibility Levels PTAL*. London

Tribby, C. P. and Zandbergen, P. A. (2012) 'High-resolution spatio-temporal modeling of public transit accessibility', *Applied Geography*. Elsevier Ltd, 34, pp. 345–355.

Tyler, N. (1999) *Measuring Accessibility to Public Transport: Concepts*. London

U.S. Environmental Protection Agency (2011) *Guide to Sustainable Transportion Performance*. Washington DC

UCLA: Statistical Consulting Group. (no date) *Introduction To Regression With Spss Lesson 2: Spss Regression Diagnostics*. https://stats.idre.ucla.edu/spss/seminars/introduction-to-regression-with-spss/introreg-lesson2/ (Accessed: 12 December 2018).

Venter, C., Bogopane, H. and Rickert, T. (2002) 'Improving accessibility for people with disabilities in urban areas', in : *CODATU X. Lome*

Venter, C. and Cross, C. (2014) 'Access envelopes: A new accessibility mapping technique for transport and settlement planning', *Town and Regional Planning*, 64(1), pp. 43–52.

Venter, C. and Mohammed, S. (2013) 'Estimating car ownership and transport energy consumption : a disaggregate study in Nelson Mandela Bay', *Journal of the South African Institution of Civil Engineering*. The Institution, 55(1), pp. 2–10.

Vickerman, R. W. (1974) 'Accessibility, attraction, and potential: a review of some concepts and their use in determining mobility', *Environment and Planning A*, 6(6), pp. 675–691.

Viegas, J. M., Martinez, L. M. and Silva, E. A. (2009) 'Effects of the modifiable areal unit problem on the delineation of traffic analysis zones', *Environment and Planning B: Planning and Design*, 36, pp. 625–644.

Visser, G. (2001) 'Social Justice, Integrated Development Planning and Post-apartheid Urban Reconstruction', *Urban Studies*, 38(10), pp. 1673–1699.

de Vries, J. J., Nijkamp, P. and Rietveld, P. (2009) 'Exponential or power distance-decay for commuting? An alternative specification', *Environment and Planning A*, 41(2), pp. 461–480.

Wachs, M. and Kumagai, T. G. G. (1973) 'Physical Accessibility As a Social Indicator', *Socio-Economic Planning Sciences*. Pergamon, 7(5), pp. 437–456.

Wang, F. (2015) *Quantitative Methods and Socio-Economic Applications in GIS*. 2nd Editio, *Taylor & Francis Group*. 2nd Editio. Taylor & Francis Group

Wee, B. and Geurs, K. (2011) 'Discussing equity and social exclusion in acessibility evaluations', *European Journal of Transport and Infrastructure Research*, 11(4), pp. 350–367.

Van Wee, B., Annema, J. A. and Banister, D. (2013) *The Transport System and Transport Policy: an introduction*. Edward Elgar Publishing Inc.

van Wee, B. and Geurs, K. (2011) 'Discussing equity and social exclusion in accessibility evaluations', *European Journal of Transport and Infrastructure Research*, 11(4), pp. 350–367.

van Wee, B., Hagoort, M. and Annema, J. A. (2001) 'Accessibility measures with competition', *Journal of Transport Geography*, 9(3), pp. 199–208.

Weibull, J. W. (1980) 'On the numerical measurement of accessibility', *Environment and Planning A*. Pion Ltd., 12(1), pp. 53–67.

Western Cape government (2017) *2017 Socio-Economic Profile: City of Cape Town*. South Africa: Western Cape Government

Whitehead, M. (2015) *Transport Development Index - A Baseline Understanding of the State of Transport in Cape Town*. Cape Town, South Africa: City of Cape Town

Widener, M. J., Farber, S., Neutens, T. and Horner, M. (2015) 'Spatiotemporal accessibility to supermarkets using public transit: an interaction potential approach in Cincinnati, Ohio', *Journal of Transport Geography*. Elsevier Ltd, 42, pp. 72–83.

Wilson, A. G. (1967) 'A statistical theory of spatial distribution models', *Transportation Research*. Pergamon, 1(3), pp. 253–269.

Woldeamanuel, M. G. and Cyganski, R. (2011) 'Factors Affecting Travellers' Satisfaction with Accessibility to Public Transportation', *Association for European Transport and Contributors*, pp. 1–19.

Wu, Y. and Miller, H. J. (2001) 'Computational Tools for Measureing Space-Time Accessibility Within Dynamic Flow Transportation Networks', *Journal of Transportation and Statistics*, 4(2/3), pp. 1–14.

Xu, W. (Ato), Ding, Y., Zhou, J. and Li, Y. (2015) 'Transit accessibility measures incorporating the temporal dimension', *Cities*. Elsevier Ltd, 46, pp. 55–66.

Yang, J., Liu, C., Wang, B. and Ding, X. (2017) 'Feedback System Control Optimized Electrospinning for Fabrication of an Excellent Superhydrophobic Surface', *Nanomaterials*, 7(10), p. 319.

Yigitcanlar, T., Sipe, N., Evans, R. and Pitot, M. (2007) 'A GIS-based land use and public transport accessibility indexing model', *Australian Planner*, 44(3), pp. 30–37.

Zhuo, H. (2012) *GIS-based Spatial Accessibility Analysis to High Schools by Transit in Toledo Area in 2010*. University of Toledo

Ziemke, D., Joubert, J. W. and Nagel, K. (2017) 'Accessibility in a Post-Apartheid City: Comparison of Two Approaches for Accessibility Computations', *Networks and Spatial Economics*. Networks and Spatial Economics, pp. 1–31.

APPENDIX 1: Distance (Time) Decay Estimation

1A: Travel time data transformation

Travel time	Frequency table: JourneyTimeby Train_Work (Spreadsheet10) Count	Cumulative Count	Percent	Cumulative Percent	100% - Percent	F(Cij)	Cij_TravelTime
5 <=x<10	2	2	0.07746	0.0775	100.0000	1	5
10 <=x<15	8	10	0.30984	0.3873	99.9225	0.99922541	10
15 <=x<20	19	29	0.73586	1.1232	99.6127	0.99612703	15
20 <=x<25	26	55	1.00697	2.1301	98.8768	0.9887684	20
25 <=x<30	22	77	0.85205	2.9822	97.8699	0.97869868	25
30 <=x<35	146	223	5.65453	8.6367	97.0178	0.97017816	30
35 <=x<40	37	260	1.43300	10.0697	91.3633	0.91363284	35
40 <=x<45	79	339	3.05964	13.1294	89.9303	0.89930287	40
45 <=x<50	171	510	6.62277	19.7521	86.8706	0.86870643	45
50 <=x<55	122	632	4.72502	24.4771	80.2479	0.8024787	50
55 <=x<60	64	696	2.47870	26.9558	75.5229	0.75522851	55
60 <=x<65	515	1211	19.94578	46.9016	73.0442	0.73044152	60
65 <=x<70	58	1269	2.24632	49.1479	53.0984	0.53098373	65
70 <=x<75	102	1371	3.95043	53.0984	50.8521	0.50852053	70
75 <=x<80	192	1563	7.43610	60.5345	46.9016	0.46901627	75
80 <=x<85	81	1644	3.13710	63.6716	39.4655	0.39465531	80
85 <=x<90	30	1674	1.16189	64.8335	36.3284	0.36328428	85
90 <=x<95	337	2011	13.05190	77.8854	35.1665	0.35166538	90
95 <=x<100	27	2038	1.04570	78.9311	22.1146	0.2211464	95
100 <=x<105	46	2084	1.78156	80.7126	21.0689	0.21068939	100
105 <=x<110	94	2178	3.64059	84.3532	19.2874	0.19287374	105
110 <=x<115	40	2218	1.54919	85.9024	15.6468	0.15646785	110
115 <=x<120	27	2245	1.04570	86.9481	14.0976	0.14097599	115
120 <=x<125	169	2414	6.54531	93.4934	13.0519	0.13051898	120
125 <=x<130	6	2420	0.23238	93.7258	6.5066	0.06506584	125
130 <=x<135	16	2436	0.61967	94.3455	6.2742	0.06274206	130

From To	Frequency table: Cij_TravelTime_MBTaxi (Spreadsheet26) Count	Cumulative Count	Percent	Cumulative Percent	100% - Percent	F(Cij) =v5/100	Cij_MBT
5 <=x<10	9	9	0.22021	0.2202	100.0000	1	5
10 <=x<15	53	62	1.29679	1.5170	99.7798	0.9977979	10
15 <=x<20	132	194	3.22975	4.7468	98.4830	0.98482995	15
20 <=x<25	192	386	4.69782	9.4446	95.2532	0.95253242	20
25 <=x<30	118	504	2.88720	12.3318	90.5554	0.9055542	25
30 <=x<35	701	1205	17.15195	29.4837	87.6682	0.87668216	30
35 <=x<40	109	1314	2.66699	32.1507	70.5163	0.70516271	35
40 <=x<45	197	1511	4.82016	36.9709	67.8493	0.67849278	40
45 <=x<50	359	1870	8.78395	45.7548	63.0291	0.63029117	45
50 <=x<55	194	2064	4.74676	50.5016	54.2452	0.54245168	50
55 <=x<60	90	2154	2.20210	52.7037	49.4984	0.4949841	55
60 <=x<65	788	2942	19.28065	71.9843	47.2963	0.47296305	60
65 <=x<70	58	3000	1.41913	73.4035	28.0157	0.28015659	65
70 <=x<75	99	3099	2.42231	75.8258	26.5965	0.26596526	70
75 <=x<80	224	3323	5.48079	81.3066	24.1742	0.24174211	75
80 <=x<85	84	3407	2.05530	83.3619	18.6934	0.18693418	80
85 <=x<90	17	3424	0.41595	83.7778	16.6381	0.16638121	85
90 <=x<95	297	3721	7.26694	91.0448	16.2222	0.16222168	90
95 <=x<100	18	3739	0.44042	91.4852	8.9552	0.08955224	95
100 <=x<105	30	3769	0.73403	92.2192	8.5148	0.08514803	100
105 <=x<110	59	3828	1.44360	93.6628	7.7808	0.07780768	105
110 <=x<115	27	3855	0.66063	94.3235	6.3372	0.06337167	110
115 <=x<120	13	3868	0.31808	94.6415	5.6765	0.05676535	115
120 <=x<125	121	3989	2.96061	97.6022	5.3585	0.05358454	120
125 <=x<130	5	3994	0.12234	97.7245	2.3978	0.02397847	125
130 <=x<135	7	4001	0.17127	97.8958	2.2755	0.02275508	130
135 <=x<140	24	4025	0.58723	98.4830	2.1042	0.02104233	135

1B: Impedance curve fitting regression output – Travel by Public Transport

Decay Function			Constant		Variable		Model Summary				
Mode	**Function Type**	**Regression Form**	α	**Std. err**	β	**Std. err**	R^2	**Adjusted R^2**	**Std. err of the est.**	**F**	**Sig**
Bus	Linear	$y = \alpha + \beta x$	0.984	0.047	-0.006	0.000	0.858	0.854	0.149	235.61	0.000
	Logarithmic	$y = \alpha + \beta\, \mathrm{In}x$	2.160	0.123	-0.412	0.027	0.852	0.849	0.152	225.36	0.000
	Inverse	$y = \alpha + \beta/x$	0.198	0.056	7.223	1.419	0.399	0.384	0.307	25.902	0.000
	Power	$\mathrm{In}\, y = \alpha + \beta\, \mathrm{In}x$	894.87	1052.39	-2.115	0.263	0.624	0.615	1.455	64.776	0.000
	Exponential	$\mathrm{In}\, y = \alpha + \beta x$	4.310	0.889	-0.038	0.002	0.925	0.923	0.649	483.15	0.000
	Logistic	$\mathrm{In}\ 1/y = \alpha + \beta x$	0.232	0.048	1.038	0.002	0.925	0.923	0.649	483.15	0.000
Minibus	Linear	$y = \alpha + \beta x$	0.884	0.050	- 0.006	0.000	0.837	0.832	0.146	174.95	0.000
	Logarithmic	$y = \alpha + \beta\, \mathrm{In}x$	1.993	0.092	- 0.395	0.021	0.911	0.908	0.108	347.28	0.000
	Inverse	$y = \alpha + \beta/x$	0.144	0.051	7.107	1.193	0.511	0.496	0.254	35.505	0.000
	Power	$\mathrm{In}\, y = \alpha + \beta\, \mathrm{In}x$	296.53	292.594	- 1.891	0.203	0.718	0.709	1.042	86.379	0.000
	Exponential	$\mathrm{In}\, y = \alpha + \beta x$	2.623	0.297	- 0.036	0.001	0.971	0.970	0.332	1148.1	0.000
	Logistic	$\mathrm{In}\ 1/y = \alpha + \beta x$	0.381	0.043	1.037	0.001	0.986	0.970	0.332	1148.19	0.000
Train	Linear	$y = \alpha + \beta x$	1.0650	0.030	- 0.007	0.000	0.918	0.916	0.103	560.036	0.000
	Logarithmic	$y = \alpha + \beta\, \mathrm{In}x$	2.2777	0.123	- 0.4303	0.028	0.822	0.819	0.152	231.609	0.000
	Inverse	$y = \alpha + \beta/x$	0.298	0.050	6.735	1.366	0.327	0.314	0.295	24.310	0.000
	Power	$\mathrm{In}\, y = \alpha + \beta\, \mathrm{In}x$	204.69	159.850	- 1.602	0.180	0.613	0.606	0.963	79.357	0.000
	Exponential	$\mathrm{In}\, y = \alpha + \beta x$	3.317	0.391	- 0.031	0.001	0.933	0.931	0.402	691.976	0.000
	Logistic	$\ln 1/y = \alpha + \beta x$	0.302	0.036	1.031	0.001	0.933	0.931	0.402	691.976	0.000
BRT	Linear	$y = \alpha + \beta x$	1.127	0.036	-0.010	0.000	0.954	0.952	0.079	437.534	0.000
	Logarithmic	$y = \alpha + \beta\, \mathrm{In}x$	2.439	0.149	-0.499	0.037	0.897	0.892	0.119	182.971	0.000
	Inverse	$y = \alpha + \beta/x$	0.135	0.071	12.955	2.191	0.625	0.607	0.227	34.966	0.000
	Power	$\mathrm{In}\, y = \alpha + \beta\, \mathrm{In}x$	132.25	118.146	-1.566	0.221	0.706	0.692	0.713	50.321	0.000
	Exponential	$\mathrm{In}\, y = \alpha + \beta x$	2.689	0.471	-0.036	0.002	0.916	0.911	0.382	227.530	0.000
	Logistic	$\mathrm{In}\ 1/y = \alpha + \beta x$	0.372	0.065	1.037	0.002	0.916	0.911	0.382	227.530	0.000

1C: Impedance curve fitting regression output – Travel by Car

Mode/	Decay Function		Constant		Variable		Coefficient of determination				
Income group	Function Type	Regression Form	α	Std. err	β	Std. err	R^2	Adjusted R^2	Std. err of the est.	F	Sig
Car (as passenger)	Linear	$y = \alpha + \beta x$	0.684	0.079	-0.005	0.001	0.706	0.690	0.187	45.584	0.000
	Logarithmic	$y = \alpha + \beta \text{ In} x$	1.2779	0.102	-0.250	0.023	0.858	0.851	0.130	114.99	0.000
	Inverse	$y = \alpha + \beta/x$	0.166	0.063	0.943	0.286	0.364	0.330	0.276	10.851	0.004
Low income	Power	$\text{In } y = \alpha + \beta \text{ In} x$	2736.182	11365	-3.340	0.948	0.395	0.363	5.291	12.410	0.002
	Exponential	$\text{In } y = \alpha + \beta x$	31.541	40.172	-0.096	0.011	0.803	0.793	3.019	77.461	0.000
	Logistic	$\text{In } 1/y = \alpha + \beta x$	0.032	0.040	1.101	0.012	0.803	0.793	3.019	77.461	0.000
Car (as passenger)	Linear	$y = \alpha + \beta x$	0.660	0.078	-0.004	0.001	0.698	0.682	0.185	43.920	0.000
	Logarithmic	$y = \alpha + \beta \text{ In} x$	1.250	0.094	-0.245	0.022	0.872	0.865	0.120	129.30	0.000
	Inverse	$y = \alpha + \beta/x$	0.157	0.060	0.947	0.273	0.387	0.355	0.263	12.012	0.003
Lower middle income	Power	$\text{In } y = \alpha + \beta \text{ In} x$	24.913	29.500	-1.585	0.270	0.644	0.625	1.508	34.382	0.000
	Exponential	$\text{In } y = \alpha + \beta x$	1.652	0.185	-0.040	0.001	0.989	0.988	0.266	1698.5	0.000
	Logistic	$\text{In } 1/y = \alpha + \beta x$	0.605	0.068	1.040	0.001	0.989	0.988	0.266	1698.5	0.000
Car (as passenger)	Linear	$y = \alpha + \beta x$	0.649	0.079	-0.004	0.001	0.689	0.673	0.187	42.104	0.000
	Logarithmic	$y = \alpha + \beta \text{ In} x$	1.240	0.095	-0.244	0.022	0.871	0.864	0.120	128.12	0.000
	Inverse	$y = \alpha + \beta/x$	0.150	0.060	0.952	0.271	0.394	0.362	0.261	12.352	0.002
Upper-middle income	Power	$\text{In } y = \alpha + \beta \text{ In} x$	7416.894	31451.	-3.872	0.968	0.457	0.429	5.402	16.008	0.001
	Exponential	$\text{In } y = \alpha + \beta x$	24.409	30.100	-0.106	0.011	0.841	0.833	2.923	100.53	0.000
	Logistic	$\text{In } 1/y = \alpha + \beta x$	0.041	0.051	1.112	0.012	0.841	0.833	2.923	100.53	0.000
Car (as passenger)	Linear	$y = \alpha + \beta x$	0.580	0.087	-0.004	0.001	0.598	0.577	0.207	28.26	0.000
	Logarithmic	$y = \alpha + \beta \text{ In} x$	1.183	0.093	-0.238	0.021	0.868	0.861	0.119	124.99	0.000
	Inverse	$y = \alpha + \beta/x$	0.119	0.056	0.981	0.254	0.440	0.411	0.244	14.956	0.001
	Power	$\text{In } y = \alpha + \beta \text{ In} x$	8005.28	33384	-4.051	0.952	0.488	0.461	5.312	18.114	0.000
High income	Exponential	$\text{In } y = \alpha + \beta x$	13.513	17.276	-0.107	0.011	0.833	0.825	3.031	95.036	0.000
	Logistic	$\text{In } 1/y = \alpha + \beta x$	0.074	0.095	1.112	0.012	0.833	0.825	3.031	95.036	0.000
Car (as driver)	Linear	$y = \alpha + \beta x$	0.682	0.083	-0.005	0.001	0.688	0.672	0.196	41.938	0.000
	Logarithmic	$y = \alpha + \beta \text{ In} x$	1.286	0.109	-0.252	0.025	0.845	0.837	0.138	103.627	0.000

Low income	Inverse	$y = \alpha + \beta/x$	0.162	0.064	0.948	0.293	0.356	0.322	0.282	10.484	0.004
	Power	$\text{In}\, y = \alpha + \beta\, \text{Inx}$	183.685	494.24	-2.307	0.614	0.426	0.396	3.427	14.117	0.001
	Exponential	$\text{In}\, y = \alpha + \beta\, x$	6.995	5.683	-0.064	0.007	0.819	0.809	1.926	85.887	0.000
	Logistic	$\text{In}\ 1/y = \alpha + \beta\, x$	0.143	0.116	1.067	0.007	0.819	0.809	1.926	85.887	0.000
Car (as	Linear	$y = \alpha + \beta\, x$	0.685	0.079	-0.005	0.001	0.707	0.691	0.188	45.761	0.000
driver)	Logarithmic	$y = \alpha + \beta\, \text{Inx}$	1.279	0.104	-0.250	0.024	0.854	0.846	0.133	110.81	0.000
	Inverse	$y = \alpha + \beta/x$	0.166	0.063	0.942	0.288	0.361	0.327	0.277	10.720	0.004
Lower	Power	$\text{In}\, y = \alpha + \beta\, \text{Inx}$	31.145	39.821	-1.663	0.292	0.631	0.612	1.629	32.499	0.000
middle	Exponential	$\text{In}\, y = \alpha + \beta\, x$	1.856	0.281	-0.042	0.001	0.982	0.981	0.359	1037.9	0.000
income	Logistic	$\text{In}\ 1/y = \alpha + \beta\, x$	0.539	0.082	1.043	0.001	0.982	0.981	0.359	1037.9	0.000
Car (as	Linear	$y = \alpha + \beta\, x$	0.690	0.078	-0.005	0.001	0.715	0.700	0.185	47.706	0.000
driver)	Logarithmic	$y = \alpha + \beta\, \text{Inx}$	1.283	0.104	-0.250	0.024	0.855	0.847	0.132	112.01	0.000
	Inverse	$y = \alpha + \beta/x$	0.168	0.063	0.939	0.288	0.358	0.325	0.278	10.618	0.004
Upper-	Power	$\text{In}\, y = \alpha + \beta\, \text{Inx}$	243.309	663.66	-2.403	0.623	0.439	0.410	3.474	14.897	0.001
middle	Exponential	$\text{In}\, y = \alpha + \beta\, x$	8.488	6.302	-0.068	0.006	0.856	0.849	1.760	113.08	0.000
income	Logistic	$\text{In}\ 1/y = \alpha + \beta\, x$	0.118	0.087	1.070	0.007	0.856	0.849	1.760	113.08	0.000
Car (as	Linear	$y = \alpha + \beta\, x$	0.675	0.077	-0.004	0.001	0.711	0.696	0.182	46.695	0.000
driver)	Logarithmic	$y = \alpha + \beta\, \text{Inx}$	1.262	0.098	-0.246	0.022	0.865	0.858	0.125	121.88	0.000
	Inverse	$y = \alpha + \beta/x$	0.164	0.061	0.940	0.278	0.375	0.342	0.268	11.400	0.003
	Power	$\text{In}\, y = \alpha + \beta\, \text{Inx}$	22.205	25.542	-1.524	0.263	0.640	0.621	1.465	33.707	0.000
High	Exponential	$\text{In}\, y = \alpha + \beta\, x$	1.635	0.223	-0.038	0.001	0.983	0.982	0.323	1068.0	0.000
income	Logistic	$\text{In}\ 1/y = \alpha + \beta\, x$	0.612	0.083	1.039	0.001	0.983	0.982	0.323	1068.0	0.000

APPENDIX 2: EXPLORATORY REGRESSION

2A: Regression 1 - Accessibility to low-income jobs by public transport

Descriptive Statistics of Variables

	Mean	Std. Deviation	N
ACC_PT60min_Inc1	165487.252	104882.330	1787
Empl_full_Inc1	146.793	362.949	1787
Empl_part_Inc1	24.886	84.844	1787
Empl_self_Inc1	19.794	72.209	1787
UnEmpl_NL_Inc1	77.726	276.193	1787
UnEmpl_L_Inc1	154.453	478.156	1787
Jobs_office_Inc1	20.753	108.106	1787
Jobs_retail_Inc1	22.313	86.576	1787
Jobs_manu_Inc1	59.029	327.493	1787
Jobs_service_Inc1	18.859	91.518	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

Dependent variable: ACC_PT60min_Inc1.

All Independent variables are common to Regression Output 1 and 2

Regression Output 1 - Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-140320.531	456343.656	165487.252	77819.936	1787
Std. Predicted Value	-3.930	3.738	.000	1.000	1787
Standard Error of Predicted Value	2404.669	39032.711	3846.826	2153.545	1787
Adjusted Predicted Value	-142098.406	479236.531	165550.373	78042.202	1787
Residual	-241290.703	190949.859	.000	70316.147	1787
Std. Residual	-3.426	2.711	.000	.998	1787
Stud. Residual	-3.466	2.719	.000	1.001	1787
Deleted Residual	-247036.922	192110.609	-63.120	70673.876	1787
Stud. Deleted Residual	-3.477	2.724	-.001	1.001	1787
Mahal. Distance	1.082	547.489	5.997	18.205	1787
Cook's Distance	.000	.186	.001	.006	1787
Centered Leverage Value	.001	.307	.003	.010	1787

Regression Output 1 – Correlations among all variables

		ACC_PT60min_Inc1	Empl_full_Inc1	Empl_part_Inc1	Empl_self_Inc1	UnEmpl_NL_Inc1	UnEmpl_L_Inc1	Jobs_office_Inc1	Jobs_retail_Inc1	Jobs_manu_Inc1	Jobs_service_Inc1	Dist_CBD	Dist_NBD	Dist_SBD
Pearson Correlation	ACC_PT60min_Inc1	1.000	.169	.127	.105	.122	.132	.099	.095	.067	.073	-.712	-.491	-.696
	Empl_full_Inc1	.169	1.000	.729	.635	.648	.787	-.029	-.012	-.024	-.017	-.039	-.076	.029
	Empl_part_Inc1	.127	.729	1.000	.520	.742	.738	-.029	-.022	-.029	-.025	-.049	-.052	.016
	Empl_self_Inc1	.105	.635	.520	1.000	.473	.634	-.015	.012	-.015	-.006	-.022	-.107	.007
	UnEmpl_NL_Inc1	.122	.648	.742	.473	1.000	.588	-.032	-.022	-.022	-.017	-.069	-.048	-.008
	UnEmpl_L_Inc1	.132	.787	.738	.634	.588	1.000	-.017	-.010	.000	.009	-.016	-.028	.050
	Jobs_office_Inc1	.099	-.029	-.029	-.015	-.032	-.017	1.000	.505	.187	.223	-.057	.008	-.123
	Jobs_retail_Inc1	.095	-.012	-.022	.012	-.022	-.010	.505	1.000	.133	.166	-.051	.005	-.078
	Jobs_manu_Inc1	.067	-.024	-.029	-.015	-.022	.000	.187	.133	1.000	.848	-.009	-.048	-.032
	Jobs_service_Inc1	.073	-.017	-.025	-.006	-.017	.009	.223	.166	.848	1.000	-.021	-.062	-.028
	Dist_CBD	-.712	-.039	-.049	-.022	-.069	-.016	-.057	-.051	-.009	-.021	1.000	.571	.933
	Dist_NBD	-.491	-.076	-.052	-.107	-.048	-.028	.008	.005	-.048	-.062	.571	1.000	.593
	Dist_SBD	-.696	.029	.016	.007	-.008	.050	-.123	-.078	-.032	-.028	.933	.593	1.000
Sig. (1-tailed)	ACC_PT60min_Inc1	.	.000	.000	.000	.000	.000	.000	.000	.002	.001	.000	.000	.000
	Empl_full_Inc1	.000	.	.000	.000	.000	.000	.108	.302	.152	.240	.051	.001	.108
	Empl_part_Inc1	.000	.000	.	.000	.000	.000	.107	.176	.112	.144	.019	.014	.245
	Empl_self_Inc1	.000	.000	.000	.	.000	.000	.260	.311	.258	.393	.176	.000	.383
	UnEmpl_NL_Inc1	.000	.000	.000	.000	.	.000	.092	.180	.179	.233	.002	.022	.368
	UnEmpl_L_Inc1	.000	.000	.000	.000	.000	.	.235	.330	.497	.359	.249	.116	.018
	Jobs_office_Inc1	.000	.108	.107	.260	.092	.235	.	.000	.000	.000	.008	.370	.000
	Jobs_retail_Inc1	.000	.302	.176	.311	.180	.330	.000	.	.000	.000	.016	.411	.001
	Jobs_manu_Inc1	.002	.152	.112	.258	.179	.497	.000	.000	.	.000	.352	.021	.090
	Jobs_service_Inc1	.001	.240	.144	.393	.233	.359	.000	.000	.000	.	.186	.004	.120
	Dist_CBD	.000	.051	.019	.176	.002	.249	.008	.016	.352	.186	.	.000	.000
	Dist_NBD	.000	.001	.014	.000	.022	.116	.370	.411	.021	.004	.000	.	.000
	Dist_SBD	.000	.108	.245	.383	.368	.018	.000	.001	.090	.120	.000	.000	.

Regression output 1 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			99.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	280882.905	3208.648		87.539	.000	272609.128	289156.681		
	Dist_CBD	-5.401	.126	-.712	-42.833	.000	-5.726	-5.076	1.000	1.000
2	(Constant)	273963.301	3241.752		84.511	.000	265604.159	282322.443		
	Dist_CBD	-5.359	.124	-.706	-43.355	.000	-5.678	-5.041	.999	1.001
	Empl_full_Inc1	41.076	4.709	.142	8.723	.000	28.934	53.218	.999	1.001
3	(Constant)	285143.145	3558.818		80.123	.000	275966.415	294319.876		
	Dist_CBD	-3.046	.346	-.402	-8.815	.000	-3.938	-2.155	.124	8.048
	Empl_full_Inc1	47.232	4.723	.163	10.001	.000	35.054	59.411	.965	1.036
	Dist_SBD	-2.717	.380	-.326	-7.152	.000	-3.696	-1.737	.124	8.043
4	(Constant)	293835.107	4053.880		72.482	.000	283381.808	304288.406		
	Dist_CBD	-2.985	.344	-.393	-8.673	.000	-3.872	-2.097	.124	8.062
	Empl_full_Inc1	45.012	4.726	.156	9.525	.000	32.826	57.198	.954	1.048
	Dist_SBD	-2.343	.387	-.281	-6.051	.000	-3.342	-1.345	.118	8.448
	Dist_NBD	-1.024	.233	-.088	-4.402	.000	-1.623	-.424	.639	1.565
5	(Constant)	291773.364	4083.300		71.455	.000	281244.197	302302.532		
	Dist_CBD	-3.054	.344	-.403	-8.888	.000	-3.940	-2.168	.124	8.088
	Empl_full_Inc1	44.885	4.711	.155	9.528	.000	32.737	57.032	.954	1.048
	Dist_SBD	-2.214	.388	-.266	-5.710	.000	-3.214	-1.214	.117	8.524
	Dist_NBD	-1.073	.232	-.092	-4.623	.000	-1.672	-.475	.637	1.571
	Jobs_retail_Inc1	68.316	19.423	.056	3.517	.000	18.232	118.400	.987	1.014
6	(Constant)	290443.382	4099.086		70.856	.000	279873.503	301013.262		
	Dist_CBD	-3.103	.343	-.409	-9.041	.000	-3.989	-2.218	.123	8.108
	Empl_full_Inc1	45.144	4.701	.156	9.602	.000	33.021	57.268	.954	1.048
	Dist_SBD	-2.170	.387	-.260	-5.603	.000	-3.168	-1.171	.117	8.537
	Dist_NBD	-1.039	.232	-.089	-4.479	.000	-1.637	-.441	.635	1.575
	Jobs_retail_Inc1	60.754	19.548	.050	3.108	.002	10.348	111.161	.970	1.031
	Jobs_manu_Inc1	15.251	5.149	.048	2.962	.003	1.974	28.529	.977	1.024

Regression Output 1 - Coefficient Correlations and Covariances

Model			Dist_CBD	Empl_full_Inc1	Dist_SBD	Dist_NBD	Jobs_retail_Inc 1	Jobs_manu_Inc 1
1	Correlations	Dist_CBD	1.000					
	Covariances	Dist_CBD	.016					
2	Correlations	Dist_CBD	1.000	.039				
		Empl_full_Inc1	.039	1.000				
	Covariances	Dist_CBD	.015	.022				
		Empl_full_Inc1	.022	22.172				
3	Correlations	Dist_CBD	1.000	.184	-.936			
		Empl_full_Inc1	.184	1.000	-.182			
		Dist_SBD	-.936	-.182	1.000			
	Covariances	Dist_CBD	.119	.300	-.123			
		Empl_full_Inc1	.300	22.306	-.327			
		Dist_SBD	-.123	-.327	.144			
4	Correlations	Dist_CBD	1.000	.178	-.903	-.041		
		Empl_full_Inc1	.178	1.000	-.200	.107		
		Dist_SBD	-.903	-.200	1.000	-.219		
		Dist_NBD	-.041	.107	-.219	1.000		
	Covariances	Dist_CBD	.118	.290	-.120	-.003		
		Empl_full_Inc1	.290	22.333	-.366	.117		
		Dist_SBD	-.120	-.366	.150	-.020		
		Dist_NBD	-.003	.117	-.020	.054		
5	Correlations	Dist_CBD	1.000	.179	-.903	-.037	-.057	
		Empl_full_Inc1	.179	1.000	-.200	.107	-.008	
		Dist_SBD	-.903	-.200	1.000	-.223	.094	
		Dist_NBD	-.037	.107	-.223	1.000	-.061	
		Jobs_retail_Inc1	-.057	-.008	.094	-.061	1.000	
	Covariances	Dist_CBD	.118	.289	-.120	-.003	-.382	
		Empl_full_Inc1	.289	22.193	-.365	.117	-.700	
		Dist_SBD	-.120	-.365	.150	-.020	.711	
		Dist_NBD	-.003	.117	-.020	.054	-.275	
		Jobs_retail_Inc1	-.382	-.700	.711	-.275	377.252	
6	Correlations	Dist_CBD	1.000	.177	-.903	-.040	-.050	-.049

	Empl_full_Inc1	.177	1.000	-.199	.108	-.010	.019
	Dist_SBD	-.903	-.199	1.000	-.221	.088	.039
	Dist_NBD	-.040	.108	-.221	1.000	-.067	.050
	Jobs_retail_Inc1	-.050	-.010	.088	-.067	1.000	-.131
	Jobs_manu_Inc1	-.049	.019	.039	.050	-.131	1.000
Covariances	Dist_CBD	.118	.286	-.120	-.003	-.338	-.086
	Empl_full_Inc1	.286	22.104	-.362	.118	-.921	.451
	Dist_SBD	-.120	-.362	.150	-.020	.670	.078
	Dist_NBD	-.003	.118	-.020	.054	-.303	.060
	Jobs_retail_Inc1	-.338	-.921	.670	-.303	382.130	-13.146
	Jobs_manu_Inc1	-.086	.451	.078	.060	-13.146	26.514

Dependent Variable: ACC_PT60min_Inc1

Regression Output 1 - Collinearity Diagnostics

				Variance Proportions						
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Dist_CBD	Empl_full_Inc1	Dist_SBD	Dist_NBD	Jobs_retail_Inc1	Jobs_man
1	1	1.840	1.000	.08	.08					
	2	.160	3.387	.92	.92					
2	1	2.053	1.000	.06	.06	.07				
	2	.791	1.611	.02	.05	.90				
	3	.156	3.629	.92	.90	.03				
3	1	2.970	1.000	.02	.00	.02	.00			
	2	.834	1.888	.00	.00	.91	.00			
	3	.180	4.065	.86	.04	.04	.01			
	4	.017	13.347	.11	.95	.03	.98			
4	1	3.844	1.000	.01	.00	.01	.00	.01		
	2	.855	2.120	.00	.00	.90	.00	.00		
	3	.189	4.512	.45	.06	.02	.02	.05		
	4	.095	6.356	.49	.01	.03	.01	.93		
	5	.016	15.267	.06	.93	.04	.97	.01		
5	1	3.907	1.000	.01	.00	.01	.00	.01	.00	
	2	.944	2.035	.00	.00	.02	.00	.00	.94	
	3	.854	2.139	.00	.00	.89	.00	.00	.01	
	4	.184	4.612	.45	.06	.02	.02	.05	.03	
	5	.095	6.407	.48	.01	.03	.01	.92	.00	
	6	.016	15.446	.06	.93	.04	.97	.01	.01	
6	1	3.943	1.000	.01	.00	.01	.00	.01	.01	
	2	1.083	1.908	.00	.00	.01	.00	.00	.35	
	3	.855	2.148	.00	.00	.83	.00	.00	.06	
	4	.826	2.185	.00	.00	.06	.00	.00	.55	
	5	.183	4.637	.44	.06	.02	.02	.05	.03	
	6	.094	6.460	.49	.01	.03	.01	.92	.00	

7	.016	15.533	.06	.93	.04	.97	.01	.01

2B: Regression 2 - Accessibility to low-income jobs by car

Descriptive Statistics of variables

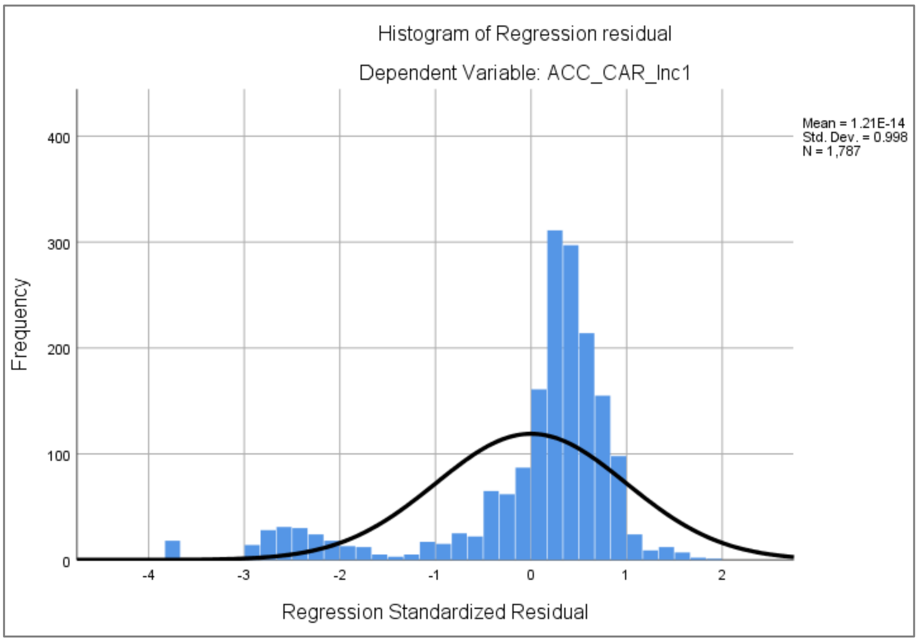
	Mean	Std. Deviation	N
ACC_CAR_Inc1	211821.704	93738.156	1787
Empl_full_Inc1	146.793	362.949	1787
Empl_part_Inc1	24.886	84.844	1787
Empl_self_Inc1	19.794	72.209	1787
UnEmpl_NL_Inc1	77.726	276.193	1787
UnEmpl_L_Inc1	154.453	478.156	1787
Jobs_office_Inc1	20.753	108.106	1787
Jobs_retail_Inc1	22.313	86.576	1787
Jobs_manu_Inc1	59.029	327.493	1787
Jobs_service_Inc1	18.859	91.518	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

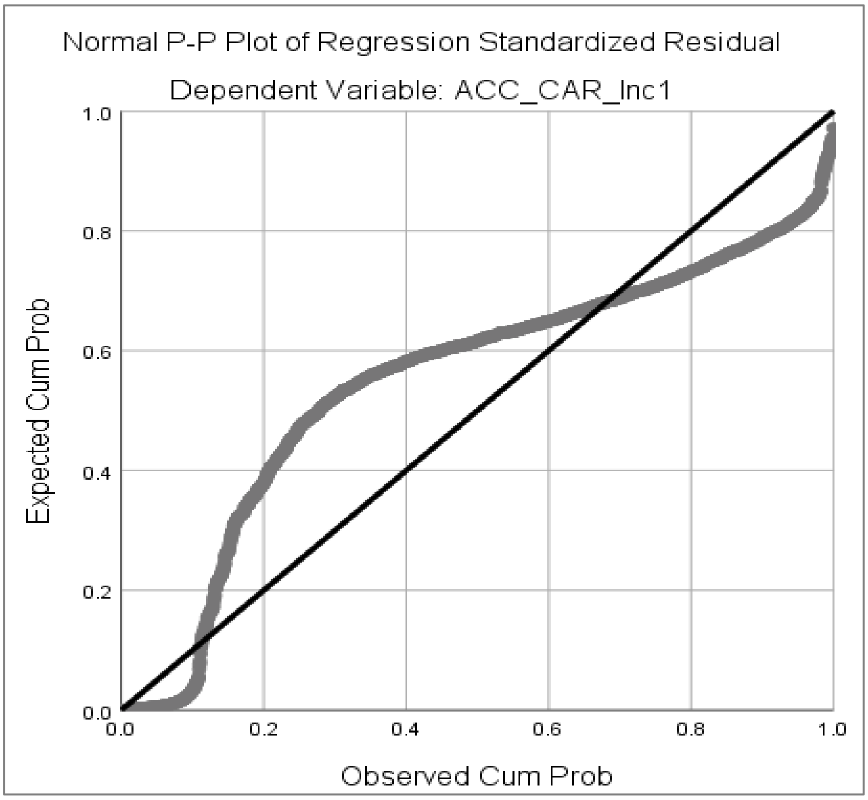
Dependent variable: ACC_CAR_Inc1

Regression Output 2 - Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-71119.008	403220.906	211821.704	66543.699	1787
Std. Predicted Value	-4.252	2.876	.000	1.000	1787
Standard Error of Predicted Value	2265.961	37512.168	3725.926	2389.712	1787
Adjusted Predicted Value	-72020.359	413261.656	211877.976	66757.868	1787
Residual	-253893.656	125730.102	.000	66021.042	1787
Std. Residual	-3.838	1.901	.000	.998	1787
Stud. Residual	-3.842	1.908	.000	1.000	1787
Deleted Residual	-254369.563	126663.477	-56.272	66271.841	1787
Stud. Deleted Residual	-3.857	1.909	-.001	1.001	1787
Mahal. Distance	1.096	573.323	6.996	23.335	1787
Cook's Distance	.000	.102	.000	.003	1787
Centered Leverage Value	.001	.321	.004	.013	1787

Regression Output 2 – Residuals and Normal P-P Plot





Regression Output 2 - Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	99.0% Confidence Interval for B Lower Bound	99.0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	304878.023	3129.701		97.414	.000	296807.819	312948.227		
	Dist_CBD	-4.355	.123	-.642	-35.412	.000	-4.673	-4.038	1.000	1.000
2	(Constant)	331009.230	3702.554		89.400	.000	321461.869	340556.590		
	Dist_CBD	-3.360	.144	-.495	-23.325	.000	-3.731	-2.988	.674	1.483
	Dist_NBD	-2.676	.221	-.257	-12.114	.000	-3.245	-2.106	.674	1.483
3	(Constant)	320952.962	3823.764		83.936	.000	311093.045	330812.880		
	Dist_CBD	-5.814	.324	-.857	-17.938	.000	-6.650	-4.978	.128	7.805
	Dist_NBD	-3.053	.221	-.294	-13.798	.000	-3.624	-2.483	.646	1.547
	Dist_SBD	3.056	.363	.410	8.414	.000	2.119	3.993	.123	8.110
4	(Constant)	316809.296	3838.328		82.538	.000	306911.819	326706.774		
	Dist_CBD	-5.445	.326	-.803	-16.711	.000	-6.285	-4.605	.124	8.062
	Dist_NBD	-2.904	.220	-.279	-13.192	.000	-3.472	-2.337	.639	1.565
	Dist_SBD	2.590	.367	.348	7.064	.000	1.645	3.536	.118	8.448
	Empl_full_Inc1	28.389	4.475	.110	6.345	.000	16.851	39.927	.954	1.048
5	(Constant)	313497.377	3850.579		81.416	.000	303568.301	323426.453		
	Dist_CBD	-5.731	.327	-.845	-17.526	.000	-6.574	-4.888	.121	8.260
	Dist_NBD	-3.020	.219	-.290	-13.774	.000	-3.585	-2.454	.634	1.578
	Dist_SBD	3.022	.372	.405	8.134	.000	2.064	3.980	.113	8.822
	Empl_full_Inc1	28.048	4.437	.109	6.322	.000	16.607	39.488	.954	1.048
	Jobs_office_Inc1	84.153	14.918	.097	5.641	.000	45.686	122.620	.951	1.051
6	(Constant)	312082.750	3857.279		80.907	.000	302136.392	322029.108		
	Dist_CBD	-5.763	.326	-.850	-17.678	.000	-6.604	-4.923	.121	8.267
	Dist_NBD	-2.972	.219	-.286	-13.580	.000	-3.537	-2.408	.631	1.584
	Dist_SBD	3.039	.370	.408	8.206	.000	2.084	3.993	.113	8.824
	Empl_full_Inc1	28.374	4.423	.110	6.416	.000	16.970	39.778	.954	1.048
	Jobs_office_Inc1	74.112	15.123	.085	4.901	.000	35.116	113.107	.919	1.088
	Jobs_manu_Inc1	17.714	4.884	.062	3.627	.000	5.120	30.309	.960	1.041
7	(Constant)	311375.839	3861.775		80.630	.000	301417.882	321333.796		

Dist_CBD	-5.743	.326	-.847	-17.638	.000	-6.583	-4.904	.121	8.272
Dist_NBD	-2.983	.219	-.287	-13.647	.000	-3.547	-2.419	.631	1.585
Dist_SBD	3.028	.370	.406	8.190	.000	2.075	3.982	.113	8.825
Empl_full_Inc1	28.352	4.416	.110	6.420	.000	16.964	39.739	.954	1.048
Jobs_office_Inc1	53.108	17.257	.061	3.078	.002	8.610	97.607	.704	1.420
Jobs_manu_Inc1	17.141	4.882	.060	3.511	.000	4.552	29.731	.958	1.043
Jobs_retail_Inc1	52.753	20.981	.049	2.514	.012	-1.350	106.855	.743	1.347

Dependent Variable: ACC_CAR_Inc1

Regression Output 2 - Collinearity Diagnostics

				Variance Proportions							
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Dist_CBD	Dist_NBD	Dist_SBD	Empl_full_Inc1	Jobs_office_Inc1	Jobs_manu_Inc1	Jobs_retail_Inc1
1	1	1.840	1.000	.08	.08						
	2	.160	3.387	.92	.92						
2	1	2.747	1.000	.02	.02	.02					
	2	.160	4.138	.59	.63	.00					
	3	.093	5.441	.38	.34	.98					
3	1	3.693	1.000	.01	.00	.01	.00				
	2	.192	4.382	.47	.06	.04	.02				
	3	.098	6.149	.44	.01	.95	.01				
	4	.017	14.681	.08	.93	.01	.97				
4	1	3.844	1.000	.01	.00	.01	.00	.01			
	2	.855	2.120	.00	.00	.00	.00	.90			
	3	.189	4.512	.45	.06	.05	.02	.02			
	4	.095	6.356	.49	.01	.93	.01	.03			
	5	.016	15.267	.06	.93	.01	.97	.04			
5	1	3.875	1.000	.01	.00	.01	.00	.01	.00		
	2	.978	1.990	.00	.00	.00	.00	.03	.90		
	3	.852	2.133	.00	.00	.00	.00	.87	.03		

	4	.183	4.598	.45	.06	.05	.02	.02	.03		
	5	.095	6.383	.47	.01	.92	.01	.03	.00		
	6	.016	15.624	.07	.93	.02	.97	.04	.04		
6	1	3.911	1.000	.01	.00	.01	.00	.01	.00	.00	
	2	1.155	1.840	.00	.00	.00	.00	.01	.37	.38	
	3	.852	2.142	.00	.00	.00	.00	.89	.01	.00	
	4	.788	2.228	.00	.00	.00	.00	.00	.55	.60	
	5	.183	4.622	.45	.06	.05	.02	.02	.03	.00	
	6	.094	6.439	.48	.01	.92	.01	.03	.00	.01	
	7	.016	15.699	.07	.93	.02	.97	.04	.04	.00	
7	1	3.996	1.000	.01	.00	.01	.00	.01	.00	.00	.00
	2	1.504	1.630	.00	.00	.00	.00	.01	.20	.08	.17
	3	.890	2.120	.00	.00	.00	.00	.09	.03	.79	.07
	4	.850	2.168	.00	.00	.00	.00	.80	.00	.11	.00
	5	.468	2.924	.00	.00	.00	.00	.00	.73	.01	.73
	6	.182	4.684	.45	.06	.05	.02	.02	.01	.00	.01
	7	.094	6.510	.48	.01	.92	.01	.03	.00	.01	.00
	8	.016	15.872	.07	.93	.02	.97	.04	.03	.00	.00

Dependent Variable: ACC_CAR_Inc1

2C: Regression 3 - Accessibility to lower-middle-income jobs by public transport

Descriptive Statistics of all variables

	Mean	Std. Deviation	N
ACC_PT60min_Inc2	406044.236	259534.192	1787
Empl_full_Inc2	445.053	858.784	1787
Empl_part_Inc2	31.056	84.908	1787
Empl_self_Inc2	56.986	108.587	1787
UnEmpl_NL_Inc2	56.272	145.842	1787
UnEmpl_L_Inc2	106.067	264.365	1787
Jobs_office_Inc2	152.620	812.182	1787
Jobs_retail_Inc2	61.635	241.311	1787
Jobs_manu_Inc2	108.298	615.821	1787
Jobs_serv_Inc2	40.382	199.918	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

Dependent variable: ACC_PT60min_Inc2.

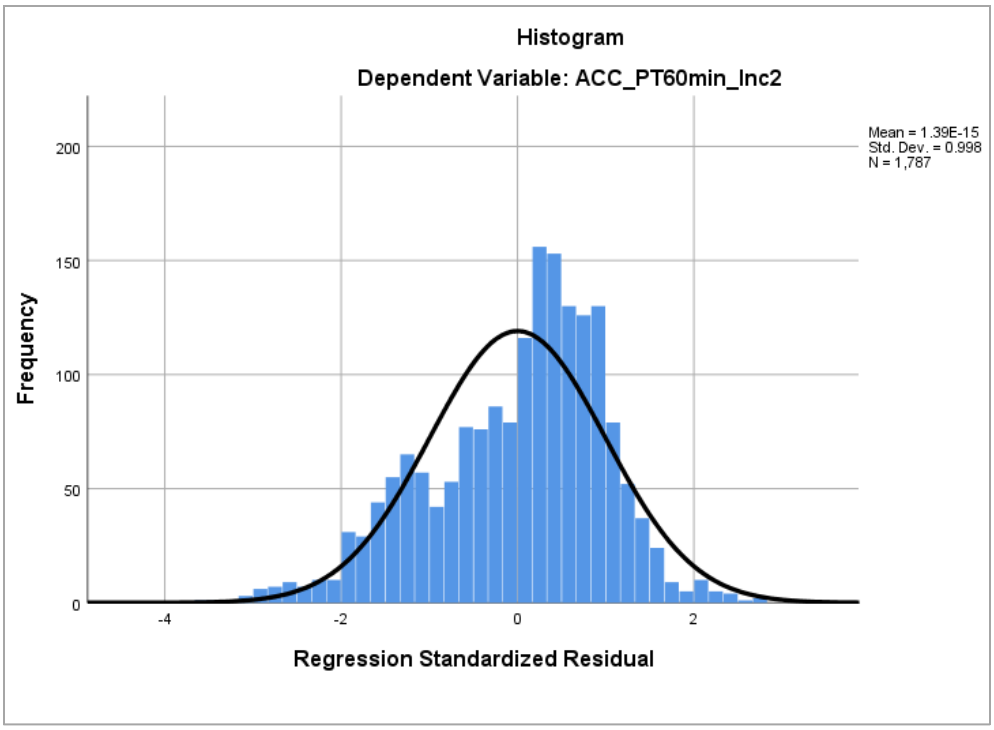
All Independent variables are common to Regression Output 3 and 4

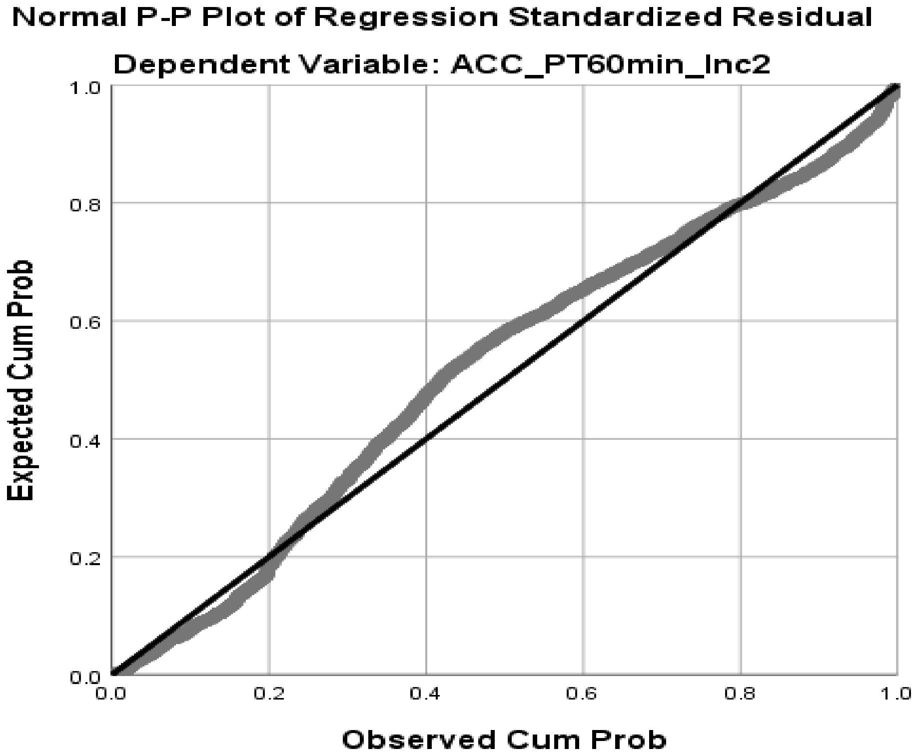
Regression Output 3 - Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-349486.625	1074955.250	406044.236	196523.198	1787
Std. Predicted Value	-3.844	3.404	.000	1.000	1787
Standard Error of Predicted Value	6001.140	96710.391	10349.150	6188.386	1787
Adjusted Predicted Value	-353975.844	1234215.000	406274.951	197262.225	1787
Residual	-598200.750	464002.000	.000	169518.818	1787
Std. Residual	-3.521	2.731	.000	.998	1787
Stud. Residual	-3.895	2.736	-.001	1.001	1787
Deleted Residual	-746163.438	465699.281	-230.714	170748.367	1787
Stud. Deleted Residual	-3.911	2.741	-.001	1.002	1787
Mahal. Distance	1.229	577.686	7.996	22.107	1787
Cook's Distance	.000	.457	.001	.012	1787
Centered Leverage Value	.001	.323	.004	.012	1787

Dependent Variable: ACC_PT60min_Inc2

Regression Output 3 – Residuals and Normal P-P Plot





Regression Output 3 – Correlations among all variables

		ACC_PT60min_Inc2	Empl_full_Inc2	Empl_part_Inc2	Empl_self_Inc2	UnEmpl_NL_Inc2	UnEmpl_L_Inc2	Jobs_office_Inc2	Jobs_retail_Inc2	Jobs_manu_Inc2	Jobs_serv_Inc2	Dist_CBD	Dist_NBD	Dist_SBD
Pearson Correlation	ACC_PT60min_Inc2	1.000	.170	.138	.097	.180	.130	.122	.118	.079	.086	-.723	-.486	-.720
	Empl_full_Inc2	.170	1.000	.601	.573	.665	.827	-.010	.032	-.033	-.022	-.040	-.042	.008
	Empl_part_Inc2	.138	.601	1.000	.431	.584	.604	-.017	.019	-.023	-.017	-.079	-.091	-.040
	Empl_self_Inc2	.097	.573	.431	1.000	.467	.449	.005	.056	-.041	-.030	-.059	-.017	-.024
	UnEmpl_NL_Inc2	.180	.665	.584	.467	1.000	.602	-.033	.016	-.031	-.023	-.093	-.095	-.035
	UnEmpl_L_Inc2	.130	.827	.604	.449	.602	1.000	-.010	.010	-.012	-.004	-.003	.005	.046
	Jobs_office_Inc2	.122	-.010	-.017	.005	-.033	-.010	1.000	.486	.165	.198	-.076	-.008	-.143
	Jobs_retail_Inc2	.118	.032	.019	.056	.016	.010	.486	1.000	.101	.131	-.076	-.015	-.104
	Jobs_manu_Inc2	.079	-.033	-.023	-.041	-.031	-.012	.165	.101	1.000	.844	-.025	-.063	-.049
	Jobs_serv_Inc2	.086	-.022	-.017	-.030	-.023	-.004	.198	.131	.844	1.000	-.040	-.080	-.048
	Dist_CBD	-.723	-.040	-.079	-.059	-.093	-.003	-.076	-.076	-.025	-.040	1.000	.571	.933
	Dist_NBD	-.486	-.042	-.091	-.017	-.095	.005	-.008	-.015	-.063	-.080	.571	1.000	.593
	Dist_SBD	-.720	.008	-.040	-.024	-.035	.046	-.143	-.104	-.049	-.048	.933	.593	1.000
Sig. (1-tailed)	ACC_PT60min_Inc2	.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Empl_full_Inc2	.000	.	.000	.000	.000	.000	.335	.087	.082	.176	.046	.039	.371
	Empl_part_Inc2	.000	.000	.	.000	.000	.000	.234	.208	.164	.239	.000	.000	.046
	Empl_self_Inc2	.000	.000	.000	.	.000	.000	.418	.009	.043	.104	.006	.235	.156
	UnEmpl_NL_Inc2	.000	.000	.000	.000	.	.000	.080	.250	.092	.171	.000	.000	.068
	UnEmpl_L_Inc2	.000	.000	.000	.000	.000	.	.335	.335	.310	.433	.454	.417	.027
	Jobs_office_Inc2	.000	.335	.234	.418	.080	.335	.	.000	.000	.000	.001	.372	.000
	Jobs_retail_Inc2	.000	.087	.208	.009	.250	.335	.000	.	.000	.000	.001	.259	.000
	Jobs_manu_Inc2	.000	.082	.164	.043	.092	.310	.000	.000	.	.000	.141	.004	.019
	Jobs_serv_Inc2	.000	.176	.239	.104	.171	.433	.000	.000	.000	.	.044	.000	.022
	Dist_CBD	.000	.046	.000	.006	.000	.454	.001	.001	.141	.044	.	.000	.000
	Dist_NBD	.000	.039	.000	.235	.000	.417	.372	.259	.004	.000	.000	.	.000
	Dist_SBD	.000	.371	.046	.156	.068	.027	.000	.000	.019	.022	.000	.000	.

Dependent variable: ACC_PT60min_Inc2

Regression Output 3 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			99.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	695916.629	7814.422		89.055	.000	675766.467	716066.791		
	Dist_CBD	-13.567	.307	-.723	-44.180	.000	-14.359	-12.775	1.000	1.000
2	(Constant)	674662.276	8023.355		84.087	.000	653973.349	695351.203		
	Dist_CBD	-13.462	.301	-.717	-44.730	.000	-14.238	-12.686	.998	1.002
	Empl_full_Inc2	42.678	4.845	.141	8.809	.000	30.185	55.171	.998	1.002
3	(Constant)	709520.175	8707.319		81.485	.000	687067.574	731972.775		
	Dist_CBD	-6.347	.827	-.338	-7.678	.000	-8.479	-4.216	.126	7.913
	Empl_full_Inc2	48.200	4.773	.159	10.099	.000	35.893	60.507	.983	1.018
	Dist_SBD	-8.362	.908	-.405	-9.208	.000	-10.704	-6.021	.127	7.901
4	(Constant)	726919.639	9876.329		73.602	.000	701452.626	752386.652		
	Dist_CBD	-6.182	.825	-.329	-7.494	.000	-8.310	-4.055	.126	7.936
	Empl_full_Inc2	47.323	4.762	.157	9.938	.000	35.044	59.602	.980	1.020
	Dist_SBD	-7.655	.925	-.371	-8.275	.000	-10.040	-5.269	.121	8.256
	Dist_NBD	-2.063	.559	-.072	-3.688	.000	-3.505	-.621	.645	1.551
5	(Constant)	722023.146	9949.880		72.566	.000	696366.458	747679.834		
	Dist_CBD	-6.340	.824	-.338	-7.695	.000	-8.464	-4.215	.126	7.961
	Empl_full_Inc2	47.775	4.749	.158	10.059	.000	35.528	60.022	.979	1.021
	Dist_SBD	-7.478	.924	-.362	-8.095	.000	-9.860	-5.096	.121	8.282
	Dist_NBD	-1.972	.558	-.068	-3.532	.000	-3.412	-.532	.643	1.554
	Jobs_manu_Inc2	22.554	6.583	.054	3.426	.001	5.579	39.529	.991	1.009
6	(Constant)	718073.024	10032.037		71.578	.000	692204.472	743941.576		
	Dist_CBD	-6.471	.824	-.345	-7.856	.000	-8.594	-4.347	.125	7.987
	Empl_full_Inc2	47.151	4.746	.156	9.935	.000	34.914	59.389	.977	1.023
	Dist_SBD	-7.212	.927	-.349	-7.781	.000	-9.603	-4.822	.119	8.371
	Dist_NBD	-2.068	.558	-.072	-3.704	.000	-3.507	-.628	.641	1.560
	Jobs_manu_Inc2	20.764	6.602	.049	3.145	.002	3.740	37.788	.982	1.018
	Jobs_retail_Inc2	47.142	16.941	.044	2.783	.005	3.458	90.826	.971	1.030
7	(Constant)	716241.120	10053.213		71.245	.000	690317.948	742164.292		
	Dist_CBD	-6.276	.827	-.334	-7.587	.000	-8.409	-4.143	.124	8.075
	Empl_full_Inc2	37.805	6.291	.125	6.010	.000	21.584	54.026	.555	1.802

	Dist_SBD	-7.408	.930	-.359	-7.966	.000	-9.806	-5.010	.118	8.444
	Dist_NBD	-1.984	.559	-.069	-3.550	.000	-3.425	-.543	.638	1.567
	Jobs_manu_Inc2	20.953	6.595	.050	3.177	.002	3.948	37.959	.982	1.018
	Jobs_retail_Inc2	47.181	16.922	.044	2.788	.005	3.546	90.815	.971	1.030
	UnEmpl_NL_Inc2	84.363	37.329	.047	2.260	.024	-11.893	180.619	.546	1.830
8	(Constant)	718439.664	10094.472		71.172	.000	692410.087	744469.242		
	Dist_CBD	-6.317	.827	-.337	-7.643	.000	-8.449	-4.186	.124	8.079
	Empl_full_Inc2	43.666	6.846	.144	6.378	.000	26.012	61.320	.468	2.139
	Dist_SBD	-7.404	.929	-.359	-7.970	.000	-9.799	-5.008	.118	8.444
	Dist_NBD	-1.932	.559	-.067	-3.457	.001	-3.373	-.491	.637	1.570
	Jobs_manu_Inc2	20.563	6.591	.049	3.120	.002	3.568	37.558	.981	1.019
	Jobs_retail_Inc2	48.853	16.922	.045	2.887	.004	5.218	92.488	.969	1.032
	UnEmpl_NL_Inc2	95.595	37.652	.054	2.539	.011	-1.495	192.685	.536	1.866
	Empl_self_Inc2	-98.757	45.775	-.041	-2.157	.031	-216.792	19.278	.654	1.529

Dependent Variable: ACC_PT60min_Inc2

Regression Output 3 - Coefficient Correlations and Covariances

Model			Dist_ CBD	Empl_full _Inc2	Dist_SBD	Dist_NBD	Jobs_manu_Inc 2	Jobs_retail_Inc2	UnEmpl_NL_Inc 2	Empl_self_Inc2
1	Correlations	Dist_CBD	1.000							
	Covariances	Dist_CBD	.094							
2	Correlations	Dist_CBD	1.000	.040						
		Empl_full_Inc2	.040	1.000						
	Covariances	Dist_CBD	.091	.058						
		Empl_full_Inc2	.058	23.473						
3	Correlations	Dist_CBD	1.000	.132	-.935					
		Empl_full_Inc2	.132	1.000	-.126					
		Dist_SBD	-.935	-.126	1.000					
	Covariances	Dist_CBD	.683	.519	-.702					
		Empl_full_Inc2	.519	22.779	-.545					
		Dist_SBD	-.702	-.545	.825					
4	Correlations	Dist_CBD	1.000	.128	-.902	-.054				
		Empl_full_Inc2	.128	1.000	-.133	.050				
		Dist_SBD	-.902	-.133	1.000	-.207				
		Dist_NBD	-.054	.050	-.207	1.000				
	Covariances	Dist_CBD	.681	.505	-.688	-.025				
		Empl_full_Inc2	.505	22.676	-.586	.133				
		Dist_SBD	-.688	-.586	.856	-.107				
		Dist_NBD	-.025	.133	-.107	.313				
5	Correlations	Dist_CBD	1.000	.127	-.902	-.057	-.056			
		Empl_full_Inc2	.127	1.000	-.131	.051	.028			
		Dist_SBD	-.902	-.131	1.000	-.204	.056			
		Dist_NBD	-.057	.051	-.204	1.000	.048			
		Jobs_manu_Inc2	-.056	.028	.056	.048	1.000			
	Covariances	Dist_CBD	.679	.496	-.686	-.026	-.302			
		Empl_full_Inc2	.496	22.558	-.576	.136	.869			
		Dist_SBD	-.686	-.576	.853	-.105	.339			
		Dist_NBD	-.026	.136	-.105	.312	.175			
		Jobs_manu_Inc2	-.302	.869	.339	.175	43.336			
6	Correlations	Dist_CBD	1.000	.129	-.902	-.053	-.050	-.057		
		Empl_full_Inc2	.129	1.000	-.135	.054	.032	-.047		

		Dist_SBD	-.902	-.135	1.000	-.209	.045	.103		
		Dist_NBD	-.053	.054	-.209	1.000	.053	-.062		
		Jobs_manu_Inc2	-.050	.032	.045	.053	1.000	-.097		
		Jobs_retail_Inc2	-.057	-.047	.103	-.062	-.097	1.000		
	Covariances	Dist_CBD	.678	.504	-.688	-.024	-.270	-.798		
		Empl_full_Inc2	.504	22.523	-.595	.143	1.010	-3.800		
		Dist_SBD	-.688	-.595	.859	-.108	.277	1.617		
		Dist_NBD	-.024	.143	-.108	.312	.196	-.583		
		Jobs_manu_Inc2	-.270	1.010	.277	.196	43.586	-10.897		
		Jobs_retail_Inc2	-.798	-3.800	1.617	-.583	-10.897	287.004		
7	Correlations	Dist_CBD	1.000	.028	-.903	-.046	-.048	-.057	.104	
		Empl_full_Inc2	.028	1.000	-.040	-.003	.016	-.036	-.657	
		Dist_SBD	-.903	-.040	1.000	-.214	.044	.102	-.093	
		Dist_NBD	-.046	-.003	-.214	1.000	.054	-.061	.066	
		Jobs_manu_Inc2	-.048	.016	.044	.054	1.000	-.097	.013	
		Jobs_retail_Inc2	-.057	-.036	.102	-.061	-.097	1.000	.001	
		UnEmpl_NL_Inc2	.104	-.657	-.093	.066	.013	.001	1.000	
	Covariances	Dist_CBD	.684	.146	-.694	-.021	-.263	-.795	3.219	
		Empl_full_Inc2	.146	39.573	-.236	-.011	.662	-3.862	-154.370	
		Dist_SBD	-.694	-.236	.865	-.111	.269	1.612	-3.230	
		Dist_NBD	-.021	-.011	-.111	.312	.199	-.581	1.383	
		Jobs_manu_Inc2	-.263	.662	.269	.199	43.493	-10.871	3.121	
		Jobs_retail_Inc2	-.795	-3.862	1.612	-.581	-10.871	286.343	.637	
		UnEmpl_NL_Inc2	3.219	-154.370	-3.230	1.383	3.121	.637	1393.439	
8	Correlations	Dist_CBD	1.000	.017	-.902	-.047	-.047	-.058	.100	.023
		Empl_full_Inc2	.017	1.000	-.036	.014	.004	-.015	-.543	-.397
		Dist_SBD	-.902	-.036	1.000	-.214	.044	.102	-.092	-.002
		Dist_NBD	-.047	.014	-.214	1.000	.053	-.059	.072	-.043
		Jobs_manu_Inc2	-.047	.004	.044	.053	1.000	-.099	.009	.027
		Jobs_retail_Inc2	-.058	-.015	.102	-.059	-.099	1.000	.007	-.046
		UnEmpl_NL_Inc2	.100	-.543	-.092	.072	.009	.007	1.000	-.138
		Empl_self_Inc2	.023	-.397	-.002	-.043	.027	-.046	-.138	1.000
	Covariances	Dist_CBD	.683	.094	-.693	-.022	-.259	-.808	3.112	.884
		Empl_full_Inc2	.094	46.873	-.230	.055	.169	-1.748	-139.909	-124.363

Dist_SBD	-.693	-.230	.863	-.111	.268	1.610	-3.213	-.088
Dist_NBD	-.022	.055	-.111	.312	.194	-.561	1.507	-1.107
Jobs_manu_Inc2	-.259	.169	.268	.194	43.437	-10.989	2.172	8.282
Jobs_retail_Inc2	-.808	-1.748	1.610	-.561	-10.989	286.357	4.672	-35.482
UnEmpl_NL_Inc2	3.112	-139.909	-3.213	1.507	2.172	4.672	1417.689	-238.321
Empl_self_Inc2	.884	-124.363	-.088	-1.107	8.282	-35.482	-238.321	2095.353

Dependent Variable: ACC_PT60min_Inc2

Regression Output 3 - Collinearity Diagnostics

				Variance Proportions								
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Dist_ CBD	Empl_full _Inc2	Dist_ SBD	Dist_ NBD	Jobs_manu_ Inc2	Jobs_retail _Inc2	UnEmpl_NL _Inc2	Empl_self_ Inc2
1	1	1.840	1.000	.08	.08							
	2	.160	3.387	.92	.92							
2	1	2.140	1.000	.05	.05	.08						
	2	.706	1.741	.02	.07	.87						
	3	.154	3.732	.93	.88	.05						
3	1	3.045	1.000	.02	.00	.03	.00					
	2	.763	1.998	.00	.00	.89	.00					
	3	.176	4.163	.87	.04	.07	.01					
	4	.017	13.391	.11	.95	.02	.98					
4	1	3.919	1.000	.01	.00	.01	.00	.01				
	2	.783	2.237	.00	.00	.90	.00	.00				
	3	.185	4.603	.45	.06	.05	.02	.06				
	4	.096	6.389	.48	.01	.02	.01	.92				
	5	.017	15.253	.06	.93	.02	.97	.01				
5	1	3.946	1.000	.01	.00	.01	.00	.01	.00			
	2	.977	2.009	.00	.00	.01	.00	.00	.96			
	3	.781	2.248	.00	.00	.89	.00	.00	.01			
	4	.184	4.637	.43	.06	.05	.02	.06	.01			

	5	.095	6.440	.49	.01	.02	.01	.92	.01			
	6	.017	15.334	.06	.93	.02	.97	.01	.00			
6	1	4.009	1.000	.01	.00	.01	.00	.01	.00	.00		
	2	1.060	1.944	.00	.00	.00	.00	.00	.49	.36		
	3	.877	2.138	.00	.00	.12	.00	.00	.41	.47		
	4	.764	2.290	.00	.00	.78	.00	.00	.08	.12		
	5	.178	4.739	.44	.06	.04	.02	.06	.00	.03		
	6	.095	6.491	.48	.01	.02	.01	.92	.01	.00		
	7	.017	15.517	.07	.93	.02	.97	.01	.00	.01		
7	1	4.201	1.000	.01	.00	.01	.00	.01	.00	.00	.01	
	2	1.322	1.783	.00	.00	.12	.00	.00	.01	.00	.17	
	3	1.060	1.991	.00	.00	.00	.00	.00	.48	.36	.00	
	4	.854	2.218	.00	.00	.00	.00	.00	.49	.59	.00	
	5	.274	3.913	.00	.00	.86	.00	.00	.00	.00	.79	
	6	.178	4.858	.43	.06	.01	.02	.06	.00	.03	.01	
	7	.095	6.664	.49	.01	.00	.01	.91	.01	.00	.01	
	8	.016	15.963	.06	.93	.00	.97	.01	.00	.01	.01	
8	1	4.547	1.000	.01	.00	.01	.00	.01	.00	.00	.01	.01
	2	1.558	1.709	.00	.00	.06	.00	.01	.01	.00	.09	.06
	3	1.060	2.071	.00	.00	.00	.00	.00	.48	.36	.00	.00
	4	.854	2.308	.00	.00	.00	.00	.00	.49	.58	.00	.00
	5	.439	3.217	.00	.00	.01	.00	.00	.00	.01	.36	.75
	6	.255	4.221	.00	.00	.92	.00	.00	.00	.00	.51	.15
	7	.175	5.097	.44	.06	.00	.02	.07	.01	.03	.01	.03
	8	.095	6.934	.49	.01	.00	.01	.91	.01	.00	.01	.00
	9	.016	16.608	.06	.93	.00	.97	.01	.00	.01	.01	.00

Dependent Variable: ACC_PT60min_Inc2

2D: Regression 4 - Accessibility to lower-middle income jobs by car

Descriptive Statistics of variables

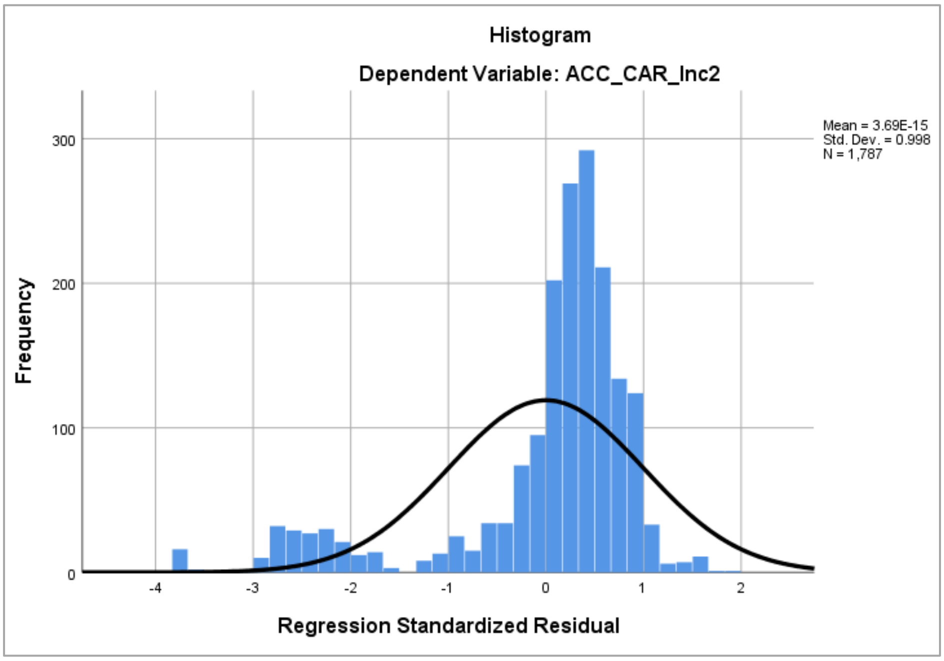
	Mean	Std. Deviation	N
ACC_CAR_Inc2	546207.433	238017.766	1787
Empl_full_Inc2	445.053	858.784	1787
Empl_part_Inc2	31.056	84.908	1787
Empl_self_Inc2	56.986	108.587	1787
UnEmpl_NL_Inc2	56.272	145.842	1787
UnEmpl_L_Inc2	106.067	264.365	1787
Jobs_office_Inc2	152.620	812.182	1787
Jobs_retail_Inc2	61.635	241.311	1787
Jobs_manu_Inc2	108.298	615.821	1787
Jobs_serv_Inc2	40.382	199.918	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

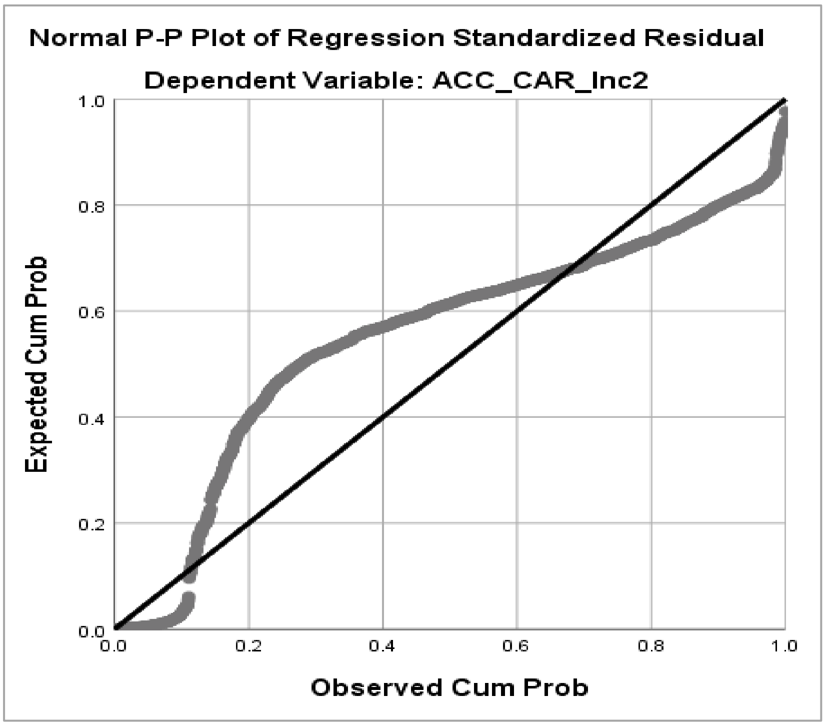
Dependent variable: ACC_CAR_Inc2

Regression Output 4 - Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-160285.375	962159.500	546207.433	168332.552	1787
Std. Predicted Value	-4.197	2.471	.000	1.000	1787
Standard Error of Predicted Value	5869.034	97726.727	10100.068	6423.895	1787
Adjusted Predicted Value	-162324.844	1022775.375	546376.531	168908.721	1787
Residual	-648004.563	333443.656	.000	168275.396	1787
Std. Residual	-3.842	1.977	.000	.998	1787
Stud. Residual	-3.846	1.984	.000	1.000	1787
Deleted Residual	-649203.063	335946.375	-169.099	168986.143	1787
Stud. Deleted Residual	-3.861	1.986	-.001	1.001	1787
Mahal. Distance	1.163	598.677	7.996	24.995	1787
Cook's Distance	.000	.090	.000	.003	1787
Centered Leverage Value	.001	.335	.004	.014	1787

Regression Output 4 – Residuals and Normal P-P Plot





Regression Output 4 - Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	99.0% Confidence Interval for B Lower Bound	99.0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	785615.590	7872.268		99.795	.000	765316.268	805914.912		
	Dist_CBD	-11.205	.309	-.651	-36.220	.000	-12.003	-10.408	1.000	1.000
2	(Constant)	840395.425	9429.445		89.125	.000	816080.773	864710.078		
	Dist_CBD	-9.118	.367	-.530	-24.857	.000	-10.063	-8.172	.674	1.483
	Dist_NBD	-5.610	.563	-.212	-9.971	.000	-7.060	-4.159	.674	1.483
3	(Constant)	818008.492	9554.821		85.612	.000	793370.531	842646.454		
	Dist_CBD	-9.054	.359	-.526	-25.226	.000	-9.980	-8.129	.674	1.484
	Dist_NBD	-5.496	.551	-.208	-9.983	.000	-6.915	-4.076	.674	1.484
	Empl_full_Inc2	42.717	4.748	.154	8.996	.000	30.472	54.961	.998	1.002
4	(Constant)	806194.724	9887.171		81.539	.000	780699.752	831689.695		
	Dist_CBD	-12.295	.826	-.714	-14.886	.000	-14.424	-10.165	.126	7.936
	Dist_NBD	-6.001	.560	-.227	-10.717	.000	-7.445	-4.557	.645	1.551
	Empl_full_Inc2	39.956	4.767	.144	8.381	.000	27.663	52.248	.980	1.020
	Dist_SBD	4.030	.926	.213	4.351	.000	1.642	6.418	.121	8.256
5	(Constant)	797241.927	9946.644		80.152	.000	771593.583	822890.270		
	Dist_CBD	-13.005	.830	-.755	-15.673	.000	-15.145	-10.865	.123	8.138
	Dist_NBD	-6.269	.558	-.237	-11.241	.000	-7.707	-4.831	.640	1.563
	Empl_full_Inc2	39.521	4.730	.143	8.355	.000	27.324	51.719	.980	1.020
	Dist_SBD	5.128	.941	.271	5.451	.000	2.702	7.554	.116	8.656
	Jobs_office_Inc2	27.638	5.089	.094	5.431	.000	14.515	40.762	.946	1.057
6	(Constant)	793024.339	9982.898		79.438	.000	767282.498	818766.181		
	Dist_CBD	-13.096	.827	-.761	-15.828	.000	-15.229	-10.962	.123	8.146
	Dist_NBD	-6.145	.557	-.233	-11.034	.000	-7.581	-4.709	.637	1.569
	Empl_full_Inc2	40.044	4.717	.144	8.490	.000	27.882	52.206	.979	1.021
	Dist_SBD	5.198	.938	.275	5.543	.000	2.780	7.617	.115	8.660
	Jobs_office_Inc2	24.727	5.137	.084	4.813	.000	11.480	37.973	.923	1.084
	Jobs_manu_Inc2	23.772	6.619	.062	3.591	.000	6.704	40.840	.967	1.034
7	(Constant)	788904.245	10017.096		78.756	.000	763074.205	814734.286		
	Dist_CBD	-12.987	.825	-.754	-15.737	.000	-15.115	-10.859	.123	8.157
	Dist_NBD	-6.214	.555	-.235	-11.188	.000	-7.647	-4.782	.637	1.571

	Empl_full_Inc2	28.468	5.713	.103	4.983	.000	13.735	43.201	.663	1.509
	Dist_SBD	5.154	.935	.272	5.514	.000	2.744	7.565	.115	8.661
	Jobs_office_Inc2	24.457	5.121	.083	4.776	.000	11.253	37.661	.923	1.084
	Jobs_manu_Inc2	24.399	6.600	.063	3.697	.000	7.381	41.417	.966	1.035
	Empl_self_Inc2	160.463	45.006	.073	3.565	.000	44.410	276.516	.668	1.497
8	(Constant)	787230.706	10037.976		78.425	.000	761346.809	813114.603		
	Dist_CBD	-12.963	.825	-.753	-15.721	.000	-15.089	-10.836	.123	8.159
	Dist_NBD	-6.234	.555	-.236	-11.234	.000	-7.665	-4.803	.636	1.571
	Empl_full_Inc2	28.346	5.708	.102	4.966	.000	13.627	43.065	.663	1.509
	Dist_SBD	5.164	.934	.273	5.529	.000	2.756	7.572	.115	8.661
	Jobs_office_Inc2	18.719	5.782	.064	3.238	.001	3.810	33.628	.722	1.385
	Jobs_manu_Inc2	24.016	6.596	.062	3.641	.000	7.009	41.023	.965	1.036
	Empl_self_Inc2	156.310	45.004	.071	3.473	.001	40.263	272.357	.667	1.499
	Jobs_retail_Inc2	40.427	18.985	.041	2.129	.033	-8.529	89.382	.759	1.318

Dependent Variable: ACC_CAR_Inc2

Regression Output 4 - Coefficient Correlations and Covariances

Model			Dist_ CBD	Dist_NB D	Empl_full _Inc2	Dist_ SBD	Jobs_office_ Inc2	Jobs_manu_Inc 2	Empl_self_Inc2	Jobs_retail_Inc2
1	Correlations	Dist_CBD	1.000							
	Covariances	Dist_CBD	.096							
2	Correlations	Dist_CBD	1.000	-.571						
		Dist_NBD	-.571	1.000						
	Covariances	Dist_CBD	.135	-.118						
		Dist_NBD	-.118	.316						
3	Correlations	Dist_CBD	1.000	-.570	.020					
		Dist_NBD	-.570	1.000	.023					
		Empl_full_Inc2	.020	.023	1.000					
	Covariances	Dist_CBD	.129	-.113	.033					
		Dist_NBD	-.113	.303	.060					
		Empl_full_Inc2	.033	.060	22.548					

4	Correlations	Dist_CBD	1.000	-.054	.128	-.902		
		Dist_NBD	-.054	1.000	.050	-.207		
		Empl_full_Inc2	.128	.050	1.000	-.133		
		Dist_SBD	-.902	-.207	-.133	1.000		
	Covariances	Dist_CBD	.682	-.025	.506	-.690		
		Dist_NBD	-.025	.314	.133	-.108		
		Empl_full_Inc2	.506	.133	22.726	-.588		
		Dist_SBD	-.690	-.108	-.588	.858		
5	Correlations	Dist_CBD	1.000	-.039	.129	-.903	-.158	
		Dist_NBD	-.039	1.000	.051	-.221	-.089	
		Empl_full_Inc2	.129	.051	1.000	-.134	-.017	
		Dist_SBD	-.903	-.221	-.134	1.000	.215	
		Jobs_office_Inc2	-.158	-.089	-.017	.215	1.000	
	Covariances	Dist_CBD	.689	-.018	.508	-.705	-.666	
		Dist_NBD	-.018	.311	.135	-.116	-.252	
		Empl_full_Inc2	.508	.135	22.375	-.595	-.407	
		Dist_SBD	-.705	-.116	-.595	.885	1.029	
		Jobs_office_Inc2	-.666	-.252	-.407	1.029	25.903	
6	Correlations	Dist_CBD	1.000	-.041	.128	-.903	-.151	-.031
		Dist_NBD	-.041	1.000	.053	-.219	-.097	.062
		Empl_full_Inc2	.128	.053	1.000	-.133	-.022	.031
		Dist_SBD	-.903	-.219	-.133	1.000	.209	.021
		Jobs_office_Inc2	-.151	-.097	-.022	.209	1.000	-.158
		Jobs_manu_Inc2	-.031	.062	.031	.021	-.158	1.000
	Covariances	Dist_CBD	.685	-.019	.501	-.701	-.641	-.167
		Dist_NBD	-.019	.310	.139	-.114	-.278	.229
		Empl_full_Inc2	.501	.139	22.247	-.588	-.522	.963
		Dist_SBD	-.701	-.114	-.588	.880	1.006	.130
		Jobs_office_Inc2	-.641	-.278	-.522	1.006	26.388	-5.367

		Jobs_manu_Inc2	-.167	.229	.963	.130	-5.367	43.812		
7	Correlations	Dist_CBD	1.000	-.042	.085	-.903	-.151	-.030	.037	
		Dist_NBD	-.042	1.000	.063	-.218	-.097	.061	-.035	
		Empl_full_Inc2	.085	.063	1.000	-.102	-.009	.010	-.568	
		Dist_SBD	-.903	-.218	-.102	1.000	.209	.021	-.013	
		Jobs_office_Inc2	-.151	-.097	-.009	.209	1.000	-.158	-.015	
		Jobs_manu_Inc2	-.030	.061	.010	.021	-.158	1.000	.027	
		Empl_self_Inc2	.037	-.035	-.568	-.013	-.015	.027	1.000	
	Covariances	Dist_CBD	.681	-.019	.399	-.697	-.639	-.161	1.375	
		Dist_NBD	-.019	.309	.201	-.113	-.275	.224	-.875	
		Empl_full_Inc2	.399	.201	32.644	-.544	-.273	.386	-146.129	
		Dist_SBD	-.697	-.113	-.544	.874	1.001	.127	-.556	
		Jobs_office_Inc2	-.639	-.275	-.273	1.001	26.221	-5.345	-3.404	
		Jobs_manu_Inc2	-.161	.224	.386	.127	-5.345	43.556	7.916	
		Empl_self_Inc2	1.375	-.875	-146.129	-.556	-3.404	7.916	2025.564	
8	Correlations	Dist_CBD	1.000	-.043	.084	-.903	-.140	-.030	.036	.014
		Dist_NBD	-.043	1.000	.064	-.218	-.078	.061	-.034	-.017
		Empl_full_Inc2	.084	.064	1.000	-.102	-.004	.011	-.567	-.010
		Dist_SBD	-.903	-.218	-.102	1.000	.183	.020	-.013	.005
		Jobs_office_Inc2	-.140	-.078	-.004	.183	1.000	-.127	.007	-.466
		Jobs_manu_Inc2	-.030	.061	.011	.020	-.127	1.000	.028	-.027
		Empl_self_Inc2	.036	-.034	-.567	-.013	.007	.028	1.000	-.043
		Jobs_retail_Inc2	.014	-.017	-.010	.005	-.466	-.027	-.043	1.000
	Covariances	Dist_CBD	.680	-.019	.397	-.695	-.668	-.163	1.350	.216
		Dist_NBD	-.019	.308	.202	-.113	-.249	.225	-.855	-.177
		Empl_full_Inc2	.397	.202	32.582	-.543	-.118	.395	-145.728	-1.088

Dist_SBD	-.695	-.113	-.543	.872	.986	.126	-.564	.088
Jobs_office_Inc2	-.668	-.249	-.118	.986	33.430	-4.850	1.859	-51.158
Jobs_manu_Inc2	-.163	.225	.395	.126	-4.850	43.502	8.251	-3.413
Empl_self_Inc2	1.350	-.855	-145.728	-.564	1.859	8.251	2025.353	-37.034
Jobs_retail_Inc2	.216	-.177	-1.088	.088	-51.158	-3.413	-37.034	360.443

Dependent Variable: ACC_CAR_Inc2

Regression Output 4 - Collinearity Diagnostics

				Variance Proportions								
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Dist_CBD	Dist_NBD	Empl_full_Inc2	Dist_SBD	Jobs_office_Inc2	Jobs_manu_Inc2	Empl_self_Inc2	Jobs_retail_Inc2
1	1	1.840	1.000	.08	.08							
	2	.160	3.387	.92	.92							
2	1	2.747	1.000	.02	.02	.02						
	2	.160	4.138	.59	.63	.00						
	3	.093	5.441	.38	.34	.98						
3	1	2.996	1.000	.02	.02	.01	.03					
	2	.758	1.988	.00	.02	.01	.91					
	3	.154	4.410	.57	.65	.00	.05					
	4	.092	5.710	.41	.31	.97	.01					
4	1	3.919	1.000	.01	.00	.01	.01	.00				
	2	.783	2.237	.00	.00	.00	.90	.00				
	3	.185	4.603	.45	.06	.06	.05	.02				
	4	.096	6.389	.48	.01	.92	.02	.01				
	5	.017	15.253	.06	.93	.01	.02	.97				
5	1	3.947	1.000	.01	.00	.01	.01	.00	.00			

	2	.979	2.008	.00	.00	.00	.00	.00	.92			
	3	.783	2.245	.00	.00	.00	.90	.00	.00			
	4	.179	4.699	.45	.06	.06	.05	.02	.04			
	5	.096	6.413	.46	.01	.92	.02	.01	.00			
	6	.016	15.625	.07	.93	.01	.02	.97	.04			
6	1	3.977	1.000	.01	.00	.01	.01	.00	.00	.00		
	2	1.140	1.868	.00	.00	.00	.00	.00	.38	.40		
	3	.821	2.201	.00	.00	.00	.18	.00	.44	.44		
	4	.773	2.269	.00	.00	.00	.72	.00	.11	.14		
	5	.178	4.723	.44	.06	.06	.05	.02	.03	.00		
	6	.095	6.469	.47	.01	.92	.02	.01	.00	.01		
	7	.016	15.691	.07	.93	.01	.02	.97	.04	.00		
7	1	4.268	1.000	.01	.00	.01	.01	.00	.00	.00	.01	
	2	1.186	1.897	.00	.00	.00	.12	.00	.11	.18	.12	
	3	1.116	1.956	.00	.00	.00	.06	.00	.29	.21	.06	
	4	.807	2.299	.00	.00	.00	.00	.00	.53	.59	.00	
	5	.336	3.565	.00	.00	.00	.78	.00	.00	.00	.77	
	6	.175	4.935	.45	.06	.06	.00	.02	.03	.00	.03	
	7	.095	6.702	.47	.01	.91	.01	.01	.00	.01	.00	
	8	.016	16.257	.07	.93	.01	.01	.97	.04	.00	.00	
8	1	4.347	1.000	.01	.00	.01	.01	.00	.00	.00	.01	.00
	2	1.479	1.714	.00	.00	.00	.00	.00	.21	.07	.00	.19
	3	1.170	1.928	.00	.00	.00	.17	.00	.00	.03	.18	.00
	4	.899	2.199	.00	.00	.00	.01	.00	.03	.87	.01	.07
	5	.484	2.997	.00	.00	.00	.00	.00	.71	.01	.00	.73
	6	.336	3.599	.00	.00	.00	.78	.00	.00	.00	.77	.00
	7	.174	4.994	.45	.06	.06	.00	.02	.01	.00	.03	.01
	8	.095	6.765	.47	.01	.91	.01	.01	.00	.01	.00	.00
	9	.016	16.407	.07	.93	.01	.01	.97	.03	.00	.00	.00

Dependent Variable: ACC_CAR_Inc2

2E: Regression 5 - Accessibility to upper-middle income jobs by public transport

Descriptive Statistics of variables

	Mean	Std. Deviation	N
ACC_PT60min_Inc3	59568.125	38037.188	1787
Empl_full_Inc3	63.989	129.995	1787
Empl_part_Inc3	2.273	11.586	1787
Empl_self_Inc3	21.634	57.469	1787
UnEmpl_NL_Inc3	3.632	15.019	1787
UnEmpl_L_Inc3	3.008	12.560	1787
Jobs_office_Inc3	34.047	176.005	1787
Jobs_retail_Inc3	9.028	35.376	1787
Jobs_manu_Inc3	13.540	73.857	1787
Jobs_serv_Inc3	4.304	20.716	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

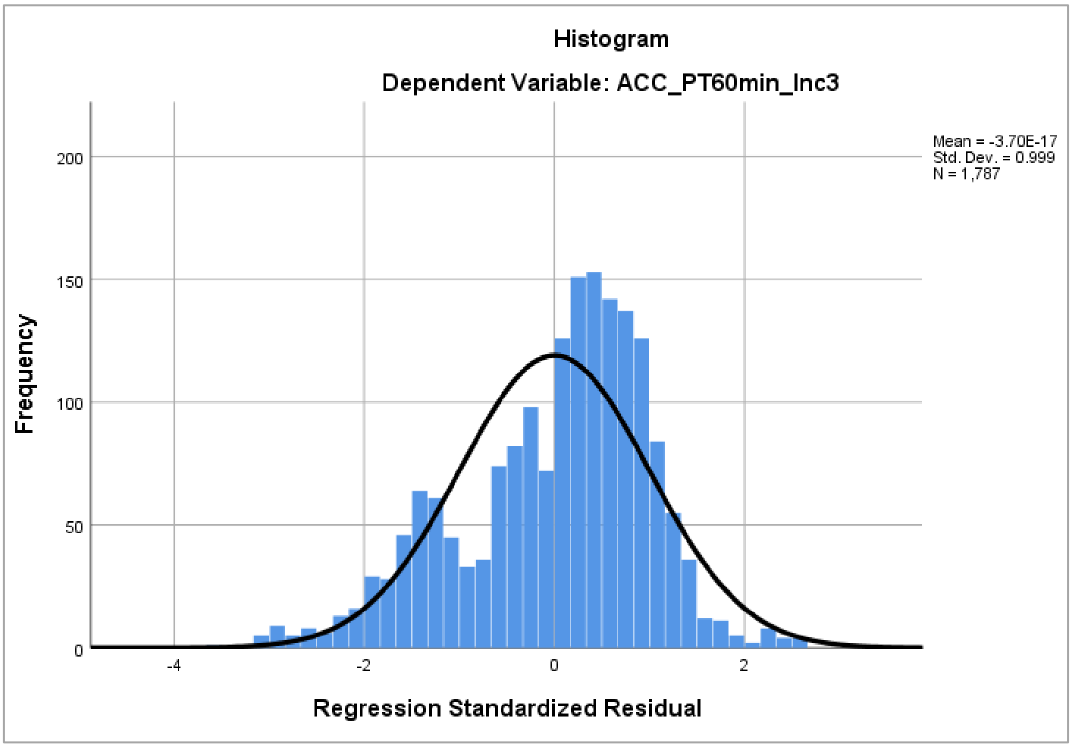
Regression Output 5 - Residuals Statistics

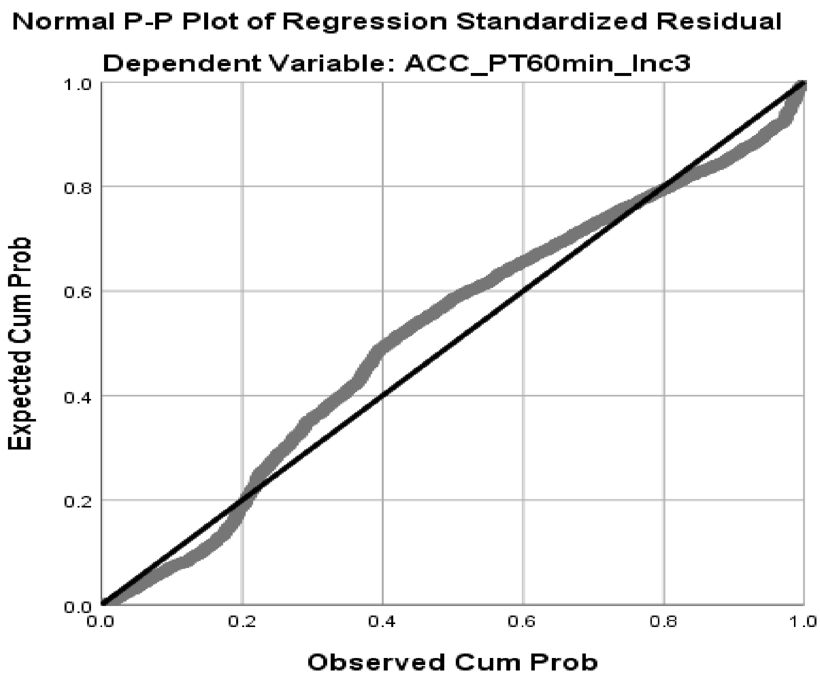
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-50334.504	132237.016	59568.125	28542.023	1787
Std. Predicted Value	-3.851	2.546	.000	1.000	1787
Standard Error of Predicted Value	849.169	13789.194	1280.086	700.151	1787
Adjusted Predicted Value	-50973.426	150471.219	59578.968	28599.809	1787
Residual	-91428.148	66144.023	.000	25143.201	1787
Std. Residual	-3.631	2.627	.000	.999	1787
Stud. Residual	-3.638	2.635	.000	1.000	1787
Deleted Residual	-91765.227	66541.344	-10.843	25240.150	1787
Stud. Deleted Residual	-3.650	2.639	.000	1.001	1787
Mahal. Distance	1.032	534.675	4.997	16.776	1787
Cook's Distance	.000	.291	.001	.007	1787
Centered Leverage Value	.001	.299	.003	.009	1787

Dependent Variable: ACC_PT60min_Inc3

The same set of independent variables applies for Regression output 5 and 6

Regression Output 5 – Residuals and Normal P-P Plot





Regression Output 5 – Correlations among all variables

	ACC_PT60 min_Inc3	Empl_full _Inc3	Empl_part _Inc3	Empl_self_ Inc3	UnEmpl_ NL_Inc3	UnEmpl_ L_Inc3	Jobs_office_ Inc3	Jobs_retail _Inc3	Jobs_man u_Inc3	Jobs_ser v_Inc3	Dist_ CBD	Dist_ NBD	Dist_ SBD
Pearson Correlation	1.000	.099	.030	.055	.053	.073	.111	.093	.061	.064	-.733	-.475	-.733
	.099	1.000	.345	.519	.368	.379	.038	.078	-.031	-.017	-.090	-.081	-.111
	.030	.345	1.000	.205	.200	.114	-.019	-.008	-.022	-.023	-.022	-.009	-.019
	.055	.519	.205	1.000	.280	.239	.011	.030	-.041	-.033	-.073	-.045	-.090
	.053	.368	.200	.280	1.000	.168	-.014	.038	-.029	-.023	-.037	-.070	-.021
	.073	.379	.114	.239	.168	1.000	.006	.030	-.005	.001	-.070	-.057	-.065
	.111	.038	-.019	.011	-.014	.006	1.000	.519	.203	.240	-.044	.019	-.107
	.093	.078	-.008	.030	.038	.030	.519	1.000	.155	.191	-.031	.020	-.056
	.061	-.031	-.022	-.041	-.029	-.005	.203	.155	1.000	.852	.003	-.038	-.019
	.064	-.017	-.023	-.033	-.023	.001	.240	.191	.852	1.000	-.007	-.050	-.013
	-.733	-.090	-.022	-.073	-.037	-.070	-.044	-.031	.003	-.007	1.000	.571	.933
	-.475	-.081	-.009	-.045	-.070	-.057	.019	.020	-.038	-.050	.571	1.000	.593
	-.733	-.111	-.019	-.090	-.021	-.065	-.107	-.056	-.019	-.013	.933	.593	1.000
Sig. (1-tailed)	.	.000	.100	.011	.013	.001	.000	.000	.005	.004	.000	.000	.000
	.000	.	.000	.000	.000	.000	.056	.001	.095	.233	.000	.000	.000
	.100	.000	.	.000	.000	.000	.212	.368	.171	.162	.173	.344	.207
	.011	.000	.000	.	.000	.000	.316	.102	.042	.083	.001	.028	.000
	.013	.000	.000	.000	.	.000	.274	.053	.107	.167	.061	.002	.185
	.001	.000	.000	.000	.000	.	.408	.100	.412	.482	.002	.008	.003
	.000	.056	.212	.316	.274	.408	.	.000	.000	.000	.033	.210	.000
	.000	.001	.368	.102	.053	.100	.000	.	.000	.000	.093	.195	.009
	.005	.095	.171	.042	.107	.412	.000	.000	.	.000	.452	.055	.212
	.004	.233	.162	.083	.167	.482	.000	.000	.000	.	.385	.018	.295
	.000	.000	.173	.001	.061	.002	.033	.093	.452	.385	.	.000	.000
	.000	.000	.344	.028	.002	.008	.210	.195	.055	.018	.000	.	.000
	.000	.000	.207	.000	.185	.003	.000	.009	.212	.295	.000	.000	.

Regression Output 5 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	99.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	102642.339	1127.608		91.027	.000	99734.704	105549.974		
	Dist_CBD	-2.016	.044	-.733	-45.496	.000	-2.130	-1.902	1.000	1.000
2	(Constant)	107792.250	1257.052		85.750	.000	104550.831	111033.669		
	Dist_CBD	-1.044	.121	-.379	-8.617	.000	-1.356	-.731	.129	7.776
	Dist_SBD	-1.145	.133	-.379	-8.600	.000	-1.488	-.802	.129	7.776
3	(Constant)	106927.448	1272.832		84.008	.000	103645.337	110209.559		
	Dist_CBD	-1.071	.121	-.389	-8.861	.000	-1.383	-.759	.128	7.804
	Dist_SBD	-1.107	.133	-.366	-8.319	.000	-1.450	-.764	.128	7.821
	Jobs_retail_Inc3	64.506	16.968	.060	3.802	.000	20.753	108.259	.993	1.007
4	(Constant)	108903.553	1435.022		75.890	.000	105203.218	112603.889		
	Dist_CBD	-1.051	.121	-.382	-8.695	.000	-1.362	-.739	.128	7.830
	Dist_SBD	-1.024	.136	-.338	-7.544	.000	-1.374	-.674	.122	8.172
	Jobs_retail_Inc3	67.687	16.965	.063	3.990	.000	23.941	111.434	.989	1.011
	Dist_NBD	-.244	.083	-.058	-2.958	.003	-.457	-.031	.644	1.553
5	(Constant)	108506.364	1439.160		75.396	.000	104795.356	112217.371		
	Dist_CBD	-1.068	.121	-.388	-8.845	.000	-1.379	-.757	.127	7.850
	Dist_SBD	-1.009	.136	-.334	-7.445	.000	-1.358	-.660	.122	8.184
	Jobs_retail_Inc3	60.258	17.136	.056	3.516	.000	16.070	104.446	.966	1.035
	Dist_NBD	-.233	.082	-.055	-2.829	.005	-.446	-.021	.642	1.557
	Jobs_manu_Inc3	23.056	8.184	.045	2.817	.005	1.953	44.160	.971	1.029

Regression Output 5 - Coefficient Correlations and Covariances

Model			Dist_CBD	Dist_SBD	Jobs_retail_Inc3	Dist_NBD	Jobs_manu_Inc3
1	Correlations	Dist_CBD	1.000				
	Covariances	Dist_CBD	.002				
2	Correlations	Dist_CBD	1.000	-.933			
		Dist_SBD	-.933	1.000			
	Covariances	Dist_CBD	.015	-.015			
		Dist_SBD	-.015	.018			
3	Correlations	Dist_CBD	1.000	-.934	-.060		
		Dist_SBD	-.934	1.000	.076		
		Jobs_retail_Inc3	-.060	.076	1.000		
	Covariances	Dist_CBD	.015	-.015	-.122		
		Dist_SBD	-.015	.018	.171		
		Jobs_retail_Inc3	-.122	.171	287.909		
4	Correlations	Dist_CBD	1.000	-.900	-.056	-.057	
		Dist_SBD	-.900	1.000	.087	-.207	
		Jobs_retail_Inc3	-.056	.087	1.000	-.063	
		Dist_NBD	-.057	-.207	-.063	1.000	
	Covariances	Dist_CBD	.015	-.015	-.114	-.001	
		Dist_SBD	-.015	.018	.200	-.002	
		Jobs_retail_Inc3	-.114	.200	287.819	-.089	
		Dist_NBD	-.001	-.002	-.089	.007	
5	Correlations	Dist_CBD	1.000	-.900	-.047	-.060	-.051
		Dist_SBD	-.900	1.000	.080	-.205	.038
		Jobs_retail_Inc3	-.047	.080	1.000	-.070	-.154
		Dist_NBD	-.060	-.205	-.070	1.000	.047
		Jobs_manu_Inc3	-.051	.038	-.154	.047	1.000
	Covariances	Dist_CBD	.015	-.015	-.097	-.001	-.051
		Dist_SBD	-.015	.018	.186	-.002	.043
		Jobs_retail_Inc3	-.097	.186	293.657	-.099	-21.582

Dist_NBD	-.001	-.002	-.099	.007	.032
Jobs_manu_Inc3	-.051	.043	-21.582	.032	66.982

Dependent Variable: ACC_PT60min_Inc3

Regression Output 5 - Collinearity Diagnostics

				Variance Proportions					
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Dist_CBD	Dist_SBD	Jobs_retail_Inc3	Dist_NBD	Jobs_manu_Inc3
1	1	1.840	1.000	.08	.08				
	2	.160	3.387	.92	.92				
2	1	2.797	1.000	.03	.00	.00			
	2	.185	3.885	.83	.05	.02			
	3	.017	12.736	.14	.95	.98			
3	1	2.867	1.000	.02	.00	.00	.01		
	2	.934	1.752	.00	.00	.00	.96		
	3	.182	3.974	.83	.05	.01	.02		
	4	.017	12.931	.15	.95	.98	.01		
4	1	3.759	1.000	.01	.00	.00	.01	.01	
	2	.938	2.002	.00	.00	.00	.96	.00	
	3	.188	4.468	.47	.06	.02	.03	.04	
	4	.098	6.205	.43	.01	.01	.00	.94	
	5	.017	14.860	.09	.93	.97	.01	.01	
5	1	3.800	1.000	.01	.00	.00	.01	.01	.00
	2	1.091	1.866	.00	.00	.00	.36	.00	.46
	3	.806	2.171	.00	.00	.00	.61	.00	.53
	4	.188	4.495	.47	.06	.02	.02	.04	.00
	5	.097	6.257	.44	.01	.01	.00	.94	.01
	6	.017	14.958	.09	.93	.97	.01	.01	.00

Dependent Variable: ACC_PT60min_Inc3

2F: Regression 6 - Accessibility to upper-middle income jobs by car

Descriptive Statistics of variables

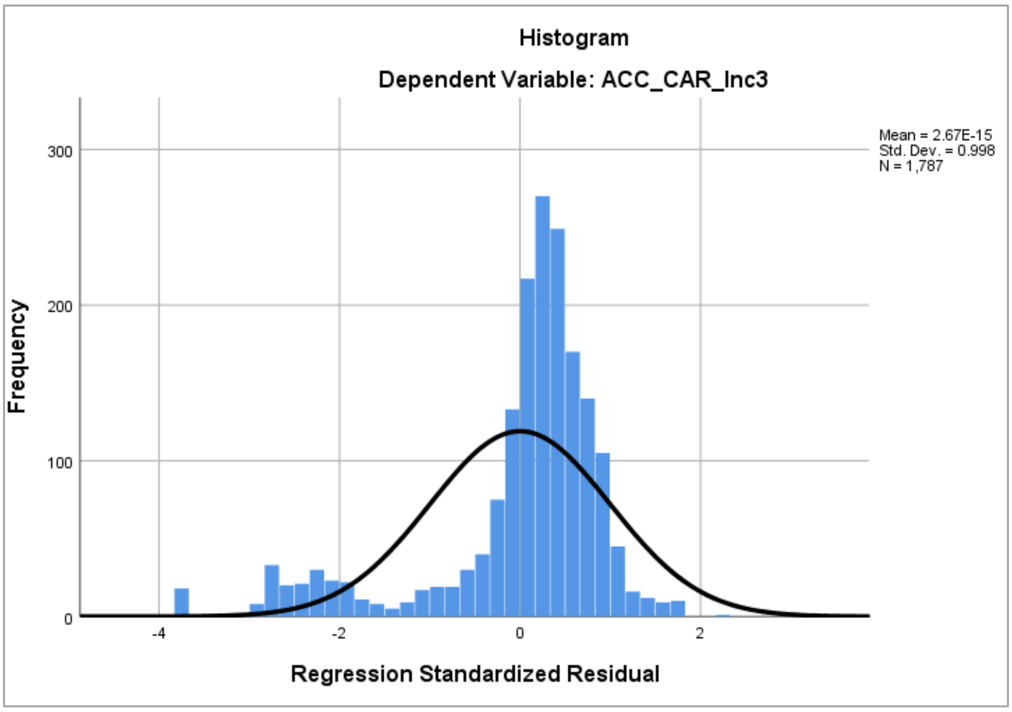
	Mean	Std. Deviation	N
ACC_CAR_Inc3	70464.145	32541.455	1787
Empl_full_Inc3	63.989	129.995	1787
Empl_part_Inc3	2.273	11.586	1787
Empl_self_Inc3	21.634	57.469	1787
UnEmpl_NL_Inc3	3.632	15.019	1787
UnEmpl_L_Inc3	3.008	12.560	1787
Jobs_office_Inc3	34.047	176.005	1787
Jobs_retail_Inc3	9.028	35.376	1787
Jobs_manu_Inc3	13.540	73.857	1787
Jobs_serv_Inc3	4.304	20.716	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

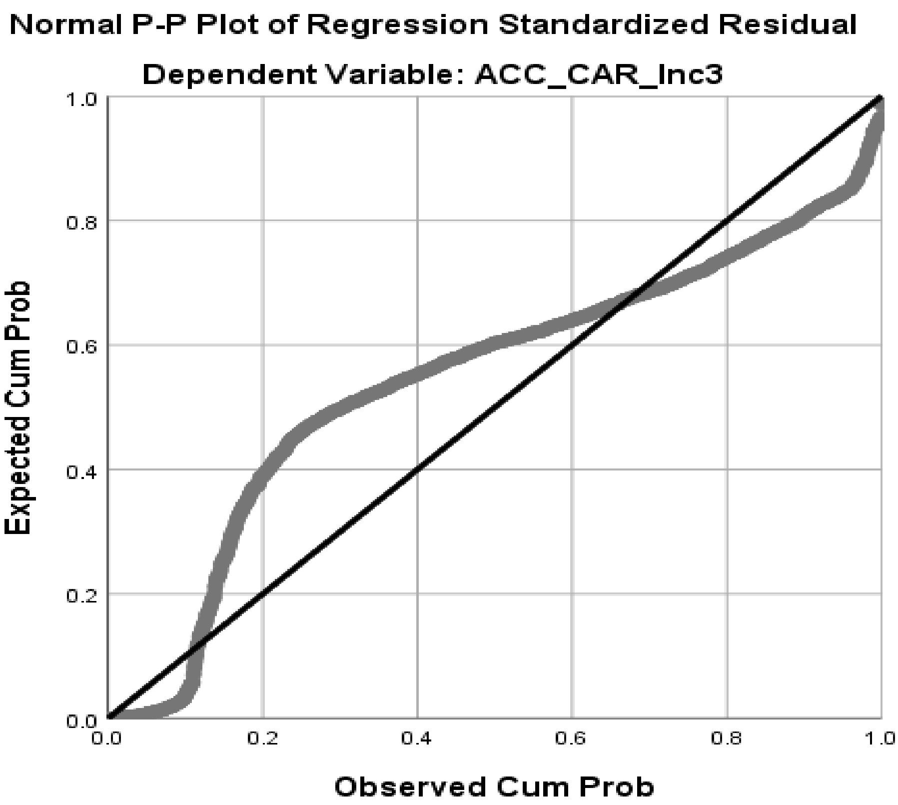
Regression Output 6 - Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-30450.438	132030.031	70464.145	24038.773	1787
Std. Predicted Value	-4.198	2.561	.000	1.000	1787
Standard Error of Predicted Value	744.244	12414.556	1241.910	787.518	1787
Adjusted Predicted Value	-30837.188	141555.422	70480.113	24103.626	1787
Residual	-84103.813	48122.477	.000	21933.619	1787
Std. Residual	-3.827	2.190	.000	.998	1787
Stud. Residual	-3.830	2.198	.000	1.000	1787
Deleted Residual	-84248.086	48476.582	-15.968	22016.041	1787
Stud. Deleted Residual	-3.845	2.200	-.001	1.001	1787
Mahal. Distance	1.049	568.926	6.996	22.709	1787
Cook's Distance	.000	.074	.000	.002	1787
Centered Leverage Value	.001	.319	.004	.013	1787

Dependent Variable: ACC_CAR_Inc3

Regression Output 6 – Residuals and Normal P-P Plot





Regression Output 6 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			99.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	105207.320	1024.952		102.646	.000	102564.392	107850.248		
	Dist_CBD	-1.626	.040	-.691	-40.372	.000	-1.730	-1.522	1.000	1.000
2	(Constant)	112867.566	1222.429		92.331	.000	109715.426	116019.707		
	Dist_CBD	-1.334	.048	-.567	-28.057	.000	-1.457	-1.212	.674	1.483
	Dist_NBD	-.784	.073	-.217	-10.756	.000	-.972	-.596	.674	1.483
3	(Constant)	109989.170	1255.007		87.640	.000	106753.022	113225.318		
	Dist_CBD	-1.314	.047	-.558	-28.073	.000	-1.435	-1.193	.672	1.488
	Dist_NBD	-.764	.072	-.212	-10.648	.000	-.949	-.579	.673	1.485
	Empl_full_Inc3	32.608	4.101	.130	7.951	.000	22.032	43.183	.991	1.010
4	(Constant)	109456.784	1245.539		87.879	.000	106245.050	112668.519		
	Dist_CBD	-1.296	.046	-.551	-27.905	.000	-1.416	-1.176	.669	1.494
	Dist_NBD	-.788	.071	-.218	-11.074	.000	-.971	-.604	.671	1.490
	Empl_full_Inc3	31.720	4.063	.127	7.807	.000	21.243	42.196	.989	1.011
	Jobs_office_Inc3	18.249	2.994	.099	6.096	.000	10.529	25.968	.994	1.006
5	(Constant)	107601.521	1315.981		81.765	.000	104208.142	110994.901		
	Dist_CBD	-1.702	.107	-.723	-15.904	.000	-1.977	-1.426	.125	8.002
	Dist_NBD	-.853	.072	-.236	-11.768	.000	-1.040	-.666	.640	1.562
	Empl_full_Inc3	32.798	4.052	.131	8.094	.000	22.349	43.247	.985	1.015
	Jobs_office_Inc3	20.788	3.040	.112	6.837	.000	12.948	28.628	.955	1.047
	Dist_SBD	.509	.121	.197	4.203	.000	.197	.821	.118	8.484
6	(Constant)	107089.326	1316.784		81.326	.000	103693.874	110484.778		
	Dist_CBD	-1.714	.107	-.728	-16.083	.000	-1.989	-1.439	.125	8.009
	Dist_NBD	-.836	.072	-.232	-11.568	.000	-1.023	-.650	.638	1.567
	Empl_full_Inc3	33.470	4.039	.134	8.287	.000	23.056	43.885	.984	1.017
	Jobs_office_Inc3	18.300	3.091	.099	5.920	.000	10.329	26.272	.916	1.092
	Dist_SBD	.515	.121	.199	4.273	.000	.204	.826	.118	8.485
	Jobs_manu_Inc3	28.801	7.221	.065	3.989	.000	10.181	47.421	.953	1.049
7	(Constant)	106982.610	1315.816		81.305	.000	103589.652	110375.569		

Dist_CBD	-1.706	.107	-.725	-16.021	.000	-1.981	-1.432	.125	8.017
Dist_NBD	-.840	.072	-.233	-11.634	.000	-1.027	-.654	.638	1.568
Empl_full_Inc3	32.771	4.044	.131	8.103	.000	22.343	43.200	.978	1.022
Jobs_office_Inc3	14.085	3.558	.076	3.959	.000	4.911	23.259	.690	1.450
Dist_SBD	.508	.120	.196	4.217	.000	.197	.819	.118	8.490
Jobs_manu_Inc3	27.703	7.226	.063	3.834	.000	9.070	46.336	.949	1.053
Jobs_retail_Inc3	41.221	17.289	.045	2.384	.017	-3.360	85.803	.723	1.383

Dependent Variable: ACC_CAR_Inc3

Regression Output 6 - Coefficient Correlations and Covariance

Model			Dist_CBD	Dist_NBD	Empl_full_Inc3	Jobs_office_Inc3	Dist_SBD	Jobs_manu_Inc3	Jobs_retail_Inc3
1	Correlations	Dist_CBD	1.000						
	Covariances	Dist_CBD	.002						
2	Correlations	Dist_CBD	1.000	-.571					
		Dist_NBD	-.571	1.000					
	Covariances	Dist_CBD	.002	-.002					
		Dist_NBD	-.002	.005					
3	Correlations	Dist_CBD	1.000	-.568	.054				
		Dist_NBD	-.568	1.000	.036				
		Empl_full_Inc3	.054	.036	1.000				
	Covariances	Dist_CBD	.002	-.002	.010				
		Dist_NBD	-.002	.005	.011				
		Empl_full_Inc3	.010	.011	16.820				
4	Correlations	Dist_CBD	1.000	-.569	.051	.064			
		Dist_NBD	-.569	1.000	.038	-.055			
		Empl_full_Inc3	.051	.038	1.000	-.036			
		Jobs_office_Inc3	.064	-.055	-.036	1.000			
	Covariances	Dist_CBD	.002	-.002	.010	.009			

		Dist_NBD	-.002	.005	.011	-.012			
		Empl_full_Inc3	.010	.011	16.507	-.436			
		Jobs_office_Inc3	.009	-.012	-.436	8.963			
5	Correlations	Dist_CBD	1.000	-.046	-.035	-.152	-.902		
		Dist_NBD	-.046	1.000	.023	-.095	-.215		
		Empl_full_Inc3	-.035	.023	1.000	-.022	.063		
		Jobs_office_Inc3	-.152	-.095	-.022	1.000	.199		
		Dist_SBD	-.902	-.215	.063	.199	1.000		
	Covariances	Dist_CBD	.011	.000	-.015	-.049	-.012		
		Dist_NBD	.000	.005	.007	-.021	-.002		
		Empl_full_Inc3	-.015	.007	16.420	-.277	.031		
		Jobs_office_Inc3	-.049	-.021	-.277	9.244	.073		
		Dist_SBD	-.012	-.002	.031	.073	.015		
6	Correlations	Dist_CBD	1.000	-.048	-.036	-.143	-.902	-.030	
		Dist_NBD	-.048	1.000	.026	-.105	-.214	.058	
		Empl_full_Inc3	-.036	.026	1.000	-.030	.064	.042	
		Jobs_office_Inc3	-.143	-.105	-.030	1.000	.192	-.202	
		Dist_SBD	-.902	-.214	.064	.192	1.000	.013	
		Jobs_manu_Inc3	-.030	.058	.042	-.202	.013	1.000	
	Covariances	Dist_CBD	.011	.000	-.016	-.047	-.012	-.023	
		Dist_NBD	.000	.005	.008	-.023	-.002	.030	
		Empl_full_Inc3	-.016	.008	16.312	-.380	.031	1.217	
		Jobs_office_Inc3	-.047	-.023	-.380	9.557	.072	-4.504	
		Dist_SBD	-.012	-.002	.031	.072	.015	.011	
		Jobs_manu_Inc3	-.023	.030	1.217	-4.504	.011	52.141	
7	Correlations	Dist_CBD	1.000	-.049	-.038	-.139	-.902	-.032	.031
		Dist_NBD	-.049	1.000	.027	-.080	-.213	.059	-.022
		Empl_full_Inc3	-.038	.027	1.000	.010	.065	.046	-.072
		Jobs_office_Inc3	-.139	-.080	.010	1.000	.179	-.143	-.497
		Dist_SBD	-.902	-.213	.065	.179	1.000	.015	-.025
		Jobs_manu_Inc3	-.032	.059	.046	-.143	.015	1.000	-.064
		Jobs_retail_Inc3	.031	-.022	-.072	-.497	-.025	-.064	1.000
	Covariances	Dist_CBD	.011	.000	-.017	-.053	-.012	-.025	.058

	Dist_NBD	.000	.005	.008	-.020	-.002	.031	-.028
	Empl_full_Inc3	-.017	.008	16.355	.139	.032	1.349	-5.068
	Jobs_office_Inc3	-.053	-.020	.139	12.657	.077	-3.677	-30.568
	Dist_SBD	-.012	-.002	.032	.077	.015	.013	-.053
	Jobs_manu_Inc3	-.025	.031	1.349	-3.677	.013	52.217	-7.963
	Jobs_retail_Inc3	.058	-.028	-5.068	-30.568	-.053	-7.963	298.911

Dependent Variable: ACC_CAR_Inc3

Regression Output 6 - Collinearity Diagnostics

				Variance Proportions							
Model	Dimension	Eigen value	Condition Index	(Constant)	Dist_CBD	Dist_NBD	Empl_full_Inc3	Jobs_office_Inc3	Dist_SBD	Jobs_manu_Inc3	Jobs_retail_Inc3
1	1	1.840	1.000	.08	.08						
	2	.160	3.387	.92	.92						
2	1	2.747	1.000	.02	.02	.02					
	2	.160	4.138	.59	.63	.00					
	3	.093	5.441	.38	.34	.98					
3	1	2.964	1.000	.02	.02	.01	.03				
	2	.794	1.932	.00	.02	.01	.89				
	3	.151	4.428	.56	.67	.01	.07				
	4	.092	5.685	.42	.30	.97	.01				
4	1	3.012	1.000	.02	.02	.01	.03	.01			
	2	.956	1.775	.00	.00	.00	.01	.96			
	3	.790	1.952	.00	.01	.01	.89	.02			
	4	.150	4.485	.57	.66	.00	.07	.01			
	5	.092	5.734	.41	.30	.97	.01	.00			
5	1	3.916	1.000	.01	.00	.01	.01	.00	.00		
	2	.980	1.999	.00	.00	.00	.04	.85	.00		
	3	.816	2.191	.00	.00	.00	.84	.09	.00		

	4	.176	4.722	.43	.06	.06	.08	.02	.02		
	5	.096	6.391	.46	.01	.92	.02	.00	.01		
	6	.016	15.428	.10	.93	.01	.00	.04	.97		
6	1	3.956	1.000	.01	.00	.01	.01	.00	.00	.00	
	2	1.159	1.848	.00	.00	.00	.00	.37	.00	.38	
	3	.854	2.152	.00	.00	.00	.64	.10	.00	.16	
	4	.744	2.305	.00	.00	.00	.24	.47	.00	.45	
	5	.176	4.747	.43	.06	.06	.08	.02	.02	.00	
	6	.095	6.449	.46	.01	.92	.02	.00	.01	.01	
	7	.016	15.509	.10	.93	.01	.00	.03	.97	.00	
7	1	4.053	1.000	.01	.00	.01	.01	.00	.00	.00	.01
	2	1.515	1.636	.00	.00	.00	.00	.19	.00	.08	.17
	3	.904	2.118	.00	.00	.00	.25	.01	.00	.63	.05
	4	.788	2.268	.00	.00	.00	.63	.04	.00	.27	.03
	5	.453	2.990	.00	.00	.00	.00	.72	.00	.01	.75
	6	.175	4.808	.43	.06	.06	.08	.01	.02	.00	.00
	7	.095	6.528	.46	.01	.92	.02	.00	.01	.01	.00
	8	.016	15.706	.10	.93	.01	.00	.03	.97	.00	.00

Dependent Variable: ACC_CAR_Inc3

2G: Regression 7 - Accessibility to high-income jobs by public transport

Descriptive Statistics of Variables

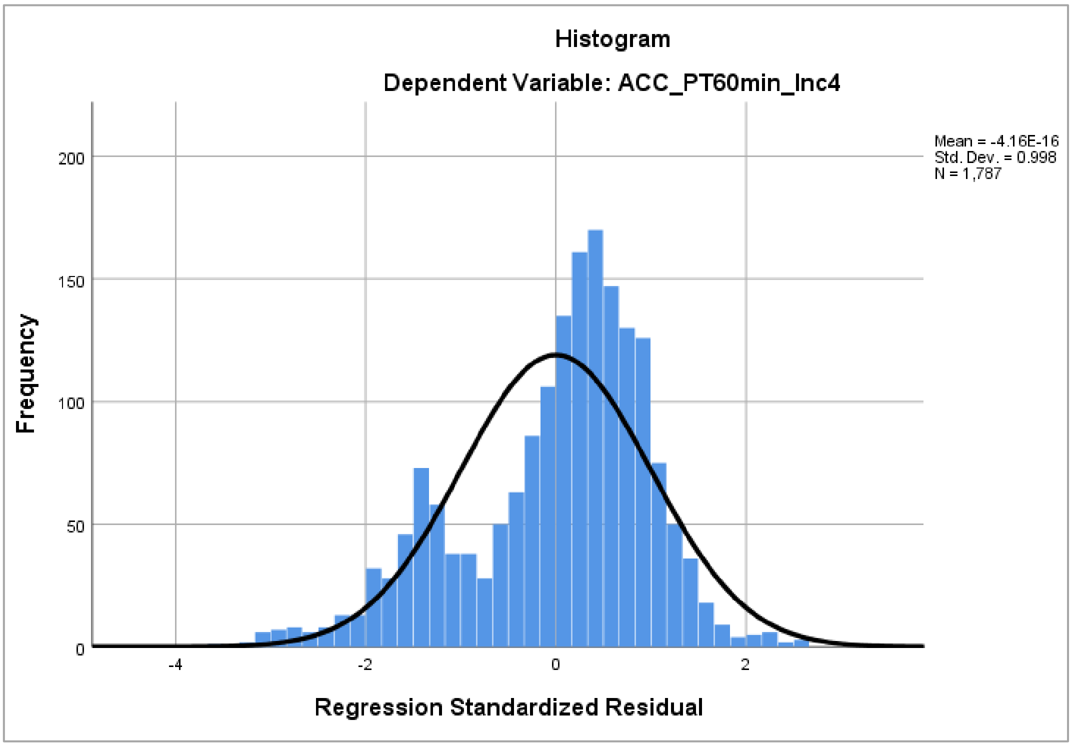
	Mean	Std. Deviation	N
ACC_PT60min_Inc4	31109.847	19662.842	1787
Empl_full_Inc4	28.136	81.690	1787
Empl_part_Inc4	1.741	10.399	1787
Empl_self_Inc4	15.099	49.652	1787
UnEmpl_NL_Inc4	1.776	11.958	1787
UnEmpl_L_Inc4	2.049	15.561	1787
Jobs_retail_Inc4	2.630	10.804	1787
Jobs_manu_Inc4	3.797	20.838	1787
Jobs_serv_Inc4	.792	3.880	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

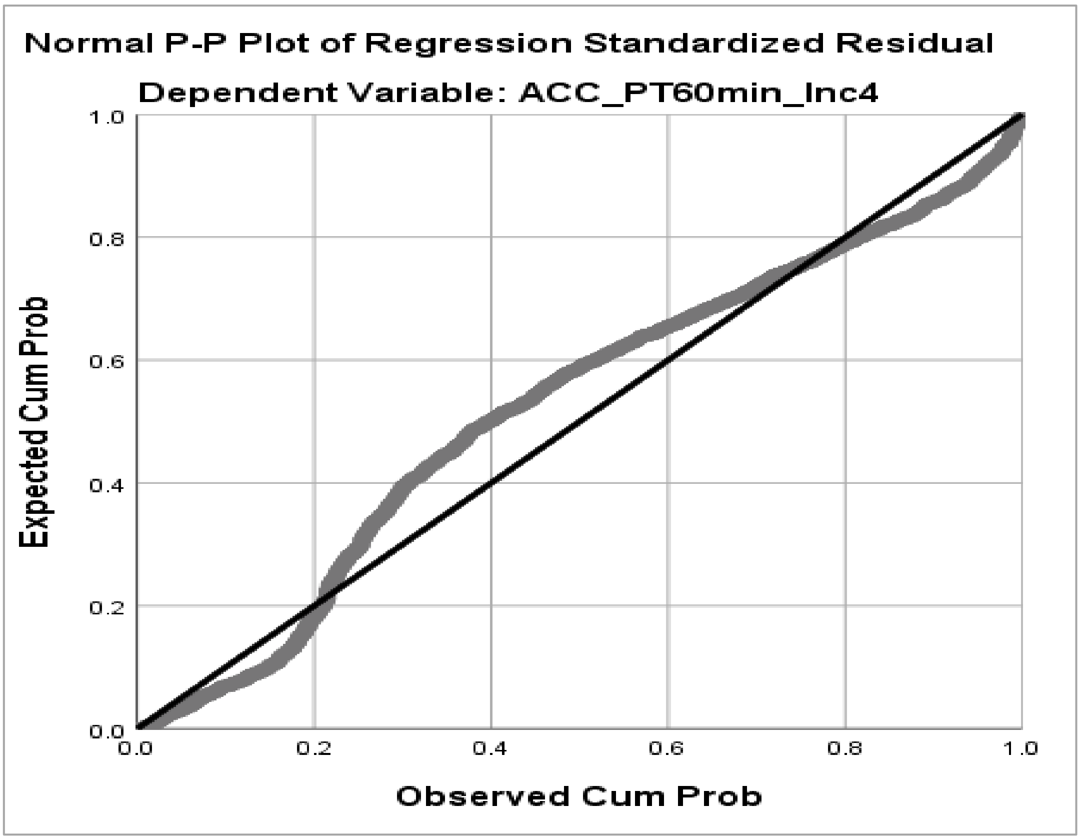
Regression Output 7 - Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-24828.141	67237.211	31109.847	14696.312	1787
Std. Predicted Value	-3.806	2.458	.000	1.000	1787
Standard Error of Predicted Value	453.225	7451.129	707.781	412.121	1787
Adjusted Predicted Value	-25143.848	77271.203	31115.751	14725.716	1787
Residual	-47903.930	33355.633	.000	13063.146	1787
Std. Residual	-3.661	2.549	.000	.998	1787
Stud. Residual	-3.668	2.557	.000	1.000	1787
Deleted Residual	-48088.094	33565.133	-5.904	13118.763	1787
Stud. Deleted Residual	-3.681	2.561	.000	1.001	1787
Mahal. Distance	1.143	578.121	5.997	18.700	1787
Cook's Distance	.000	.259	.001	.006	1787
Centered Leverage Value	.001	.324	.003	.010	1787

Dependent Variable: ACC_PT60min_Inc4

Regression Output 7 – Residuals and Normal P-P Plot





Regression Output 7 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			99.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	53358.359	583.453		91.453	.000	51853.873	54862.844		
	Dist_CBD	-1.041	.023	-.732	-45.416	.000	-1.100	-.982	1.000	1.000
2	(Constant)	55805.750	652.537		85.521	.000	54123.126	57488.374		
	Dist_CBD	-.579	.063	-.407	-9.213	.000	-.741	-.417	.129	7.776
	Dist_SBD	-.544	.069	-.348	-7.873	.000	-.722	-.366	.129	7.776
3	(Constant)	55383.502	662.708		83.572	.000	53674.650	57092.353		
	Dist_CBD	-.591	.063	-.416	-9.417	.000	-.753	-.429	.128	7.802
	Dist_SBD	-.525	.069	-.336	-7.598	.000	-.704	-.347	.128	7.827
	Jobs_retail_Inc4	97.040	28.901	.053	3.358	.001	22.515	171.565	.991	1.009
4	(Constant)	55193.937	665.290		82.962	.000	53478.426	56909.448		
	Dist_CBD	-.599	.063	-.421	-9.549	.000	-.761	-.437	.128	7.819
	Dist_SBD	-.515	.069	-.330	-7.455	.000	-.694	-.337	.127	7.850
	Jobs_retail_Inc4	88.716	29.016	.049	3.057	.002	13.895	163.537	.980	1.021
	Jobs_manu_Inc4	40.386	15.006	.043	2.691	.007	1.691	79.081	.985	1.016
5	(Constant)	56018.407	752.242		74.469	.000	54078.681	57958.133		
	Dist_CBD	-.590	.063	-.415	-9.400	.000	-.752	-.428	.127	7.848
	Dist_SBD	-.482	.071	-.308	-6.834	.000	-.664	-.300	.122	8.188
	Jobs_retail_Inc4	92.293	29.020	.051	3.180	.001	17.461	167.125	.977	1.024
	Jobs_manu_Inc4	38.379	15.012	.041	2.557	.011	-.332	77.089	.981	1.019
	Dist_NBD	-.100	.043	-.046	-2.338	.020	-.211	.010	.643	1.555
6	(Constant)	56208.780	757.547		74.198	.000	54255.373	58162.186		
	Dist_CBD	-.594	.063	-.418	-9.462	.000	-.756	-.432	.127	7.855
	Dist_SBD	-.485	.070	-.310	-6.879	.000	-.666	-.303	.122	8.191
	Jobs_retail_Inc4	93.859	29.006	.052	3.236	.001	19.064	168.654	.976	1.024
	Jobs_manu_Inc4	37.384	15.008	.040	2.491	.013	-1.314	76.083	.980	1.020
	Dist_NBD	-.092	.043	-.042	-2.144	.032	-.203	.019	.637	1.569
	Empl_self_Inc4	-12.630	6.285	-.032	-2.010	.045	-28.835	3.575	.985	1.016

Dependent Variable: ACC_PT60min_Inc4

Regression Output 7 - Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Dist_CBD	Dist_SBD	Jobs_retail_Inc4	Jobs_manu_Inc4	Dist_NBD	Empl_self_Inc4
1	1	1.840	1.000	.08	.08					
	2	.160	3.387	.92	.92					
2	1	2.797	1.000	.03	.00	.00				
	2	.185	3.885	.83	.05	.02				
	3	.017	12.736	.14	.95	.98				
3	1	2.857	1.000	.02	.00	.00	.01			
	2	.945	1.739	.00	.00	.00	.95			
	3	.181	3.976	.83	.05	.01	.03			
	4	.017	12.910	.15	.95	.98	.01			
4	1	2.901	1.000	.02	.00	.00	.01	.01		
	2	1.053	1.660	.00	.00	.00	.37	.47		
	3	.850	1.848	.00	.00	.00	.59	.51		
	4	.180	4.017	.83	.05	.01	.03	.01		
	5	.017	13.027	.15	.95	.98	.01	.00		
5	1	3.785	1.000	.01	.00	.00	.01	.00	.01	
	2	1.065	1.885	.00	.00	.00	.37	.47	.00	
	3	.850	2.110	.00	.00	.00	.59	.51	.00	
	4	.187	4.498	.46	.06	.02	.03	.00	.04	
	5	.097	6.252	.44	.01	.01	.00	.01	.94	
	6	.017	14.929	.09	.93	.97	.01	.00	.01	
6	1	3.874	1.000	.01	.00	.00	.00	.00	.01	.01
	2	1.065	1.907	.00	.00	.00	.37	.48	.00	.00
	3	.939	2.031	.00	.00	.00	.11	.08	.00	.74
	4	.828	2.164	.00	.00	.00	.50	.41	.00	.21
	5	.180	4.637	.48	.06	.02	.02	.00	.04	.05

6	.097	6.329	.42	.01	.01	.00	.01	.94	.00
7	.017	15.105	.09	.93	.97	.01	.00	.01	.00

Regression Output 7 - Coefficient Correlations and Covariances

Model			Dist_CBD	Dist_SBD	Jobs_retail_Inc4	Jobs_manu_Inc4	Dist_NBD	Empl_self_Inc4
1	Correlations	Dist_CBD	1.000					
	Covariances	Dist_CBD	.001					
2	Correlations	Dist_CBD	1.000	-.933				
		Dist_SBD	-.933	1.000				
	Covariances	Dist_CBD	.004	-.004				
		Dist_SBD	-.004	.005				
3	Correlations	Dist_CBD	1.000	-.934	-.057			
		Dist_SBD	-.934	1.000	.081			
		Jobs_retail_Inc4	-.057	.081	1.000			
	Covariances	Dist_CBD	.004	-.004	-.104			
		Dist_SBD	-.004	.005	.162			
		Jobs_retail_Inc4	-.104	.162	835.295			
4	Correlations	Dist_CBD	1.000	-.934	-.052	-.047		
		Dist_SBD	-.934	1.000	.075	.054		
		Jobs_retail_Inc4	-.052	.075	1.000	-.107		
		Jobs_manu_Inc4	-.047	.054	-.107	1.000		
	Covariances	Dist_CBD	.004	-.004	-.095	-.044		
		Dist_SBD	-.004	.005	.150	.056		
		Jobs_retail_Inc4	-.095	.150	841.946	-46.412		
		Jobs_manu_Inc4	-.044	.056	-46.412	225.193		
5	Correlations	Dist_CBD	1.000	-.900	-.049	-.050	-.061	
		Dist_SBD	-.900	1.000	.084	.041	-.203	
		Jobs_retail_Inc4	-.049	.084	1.000	-.109	-.053	
		Jobs_manu_Inc4	-.050	.041	-.109	1.000	.057	
		Dist_NBD	-.061	-.203	-.053	.057	1.000	
	Covariances	Dist_CBD	.004	-.004	-.088	-.047	.000	
		Dist_SBD	-.004	.005	.171	.044	-.001	

		Jobs_retail_Inc4	-.088	.171	842.182	-47.609	-.066	
		Jobs_manu_Inc4	-.047	.044	-47.609	225.367	.037	
		Dist_NBD	.000	-.001	-.066	.037	.002	
6	Correlations	Dist_CBD	1.000	-.899	-.049	-.049	-.064	.028
		Dist_SBD	-.899	1.000	.083	.042	-.204	.020
		Jobs_retail_Inc4	-.049	.083	1.000	-.110	-.050	-.027
		Jobs_manu_Inc4	-.049	.042	-.110	1.000	.054	.033
		Dist_NBD	-.064	-.204	-.050	.054	1.000	-.093
		Empl_self_Inc4	.028	.020	-.027	.033	-.093	1.000
	Covariances	Dist_CBD	.004	-.004	-.090	-.046	.000	.011
		Dist_SBD	-.004	.005	.170	.044	-.001	.009
		Jobs_retail_Inc4	-.090	.170	841.355	-47.914	-.062	-4.898
		Jobs_manu_Inc4	-.046	.044	-47.914	225.228	.035	3.110
		Dist_NBD	.000	-.001	-.062	.035	.002	-.025
		Empl_self_Inc4	.011	.009	-4.898	3.110	-.025	39.495

Dependent Variable: ACC_PT60min_Inc4

2H: Regression 8 - Accessibility to high-income jobs by car

Descriptive Statistics of Variables

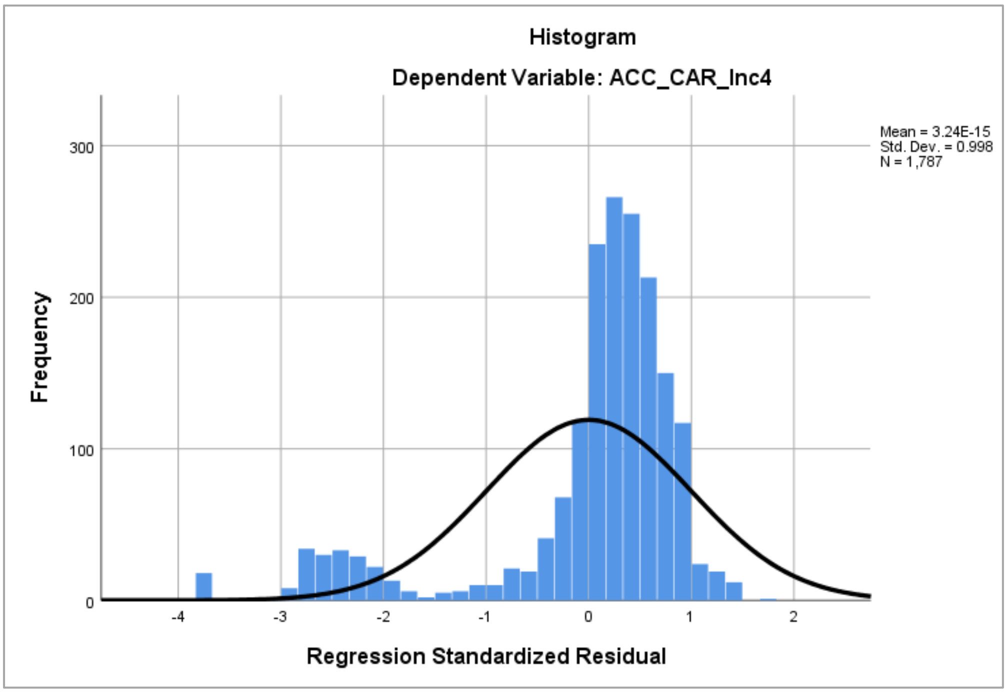
	Mean	Std. Deviation	N
ACC_CAR_Inc4	46979.249	19922.104	1787
Empl_full_Inc4	28.136	81.690	1787
Empl_part_Inc4	1.741	10.399	1787
Empl_self_Inc4	15.099	49.652	1787
UnEmpl_NL_Inc4	1.776	11.958	1787
UnEmpl_L_Inc4	2.049	15.561	1787
Jobs_office_Inc4	23.437	123.748	1787
Jobs_retail_Inc4	2.630	10.804	1787
Jobs_manu_Inc4	3.797	20.838	1787
Jobs_serv_Inc4	.792	3.880	1787
Dist_CBD	21365.449	13825.127	1787
Dist_NBD	17717.551	9014.426	1787
Dist_SBD	22639.154	12575.625	1787

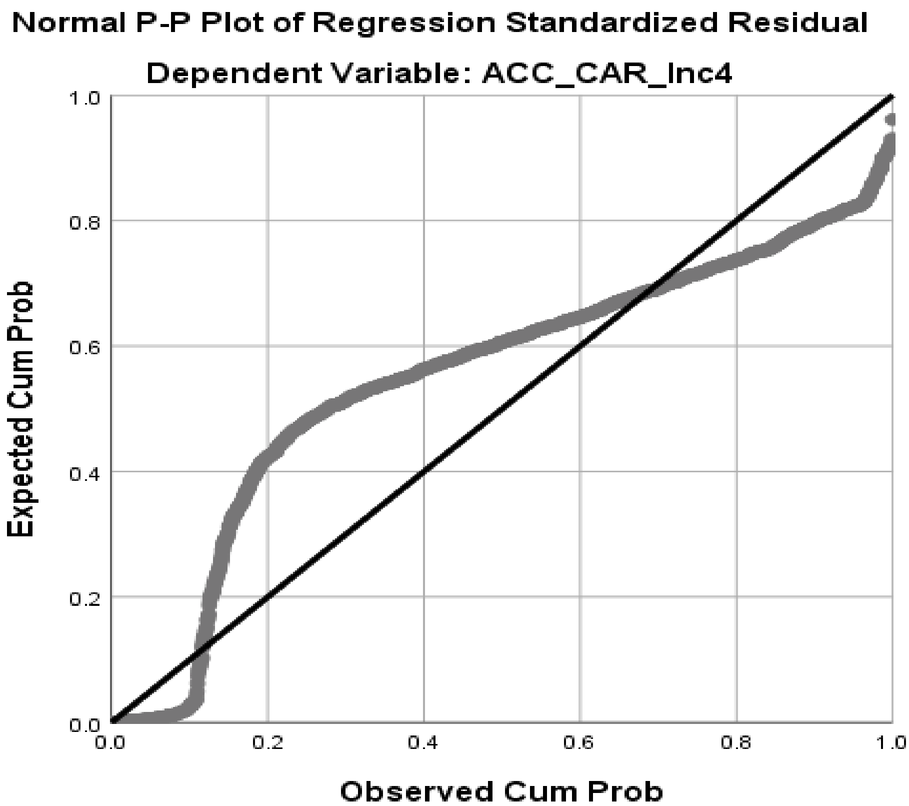
Regression Output 8 - Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-8530.852	86924.063	46979.249	13403.669	1787
Std. Predicted Value	-4.141	2.980	.000	1.000	1787
Standard Error of Predicted Value	517.488	8625.437	865.314	591.956	1787
Adjusted Predicted Value	-8639.395	96573.008	46993.815	13458.544	1787
Residual	-56118.180	26027.559	.000	14738.789	1787
Std. Residual	-3.799	1.762	.000	.998	1787
Stud. Residual	-3.802	1.768	.000	1.000	1787
Deleted Residual	-56218.895	26219.490	-14.566	14800.730	1787
Stud. Deleted Residual	-3.817	1.770	-.001	1.001	1787
Mahal. Distance	1.192	607.935	7.996	25.381	1787
Cook's Distance	.000	.139	.000	.004	1787
Centered Leverage Value	.001	.340	.004	.014	1787

Dependent Variable: ACC_CAR_Inc4

Regression Output 8 – Residuals and Normal P-P Plot





Regression Output 8 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			99.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	66526.986	670.522		99.217	.000	64797.988	68255.984		
	Dist_CBD	-.915	.026	-.635	-34.721	.000	-.983	-.847	1.000	1.000
2	(Constant)	70109.868	812.287		86.312	.000	68015.315	72204.420		
	Dist_CBD	-.778	.032	-.540	-24.633	.000	-.860	-.697	.674	1.483
	Dist_NBD	-.367	.048	-.166	-7.571	.000	-.492	-.242	.674	1.483
3	(Constant)	69700.602	811.335		85.909	.000	67608.502	71792.702		
	Dist_CBD	-.767	.031	-.532	-24.366	.000	-.848	-.686	.671	1.491
	Dist_NBD	-.376	.048	-.170	-7.808	.000	-.501	-.252	.673	1.486
	Jobs_office_Inc4	14.203	2.888	.088	4.919	.000	6.757	21.649	.995	1.005
4	(Constant)	68018.604	853.022		79.738	.000	65819.010	70218.197		
	Dist_CBD	-1.150	.072	-.798	-15.938	.000	-1.336	-.964	.125	7.988
	Dist_NBD	-.438	.049	-.198	-8.961	.000	-.564	-.312	.642	1.557
	Jobs_office_Inc4	17.678	2.921	.110	6.052	.000	10.146	25.210	.954	1.048
	Dist_SBD	.481	.082	.303	5.889	.000	.270	.691	.118	8.455
5	(Constant)	67321.228	863.152		77.995	.000	65095.511	69546.946		
	Dist_CBD	-1.156	.072	-.802	-16.097	.000	-1.341	-.971	.125	7.991
	Dist_NBD	-.448	.049	-.203	-9.203	.000	-.573	-.322	.641	1.561
	Jobs_office_Inc4	18.140	2.908	.113	6.238	.000	10.642	25.638	.953	1.050
	Dist_SBD	.501	.081	.316	6.154	.000	.291	.710	.118	8.480
	Empl_full_Inc4	19.094	4.319	.078	4.421	.000	7.958	30.230	.991	1.009
6	(Constant)	67002.377	866.641		77.313	.000	64767.661	69237.092		
	Dist_CBD	-1.163	.072	-.807	-16.231	.000	-1.348	-.978	.125	7.998
	Dist_NBD	-.438	.049	-.198	-9.001	.000	-.563	-.312	.638	1.567
	Jobs_office_Inc4	16.552	2.942	.103	5.626	.000	8.966	24.139	.926	1.080
	Dist_SBD	.505	.081	.319	6.226	.000	.296	.714	.118	8.483
	Empl_full_Inc4	19.648	4.311	.081	4.558	.000	8.531	30.764	.990	1.011
	Jobs_manu_Inc4	54.912	17.131	.057	3.205	.001	10.738	99.087	.963	1.038
7	(Constant)	66865.581	867.496		77.079	.000	64628.659	69102.503		
	Dist_CBD	-1.159	.072	-.804	-16.188	.000	-1.344	-.974	.125	8.003
	Dist_NBD	-.439	.049	-.199	-9.034	.000	-.564	-.314	.638	1.567

	Jobs_office_Inc4	12.730	3.358	.079	3.790	.000	4.070	21.390	.709	1.411
	Dist_SBD	.502	.081	.317	6.197	.000	.293	.711	.118	8.485
	Empl_full_Inc4	19.476	4.306	.080	4.523	.000	8.372	30.580	.989	1.011
	Jobs_manu_Inc4	53.680	17.118	.056	3.136	.002	9.541	97.820	.962	1.039
	Jobs_retail_Inc4	88.021	37.449	.048	2.350	.019	-8.544	184.586	.748	1.337
8	(Constant)	66768.989	867.860		76.935	.000	64531.129	69006.850		
	Dist_CBD	-1.153	.072	-.800	-16.114	.000	-1.338	-.969	.125	8.014
	Dist_NBD	-.447	.049	-.202	-9.187	.000	-.573	-.322	.634	1.578
	Jobs_office_Inc4	12.772	3.355	.079	3.807	.000	4.120	21.424	.709	1.411
	Dist_SBD	.502	.081	.317	6.203	.000	.293	.711	.118	8.485
	Empl_full_Inc4	15.290	4.737	.063	3.228	.001	3.077	27.504	.816	1.225
	Jobs_manu_Inc4	54.201	17.103	.057	3.169	.002	10.100	98.302	.962	1.040
	Jobs_retail_Inc4	85.778	37.427	.047	2.292	.022	-10.732	182.288	.747	1.338
	Empl_self_Inc4	16.500	7.813	.041	2.112	.035	-3.646	36.646	.812	1.232

Dependent Variable: ACC_CAR_Inc4

Regression Output 8 - Coefficient Correlations & Covariances

Model			Dist_ CBD	Dist_NB D	Jobs_office _Inc4	Dist_SBD	Empl_full _Inc4	Jobs_manu_Inc 4	Jobs_retail_ Inc4	Empl_self_Inc4
1	Correlations	Dist_CBD	1.000							
	Covariances	Dist_CBD	.001							
2	Correlations	Dist_CBD	1.000	-.571						
		Dist_NBD	-.571	1.000						
	Covariances	Dist_CBD	.001	-.001						
		Dist_NBD	-.001	.002						
3	Correlations	Dist_CBD	1.000	-.572	.073					
		Dist_NBD	-.572	1.000	-.039					
		Jobs_office_Inc4	.073	-.039	1.000					
	Covariances	Dist_CBD	.001	-.001	.007					
		Dist_NBD	-.001	.002	-.005					

		Jobs_office_Inc4	.007	-.005	8.338				
4	Correlations	Dist_CBD	1.000	-.048	-.151	-.902			
		Dist_NBD	-.048	1.000	-.081	-.214			
		Jobs_office_Inc4	-.151	-.081	1.000	.202			
		Dist_SBD	-.902	-.214	.202	1.000			
	Covariances	Dist_CBD	.005	.000	-.032	-.005			
		Dist_NBD	.000	.002	-.012	-.001			
		Jobs_office_Inc4	-.032	-.012	8.532	.048			
		Dist_SBD	-.005	-.001	.048	.007			
5	Correlations	Dist_CBD	1.000	-.047	-.152	-.901	-.018		
		Dist_NBD	-.047	1.000	-.083	-.216	-.047		
		Jobs_office_Inc4	-.152	-.083	1.000	.204	.036		
		Dist_SBD	-.901	-.216	.204	1.000	.055		
		Empl_full_Inc4	-.018	-.047	.036	.055	1.000		
	Covariances	Dist_CBD	.005	.000	-.032	-.005	-.006		
		Dist_NBD	.000	.002	-.012	-.001	-.010		
		Jobs_office_Inc4	-.032	-.012	8.455	.048	.451		
		Dist_SBD	-.005	-.001	.048	.007	.019		
		Empl_full_Inc4	-.006	-.010	.451	.019	18.651		
6	Correlations	Dist_CBD	1.000	-.049	-.144	-.901	-.019	-.031	
		Dist_NBD	-.049	1.000	-.092	-.215	-.044	.064	
		Jobs_office_Inc4	-.144	-.092	1.000	.198	.029	-.168	
		Dist_SBD	-.901	-.215	.198	1.000	.056	.018	
		Empl_full_Inc4	-.019	-.044	.029	.056	1.000	.040	
		Jobs_manu_Inc4	-.031	.064	-.168	.018	.040	1.000	
	Covariances	Dist_CBD	.005	.000	-.030	-.005	-.006	-.038	
		Dist_NBD	.000	.002	-.013	-.001	-.009	.054	
		Jobs_office_Inc4	-.030	-.013	8.656	.047	.363	-8.484	
		Dist_SBD	-.005	-.001	.047	.007	.019	.025	
		Empl_full_Inc4	-.006	-.009	.363	.019	18.585	2.960	
		Jobs_manu_Inc4	-.038	.054	-8.484	.025	2.960	293.480	
7	Correlations	Dist_CBD	1.000	-.049	-.138	-.901	-.020	-.032	.025
		Dist_NBD	-.049	1.000	-.076	-.215	-.044	.065	-.009
		Jobs_office_Inc4	-.138	-.076	1.000	.180	.033	-.132	-.484
		Dist_SBD	-.901	-.215	.180	1.000	.056	.018	-.016

		Empl_full_Inc4	-.020	-.044	.033	.056	1.000	.041	-.017	
		Jobs_manu_Inc4	-.032	.065	-.132	.018	.041	1.000	-.031	
		Jobs_retail_Inc4	.025	-.009	-.484	-.016	-.017	-.031	1.000	
	Covariances	Dist_CBD	.005	.000	-.033	-.005	-.006	-.039	.067	
		Dist_NBD	.000	.002	-.012	-.001	-.009	.054	-.016	
		Jobs_office_Inc4	-.033	-.012	11.279	.049	.481	-7.610	-60.902	
		Dist_SBD	-.005	-.001	.049	.007	.020	.026	-.047	
		Empl_full_Inc4	-.006	-.009	.481	.020	18.543	2.991	-2.738	
		Jobs_manu_Inc4	-.039	.054	-7.610	.026	2.991	293.010	-19.626	
		Jobs_retail_Inc4	.067	-.016	-60.902	-.047	-2.738	-19.626	1402.400	
8	Correlations	Dist_CBD	1.000	-.052	-.138	-.901	-.033	-.031	.024	.037
		Dist_NBD	-.052	1.000	-.076	-.214	-.005	.063	-.007	-.083
		Jobs_office_Inc4	-.138	-.076	1.000	.180	.028	-.132	-.484	.006
		Dist_SBD	-.901	-.214	.180	1.000	.051	.018	-.016	.000
		Empl_full_Inc4	-.033	-.005	.028	.051	1.000	.031	-.004	-.418
		Jobs_manu_Inc4	-.031	.063	-.132	.018	.031	1.000	-.031	.014
		Jobs_retail_Inc4	.024	-.007	-.484	-.016	-.004	-.031	1.000	-.028
		Empl_self_Inc4	.037	-.083	.006	.000	-.418	.014	-.028	1.000
	Covariances	Dist_CBD	.005	.000	-.033	-.005	-.011	-.038	.064	.021
		Dist_NBD	.000	.002	-.012	-.001	-.001	.053	-.012	-.032
		Jobs_office_Inc4	-.033	-.012	11.258	.049	.440	-7.590	-60.805	.157
		Dist_SBD	-.005	-.001	.049	.007	.019	.026	-.047	-3.836E-6
		Empl_full_Inc4	-.011	-.001	.440	.019	22.435	2.496	-.628	-15.484
		Jobs_manu_Inc4	-.038	.053	-7.590	.026	2.496	292.502	-19.850	1.928
		Jobs_retail_Inc4	.064	-.012	-60.805	-.047	-.628	-19.850	1400.805	-8.299
		Empl_self_Inc4	.021	-.032	.157	-3.836E-6	-15.484	1.928	-8.299	61.039

Dependent Variable: ACC_CAR_Inc4

Regression Output 8 - Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions								
				(Constant)	Dist_ CBD	Dist_ NBD	Jobs_office_ Inc4	Dist_ SBD	Empl_full _Inc4	Jobs_manu_ Inc4	Jobs_retail _Inc4	Empl_self_ Inc4
1	1	1.840	1.000	.08	.08							
	2	.160	3.387	.92	.92							
2	1	2.747	1.000	.02	.02	.02						
	2	.160	4.138	.59	.63	.00						
	3	.093	5.441	.38	.34	.98						
3	1	2.789	1.000	.02	.02	.02	.01					
	2	.961	1.704	.00	.00	.00	.97					
	3	.158	4.202	.60	.63	.00	.02					
	4	.093	5.483	.37	.34	.98	.00					
4	1	3.723	1.000	.01	.00	.01	.00	.00				
	2	.976	1.953	.00	.00	.00	.93	.00				
	3	.187	4.464	.47	.06	.04	.03	.02				
	4	.098	6.176	.42	.01	.94	.00	.01				
	5	.017	15.016	.10	.93	.01	.04	.97				
5	1	3.831	1.000	.01	.00	.01	.00	.00	.01			
	2	.977	1.980	.00	.00	.00	.92	.00	.01			
	3	.898	2.065	.00	.00	.00	.01	.00	.93			
	4	.179	4.622	.47	.06	.04	.03	.02	.05			
	5	.098	6.267	.42	.01	.94	.00	.01	.00			
	6	.016	15.249	.10	.93	.01	.04	.97	.00			
6	1	3.866	1.000	.01	.00	.01	.00	.00	.01	.00		
	2	1.147	1.836	.00	.00	.00	.37	.00	.02	.39		
	3	.900	2.073	.00	.00	.00	.05	.00	.87	.00		
	4	.796	2.204	.00	.00	.00	.51	.00	.05	.59		
	5	.179	4.647	.46	.06	.05	.03	.02	.05	.00		
	6	.097	6.326	.43	.01	.93	.00	.01	.00	.01		
	7	.016	15.322	.10	.93	.01	.03	.97	.00	.00		
7	1	3.943	1.000	.01	.00	.01	.00	.00	.01	.00	.00	

	2	1.493	1.625	.00	.00	.00	.20	.00	.00	.07	.18	
	3	.936	2.052	.00	.00	.00	.01	.00	.44	.44	.04	
	4	.864	2.136	.00	.00	.00	.01	.00	.50	.46	.03	
	5	.473	2.889	.00	.00	.00	.72	.00	.00	.02	.73	
	6	.178	4.702	.46	.06	.05	.01	.02	.05	.00	.01	
	7	.097	6.390	.43	.01	.93	.00	.01	.00	.01	.00	
	8	.016	15.477	.10	.93	.01	.03	.97	.00	.00	.00	
8	1	4.059	1.000	.01	.00	.01	.00	.00	.01	.00	.00	.01
	2	1.496	1.647	.00	.00	.00	.20	.00	.01	.07	.18	.00
	3	1.269	1.789	.00	.00	.00	.00	.00	.24	.01	.01	.27
	4	.894	2.131	.00	.00	.00	.03	.00	.01	.89	.07	.01
	5	.522	2.789	.00	.00	.00	.00	.00	.71	.00	.00	.70
	6	.472	2.931	.00	.00	.00	.72	.00	.00	.01	.73	.00
	7	.176	4.796	.48	.06	.05	.01	.02	.02	.00	.00	.01
	8	.096	6.493	.42	.01	.93	.00	.01	.00	.01	.00	.00
	9	.016	15.705	.10	.93	.01	.03	.97	.00	.00	.00	.00

Dependent Variable: ACC_CAR_Inc4