

**A GEOSPATIAL INVESTIGATION OF DESTINATION  
CHOICE MODELLING**

THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS  
SYSTEM, CAPE TOWN, SOUTH AFRICA

**J SMITH**

STYJOA002



Submitted in fulfilment of the requirements for the degree of

*Master of Science*

In the Department of Civil Engineering

Faculty of Engineering and the Built Environment

UNIVERSITY OF CAPE TOWN

January 2021

Supervisor: Prof Mark Zuidgeest

The copyright of this thesis vests in the author. No quotation from it or information derived from it is to be published without full acknowledgement of the source. The thesis is to be used for private study or non-commercial research purposes only.

Published by the University of Cape Town (UCT) in terms of the non-exclusive license granted to UCT by the author.

**Declaration**

“I know the meaning of plagiarism and declare that all the work in this document, save for that which is properly acknowledged, is my own. This thesis/dissertation has been submitted to the Turnitin module (or equivalent similarity and originality checking software), and I confirm that my supervisor has seen my report and any concerns revealed by such have been resolved with my supervisor.”

Signed by candidate

---

J Smith

Date: January 2021

## **Acknowledgements**

The year 2020 was unprecedented and unpredictable. COVID-19 brought the world to an abrupt standstill. Not acknowledging the pandemic in this thesis would be to exclude a pivotal point in history, as the worldly systems we were accustomed to are deemed to be affected by this pandemic and its aftermath.

With the Olympic Games initially planned for 2020 and myself being a big fanatic thereof, I deem it adequate to write my acknowledgements for this thesis with subtle references to a sporting race.

A few companies influenced the compilation of this thesis. Firstly, to JG Afrika, thank you for igniting my passion for research and for providing the starting blocks to get me across the starting line. To Jones & Wagener, thank you for your industry-renowned academic prestige – you provided the lines of motivation to keep me inspired and on track. To Tonkin & Taylor, thank you for the international recognition of my career, which encouraged me to complete this study during the most unprecedented year.

Thank you to the City of Cape Town, for gearing me with the MyCiTi Integrated Rapid Transit system data, which made this study possible.

To Prof Mark Zuidgeest, thank you for introducing me to choice modelling and for being a valuable coach. Thank you for your motivation, inputs and for never doubting my capabilities. To Prof Stephane Hess, your celebrated contribution to and passion for the sport of choice modelling is of immeasurable value.

To my sisters, who both successfully crossed the postgraduate finish line before me, thank you for inspiring me to start this race and for completing your degrees so gracefully to motivate me to enter. To my mom and dad, thank you for always being next to the track of every race. You are my biggest supporters, and I would not have been able to finish this study without your encouragement and motivation.

To my husband, thank you for running every step of this race with me. Thank you for picking me up every time I fell and for motivating me never to give up.

The last and most important thank you is to God, for the humble ability to run this race. The only constant in an unpredictable world. Without Him, I am none.

Joanet Smith

## **Abstract**

The transport sector plays an integral role in a country's development and economy. Optimised transport networks and infrastructure can lead to increased economic development. Effective transport networks and public transportation systems are, therefore, essential to growing the South African economy. With an increasing demand for transportation services required by the South African population, the need exists to expand the capacity of local public transport networks. With this need declared, and grants released by the government, a high demand exists for the estimation, analysis, optimisation and forecast of public transport systems in South Africa.

Public transportation studies are directly related to commuter demand as a result of commuter choices. Therefore, a key component for understanding the operational functionality of a public transport system lies in the accurate modelling of commuter choices.

Although the spatial separation of activities forms the essence of travel demand, incorporating the effects of geospatial properties in travel behaviour modelling has only been formally studied in recent years. These recent studies noted a trend proposing that geospatial properties can influence travel behaviour. In the stated research, the need to investigate the effect of geospatial properties on travel behaviour was highlighted. With travel behaviour being the result of commuter choices, a multinomial logit choice modelling study was conducted to investigate the effect of geospatial properties on commuter destination choice for the case of the MyCiTi Integrated Rapid Transit system in Cape Town, South Africa.

# A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING

## THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN, SOUTH AFRICA

<u>CONTENTS</u>		PAGE
1.	INTRODUCTION	8
1.1	Motivation.....	8
1.2	Aims and Objectives .....	9
1.3	Research Approach .....	9
1.4	Thesis Outline .....	11
2.	LITERATURE REVIEW	12
2.1	Transportation.....	12
2.2	Public Transport.....	12
2.3	Public Transport in South Africa.....	12
2.4	The Area of Study .....	14
2.5	Automatic Fare Collection .....	14
2.6	The MyCiTi IRT System .....	15
2.7	Choice Modelling.....	17
2.8	Revealed and Stated Preference Data .....	21
2.9	Geospatial Influence on Travel Behaviour .....	22
3.	THE DATA	24
3.1	MyCiTi IRT Data.....	24
3.2	Origin-Destination Classification.....	27
3.3	Geospatial Data Extension .....	29
3.4	Personal Characteristics .....	41
3.5	Data Summary .....	41
4.	THE CHOICE MODEL	43
4.1	The Objective.....	43
4.2	Model Specification .....	43
4.3	Defining the Attributes .....	44
4.4	Computational Implementation.....	45
4.5	Model Development .....	45
4.6	Model Improvement .....	45
4.7	Model Estimation and Results.....	47
5.	LIMITATIONS AND FUTURE WORK	63
6.	CONCLUSION	64
	REFERENCES	67

## LIST OF TABLES

Table 4-1: Choice Destination Base Model.....	48
Table 4-2: Choice Destination Model, CBD zonification incorporated. ....	49
Table 4-3: Choice Destination Model, CBD zonification shift incorporated.....	53
Table 4-4: Choice Destination Model, land use classification specified.....	55
Table 4-5: Choice Destination Model, land use specified, and CBD zonification shift included for General Business. ....	57
Table 4-6: Model Development Summary.....	59

## LIST OF FIGURES

Figure 1-1: Schematic presentation of the Research Approach.....	10
Figure 2-1: MyCiTi IRT service Standard and Mover fares during peak and off-peak periods for November 2015 (City of Cape Town, 2020).....	16
Figure 2-2: MyCiTi service travel packages (The Transport and Urban Development Authority, 2017).....	16
Figure 3-1: Differentiating between Conventional and Trunk and Feeder Systems (Asian Development Bank, 2008). ....	24
Figure 3-2: Daily recorded AFC transactions for the MyCiTi IRT system in November 2015. ...	26
Figure 3-3: AFC Transaction Sorting. ....	27
Figure 3-4: Search procedure of distance $d$ (Munizaga & Palma, 2012). ....	30
Figure 3-5: MyCiTi IRT stops (Google Earth, 2019).....	31
Figure 3-6: Distance versus displacement (Kenney, 2017).....	31
Figure 3-7: Visual representation of the density count perimeter for the Airport IRT stop (Google Earth, 2019). ....	32
Figure 3-8: Visual representation of the density count perimeters for the various MyCiTi IRT destinations (Google Earth, 2019). ....	33
Figure 3-9: Grouped land use classification for the City of Cape Town (Google Earth, 2019)...	35
Figure 3-10: MyCiTi IRT stops projected on the land use classification for the City of Cape Town (Google Earth, 2019).....	36
Figure 3-11: MyCiTi IRT Stop Land Use Classification. ....	37
Figure 3-12: IRT stop grouped land use classification percentage distribution.....	38
Figure 3-13: Cumulative s-curve presentation of land use rating in terms of the MyCiTi IRT stop distribution.....	39
Figure 3-14: Origin and destination distribution per land use rating. ....	40
Figure 4-1: Choice destination model development. ....	45
Figure 4-2: Model 1 spatial dimension illustration. ....	51
Figure 4-3: Model 2 spatial dimension illustration. ....	52

**List of acronyms and abbreviations**

AFC = Automatic Fare Collection

ASC = Alternative Specific Constant

BRT = Bus Rapid Transit

CBD = Central Business District

DCE = Discrete Choice Experiment

GIS = Geographic Information System

IDP = Integrated Development Plan

IIA = Independence of Irrelevant Alternatives

IRPTN = Integrated Rapid Public Transport Network

IRT = Integrated Rapid Transit

MLE = Maximum Likelihood Estimation

MNL = Multinomial Logit

MSDF = Municipal Spatial Development Framework

OD = Origin-Destination

PTISG = Public Transport Infrastructure and Systems Grant

PTNOG = Public Transport Network Operating Grant

RP = Revealed Preference

RUM = Random Utility Maximization

RUT = Random Utility Theory

SC = Stated Choice

shp = Shapefile

SP = Stated Preference

SPLUMA = Spatial Planning Land Use Management Act

TIC = Transport Information Centre

TOD = Transit-Oriented Development

TTF = Tourism and Transport Forum

### **Glossary of terms**

“Access Act” refers to the Control of Access to Public Premises and Vehicles Act, 53 of 1985.

“Airport Service” refers to the rapid bus service between Cape Town International Airport and the various MyCiTi bus stations in the Cape Town City.

“City” refers to the municipality of the City of Cape Town duly established in terms of the Local Government: Municipal Structures Act, 117 of 1998.

“Conductor” refers to authorised personnel in charge of access control to any smartcard-controlled area.

“Controlled Area” refers to an access-controlled area that cannot be entered without smartcard validation.

“Commuter” refers to any person using the MyCiTi rapid bus service or entering a smartcard-controlled area, excluding any authorised personnel.

“Feeder vehicles” refers to MyCiTi vehicles that run on secondary routes.

“MyCiTi” refers to the MyCiTi rapid bus service, implemented as part of the City of Cape Town’s Integrated Rapid Transit system.

“NLTA” refers to the South African National Land Transport Act, 5 of 2009.

“Smartcard” refers to an electronic Europay-Mastercard-Visa compliant smartcard accepted by the MyCiTi automatic fare collection system.

“Station” refers to an area within a MyCiTi premise designed for the boarding of MyCiTi vehicles (busses) or departing from such vehicles by commuters, through controlled access.

“Stop” refers to a bus stop used for boarding or departing from a MyCiTi vehicle, identified as a MyCiTi Stop by means of a MyCiTi bus stop sign or identified as a MyCiTi Stop by authorised personnel.

“Ticket Controlled Area” refers to an area to which commuters of the MyCiTi system can access with a valid smartcard.

## A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING

### THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN, SOUTH AFRICA

#### 1. **Introduction**

This chapter introduces the framework around which this study was structured. The motivation, followed by the aims and research objectives for this study, are presented. The motivation outlines the problem statement and details the reasoning behind conducting this study. The aims and objectives will summarise the study goals and discuss the approach explored to achieve these. The thesis outline is introduced, and the research approach is discussed.

##### 1.1 **Motivation**

As presented in the literature review of this study, it is widely stated that the quality and quantity of transport infrastructure influences the development and, therefore, the country's economic growth. An urbanisation trend is identified in South Africa where the major metropolitans, the City of Cape Town included, attracts a higher percentage of the population annually. This population increase directly influences the operational structure and workings of local infrastructure and transportation services. With road-based transportation preferred by the South African population for daily commute, continuous upgrades to public transport systems are required to satisfy the increasing demands.

South Africa's government released specific grants as new initiatives to develop Integrated Rapid Public Transport Networks (IRPTNs) in the major metropolitan cities of South Africa. The Department of Transport further aims to implement systems allowing the majority of a metropolitan's population unrestricted access to an IRPTN. The development of the IRPTNs aim to significantly reduce work trips from private cars to public transport networks, ensuring relief by producing uncongested transport in the cities. The City of Cape Town's Municipal Spatial Development Framework's philosophy structures the city's future urban form and function around the MyCiTi IRT stations. The MyCiTi Integrated Rapid Transit (IRT) system is a critical component of the City of Cape Town's transportation network and, therefore, a key focus of published development strategies.

Studies into the estimation, analysis, optimisation and forecasting of passenger demand of IRPTNs are required to develop, expand and improve these transport systems. These studies are directly related to commuter demand as a result of IRPTN commuter choices. A key component for understanding the operational functionality of a public transport system, therefore, lies in the accurate modelling of its commuter choices. Destination choice modelling can be applied to provide insight and an understanding of the factors influencing commuter choice.

The spatial separation of activities is known to form the essence of travel demand and travel patterns. In studies discussed in this research, a trend is noted where it is proposed that built environment properties can impact destination choice and, therefore, travel behaviour. These built environment properties form the foundation of the geospatial properties. Geospatial properties combine location and attribute information (the built environment properties) with temporal information, i.e. actual IRT commuter trip data. The investigation towards the effects of geospatial properties on travel behaviour modelling has only in recent years been formally studied. The need to further investigate this geospatial effect is highlighted and encouraged.

With travel behaviour the result of commuter choices, a choice modelling study is proposed to investigate the effect of geospatial properties on destination choice and travel behaviour. Understanding destination choice and the effect geospatial properties have on this behaviour can provide insight into the operation of IRT systems and IRPTNs. This understanding can lead to specific development and improvement strategies to ensure optimised and efficient IRT systems. Efficient transport systems lead to accessibility, employment and investment growth, increasing economic and social opportunities.

This study's key motivation is to investigate and analyse geospatial properties' significance in destination choice modelling. A geospatial investigation of destination choice modelling for the MyCiTi Integrated Rapid Transit bus system in the City of Cape Town is presented.

## 1.2 Aims and Objectives

A key component to understanding a public transport system's operational functionality lies in accurately modelling its commuter choices. This study is focused on the analysis of commuter destination choices of the MyCiTi Integrated Rapid Transit (IRT) system in Cape Town. This study aims to investigate the significance geospatial properties have on destination choice. A discrete choice approach is applied to explore and analyse various geospatial properties' influence on commuter destination choices. Understanding commuter destination choice behaviour can lead to the development of improved planning and policy strategies to optimise IRT systems and create attractive, integrated, user-friendly Integrated Rapid Public Transport Networks (IRPTN)s. Therefore, the main aim of this study is to identify and investigate geospatial properties that influence commuter destination choice in the MyCiTi IRT system.

This study's main objectives are to develop discrete choice models that identify and analyse the effect geospatial variables have on commuter destination choice.

Sub-objectives of this study include:

- Defining the area of study and exploring the geospatial characteristics unique to this setting.
- Investigating the MyCiTi IRT System, its operational structure and the commuter choice data captured within the system.
- The identification of primary geospatial properties to effectively support the geospatial investigation on destination choice.
- MyCiTi commuter and geospatial data capturing and verification. The combination of multiple data sources allows an accurate, unbiased analysis and adds credibility to this study and the future application thereof.
- The development of a destination choice model by applying the multinomial logit theory to analyse destination choice attributes' coefficients.

This study aims to identify the geospatial factors that contribute to the decision a commuter of the MyCiTi IRT system makes when choosing a destination. Destination choice modelling forms part of trip distribution within the four-stage transportation model. Understanding the destination choice can provide insight into commuter travel behaviour and demand. This insight can help transport engineers, planners, and policymakers optimise IRT systems to create efficient public transportation systems.

## 1.3 Research Approach

A systematic research approach was undertaken for this study, as presented in Figure 1-1. It should be noted that a generalised research approach is presented and that a detailed

description of the approach performed is discussed in the introduction to the various chapters of this study.

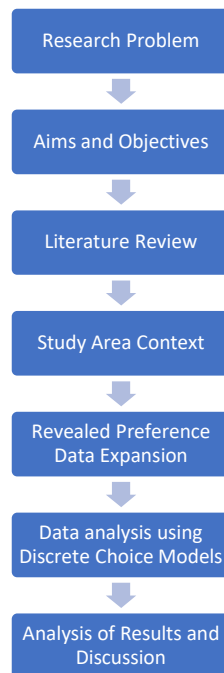


Figure 1-1: Schematic presentation of the Research Approach.

The research problem was defined, subsequently forming the framework for the aims and objectives of this study. A geospatial investigation of destination choice modelling for the MyCiTi Integrated Rapid Transit bus system in the City of Cape Town was presented to explore and analyse geospatial properties' significance in destination choice.

The aims and objectives were developed to address the research problem. The aims defined the study's general goals, and the objectives specified the aspects that required investigation to address the research problem. This study aims to identify the geospatial factors that contribute to the decision a commuter of the MyCiTi IRT system makes when choosing a destination.

The objectives to achieve this study's aim include the development of discrete choice models to identify and analyse the effect geospatial variables have on commuter destination choice.

A literature review is included as the foundation of this study to obtain insight into studies linking to the investigation of geospatial properties in destination choice modelling. An understanding of the application of destination choice models is required. A thorough investigation into the MyCiTi IRT system's operational workings as a primary focus of this study is required.

The exploration into the City of Cape Town as a study area is required to identify critical geospatial properties that will form the basis of application and analysis. Revealed preference actual commuter data from the Cape Town MyCiTi IRT system was sourced for this study. This automatic fare collected data is aimed to be expanded by complementary geospatial datasets to create a substantial set of data required for an effective choice modelling study.

Model development aims to create an accurate choice model to investigate the effect of geospatial properties on destination choice for the MyCiTi IRT system. The choice model is

estimated using *Apollo* (Hess & Palma, 2019), a software package developed explicitly by Hess & Palma for choice model estimation. The results are analysed and discussed, and recommendations are focused on transportation planning and policy applications.

#### **1.4 Thesis Outline**

This study is structured to introduce the reader to the application of choice modelling in transport systems. Exploration of the choice modelling theories gives insight into the fundamentals applied in this study. The reader is introduced to the City of Cape Town as the study area where the MyCiTi Integrated Rapid Transit system forms a crucial core of the City's transportation network. The dataset is defined, and the model development is explored. The estimation of the various choice models developed is continuously presented. This study's limitations are noted, and finally, the conclusion and research recommendations are reported.

## **2. Literature Review**

Forming this study's foundation, this chapter documents the investigation into destination choice models conducted in literature. The literature review provides valuable insight to studies linking to the investigation of geospatial properties in destination choice modelling. This chapter introduces the City of Cape Town as the area of study and the MyCiTi Integrated Rapid Transit system as a critical component of its transportation network. This chapter gives insight into the MyCiTi transportation system's operational workings to provide a framework for the analysis thereof.

### **2.1 Transportation**

Throughout history, economic growth has been linked to the mobility of people and freight. Rodrigue et al. (2017) state that a clear relationship exists between the quality and quantity of transport infrastructure and the development of a country. Efficient transport systems lead to accessibility, employment and investment growth, which subsequently increase economic and social opportunities. Inefficient systems, on the other hand, can lead to missed economic opportunities and substantial losses to an economy. With its diverse infrastructure usage, the transport sector plays an integral role in a country's development and economy. Optimised transport networks with densified transportation infrastructure can, therefore, lead to increased economic development (Rodrigue, et al., 2017).

### **2.2 Public Transport**

The Tourism and Transport Forum (TTF) (2010) states that public transport promotes investment due to its social, economic and environmental benefits. The social benefit of public transportation includes the provision of access to education, employment, health services and recreational facilities. It operates as a connecting point between the public and vital services and goods. TTF proclaims that public transport acts as a vehicle for social cohesion between the diverse demographics in society (Tourism & Transport Forum Australia, 2010). Public transport provides the connection between wealth and labour; it maximises opportunities for individuals and businesses alike. In major urban areas, public transport is the key to economic connectivity. TTF (2010) explains that as an alternate means of travel to the private vehicle and being less resource-intensive, public transport plays a vital role in reducing congestion and the carbon emissions footprint, especially in major metropolitan cities. To harness the full social and economic potential of public transport, continuous investment into transport infrastructure and services, as well as the optimisation of existing services are required (Tourism & Transport Forum Australia, 2010). TTF (2010) states that commuters should be encouraged to select public transport as their preferred mode of choice, and it should therefore be a priority for authorities to create attractive, integrated, user-friendly public transport networks.

If transport is deemed a catalyst in economic development, public transport can be signified as the momentum to this catalyst.

### **2.3 Public Transport in South Africa**

A study done by van Ryneveld (2014) on South Africa's public transport system noted that a gradual trend of urbanisation is seen in South Africa, with major metropolitans attracting a higher percentage of the population annually. It was further stated that an increase in population directly influences these metropolitans' operational structure and workings. Continuous upgrades are therefore required to satisfy the increasing demands of infrastructure and transportation services. Transport systems, therefore, shape urban growth by guiding spatial diversification and population settlement (van Ryneveld, 2014).

Metropolitan municipalities currently govern eight of the largest cities in the Republic of South Africa (Government of South Africa, 2019). These metropolitans include the City of

Cape Town, Nelson Mandela Metropolitan Municipality (Port Elizabeth), Buffalo City (East London), City of eThekweni (Durban), Mangaung Municipality (Bloemfontein), Ekurhuleni Metropolitan Municipality (East Rand), City of Johannesburg and City of Tshwane (Pretoria).

Statistics from the six main metropolitans in South Africa (excluding Buffalo City and Mangaung Municipality) as reported by the South African National Household Travel Survey(s) of 2003 and 2013 (Statistics South Africa, 2013), indicates that road-based transport usage has shown an increase of 51.4% over these ten years. A curious observation notes that South Africa's population has only grown by 27.3% during the same period (van Ryneveld, 2014). The 2013 survey also indicated a preference of local households: 68.8% use taxi services, 21.1% use commuter bus services and only 9.9% use commuter rail services daily (Statistics South Africa, 2013). A trend is identified in the South African population to prefer road-based transportation for daily commute, adding to the demand of the public transport systems.

An interesting but alarming finding was noted in the South African National Household Travel Survey of 2013 where commuters stated that they tend to wait longer for public transport (train, bus and taxi services) in urban and metropolitan households than when compared to the initial survey done in 2003 (Statistics South Africa, 2013). The National Land Transport Transition Act (Act No. 22 of 2000) introduced the process of transforming and restructuring the South African National Transportation System. This process aims to provide affordable public transport to the nation and subsequently address the continuous demand for transportation. The implementation of the National Land Transport Act (Act No. 5 of 2009) followed the transformation process initiated by the Transition Act.

The Department of Transport released a Public Transport Strategy and Action Plan in 2007, intending to create car-competitive public transport options (Department of Transport, 2007). The target of this strategy was to implement a public transport operating system in twelve main South African cities by 2014. The long-term vision for the year 2020 was to implement a system to allow 85% of a metropolitan's population access within 1 km to an Integrated Rapid Public Transport Network (IRPTN). These IRPTNs would constitute trunk (road and rail) or feeder (road) corridors (Browning, 2017). This strategy would result in significantly reducing work trips from private cars to public transport networks, ensuring relief by producing uncongested transport in cities and districts. Browning (2017) notes that a serious investigation into the analysis of local transportation services is required to meet the current and future transportation strategies in South Africa. This concern is also raised by van Ryneveld (2014), stating that a significant need exists to study the operation of public transportation systems (with regards to travel times, cost of transportation, availability of public transport, road conditions and commuter safety) in South Africa (van Ryneveld, 2014).

In van Ryneveld's study (2014), it is furthermore noted that the South African government spent an estimated R133.57 billion over five financial years between 2012/2013 and 2016/2017 on public transport. This expenditure included capital and operating expenses. Of this spending, 21.6% was shared between the Public Transport Infrastructure and Systems Grant (PTISG) and Public Transport Network Operating Grant (PTNOG) (van Ryneveld, 2014). These grants are stated as new initiatives by the government to develop Integrated Rapid Public Transport Networks in the major metropolitan cities of South Africa. The expenditures were mainly applied to new road-based bus rapid transit projects, including the MyCiTi Integrated Rapid Transit bus service in Cape Town and the Rea Vaya Integrated Rapid Transit bus service in Johannesburg (van Ryneveld, 2014).

The City of Cape Town released a Municipal Spatial Development Framework (MSDF) in 2017, which incorporates the City's Integrated Development Plan (IDP) and Spatial Planning Land Use Management Act (SPLUMA) (City of Cape Town, 2017). This MSDF

aims to transform the fragmented urbanisation, where citizens are disconnected from economic opportunities and local economic investment. Transformation is proposed within this MSDP by a Transit-Oriented Development (TOD) philosophy. This philosophy is expected to structure the future urban form and function of the City of Cape Town around the MyCiTi IRT stations (City of Cape Town, 2017).

Transport and the need for public transportation are essential to the South African economy. With a stated road-based transportation preference and increasing demand for transportation services required by the South African population, the need exists to expand the capacity of local public transport networks. Public transport systems increase investment opportunities due to their economic, environmental and social benefits. With this need declared and funding being accrued, a high demand exists for the estimation, analysis, optimisation and forecast of public transport systems in South Africa. These studies are directly related to commuter demand as a result of commuter choices. Therefore, a key component for understanding the operational functionality of a public transport system lies in the accurate modelling of its commuter choices.

## **2.4 The Area of Study**

After almost two decades into democracy, many South African cities are still found segregated due to the residue of apartheid spatial planning (Thompson, 2017). Thompson (2017) states that the lack of infrastructure and access to adequate transport systems are among the biggest dividers that continue to contribute to segregation in the City of Cape Town.

The United Nations estimated a population of 3.78 million inhabitants in 2018 for the City of Cape Town (United Nations, 2018). This City boasts a heterogeneous population diversification with low- and high-income neighbourhoods and is the most traffic-congested city in South Africa (City of Cape Town, 2019). With the release of the City of Cape Town's Municipal Spatial Development Framework, the critical need to connect the city's citizens to economic opportunities and local economic investment was raised. The City of Cape Town (2017) stated that the existing MyCiTi Integrated Rapid Transit (IRT) system would form the basis of the initiated Transit-Oriented Development (TOD) philosophy. Furthermore, the City of Cape Town's future urban form and function will be structured around this transportation system (City of Cape Town, 2017).

The MyCiTi IRT system can be developed to counter the current segregation found in the City of Cape Town. Studies propose that geospatial properties can impact travel behaviour (Hammadou, et al., 2008) and, therefore, the MyCiTi IRT system's operation. By investigating the effect geospatial properties have on commuter choices, insight might be provided on how the MyCiTi IRT system can be developed to meet commuter demand and accelerate the aimed diversification of the City of Cape Town. Understanding travel behaviour and the effect geospatial properties have on the operation of the MyCiTi IRT system can unfold significant stated economic, environmental and social value for the City of Cape Town.

## **2.5 Automatic Fare Collection**

Smartcard payment systems have become increasingly popular since their incorporation in the late 1990s as a method of collecting transport service fares. Smartcard payment systems are referred to as automatic fare collection systems. Automatic fare collection (AFC) systems are a recent popular method of obtaining commuter data (Munizaga & Palma, 2012). The Oyster card smartcard payment system was implemented in London in 2003 and is currently the most popular fare payment method. Other popular cities and countries that have implemented smartcard payment possibilities for their transport systems include Chicago, San Francisco, Portland, New York, The Netherlands, Changchun and

Quebec (Munizaga & Palma, 2012). AFC data was applied in the destination choice modelling study done by Cai et al. (Cai, et al., 2015).

Additional to the benefit of capturing commuter travel data, AFC systems result in efficient fare collection. No time is wasted to calculate the trip charge, for commuters to find cash or to receive change when using the system (City of Cape Town, 2020). The City of Cape Town resonates with the international smartcard payment system and only allows this smartcard payment option in the MyCiTi Integrated Rapid Transit bus system (MyCiTi, 2018).

## 2.6 The MyCiTi IRT System

The City of Cape Town has a stated increasing transportation demand to satisfy, with limited space to do so (Statistics South Africa, 2013). This traffic-congested city reported a preference for road-based transportation (including private vehicles and public transport) with an average of 1.9 passengers per vehicle in 2013 (Statistics South Africa, 2013). 95% of public transport users are in the low to low-middle income brackets (City of Cape Town, 2019). The National Household Travel Survey (2013) reports that a distinct general trip pattern is found with a large portion of the population heading from the suburbs to the city centre in the mornings and returning in the opposite direction in the evenings (Statistics South Africa, 2013). It is expected that this phenomenon is due to the residual segregation of Capetonians.

Significant congestion is found in the City of Cape Town with vehicles contributing to the rising carbon emissions levels polluting the local air. MyCiTi (2018) states that the MyCiTi Integrated Rapid Transit (IRT) bus system is prioritising public transport and lowering the carbon footprint. The MyCiTi busses were introduced to the City of Cape Town in 2011, complying with the Euro 4 emissions standard (MyCiTi, 2018). Even smaller busses were introduced to the system in December 2012, complying with the stricter Euro 5 emissions standard. Special additives are added to the diesel fuel used in the MyCiTi busses to reduce emissions further and lower the system's environmental impact (MyCiTi, 2018).

In 2018, the MyCiTi IRT system had 760 bus stops and 42 stations located dispersedly in the City of Cape Town (MyCiTi, 2018). This IRT system serves as the connection between rail, air and road networks and is therefore classified as a multimodal system. 32 km of road has been dedicated to the MyCiTi IRT system (City of Cape Town, 2019). Apart from reducing congestion in the City and lowering carbon emissions, advantages of using the MyCiTi service include reliability (90% of busses arrive on time), affordability when compared to other public transport services and commuter-friendly service (ease of use). The MyCiTi IRT system is stated as dynamic, and changes are regularly incorporated to increase efficiency and meet passenger demand (MyCiTi, 2018).

The *Your MyCiTi Guide* published by MyCiTi (2018) describes the operational workings of the MyCiTi IRT system. Each commuter who wants to use the MyCiTi rapid bus networks needs to possess a valid smartcard (the *myconnect* card) to be used as payment method. This smartcard is the only payment method used by the MyCiTi IRT service. A *myconnect* smartcard can be bought at any MyCiTi station kiosk or participating retailers for R35 and needs to be pre-loaded with Rands value to travel. Children less than 1 metre tall or under four years of age do not require a card and can travel free when accompanied by an adult. The *myconnect* card is issued with a required pin whenever Rands value is loaded onto the smartcard. By accepting this smartcard, the user accepts all respective MyCiTi rules. Commuters using the MyCiTi IRT system once-off can buy single-trip cards from selective station kiosks or vending machines for R30, or R100 including the Airport route. Single-trip smartcards are non-refundable and are valid for one journey only, anywhere on the system, including any transfers (The Transport and Urban Development Authority, 2018).

Money can be loaded onto the *myconnect* smartcard for *Standard fares* or *Mover fares*. Mover fares differ from standard as a commuter can save up to 30%, as shown in Figure 2-1. Discounted fares apply to journeys outside the weekday peak periods from 06:45-08:00 and 16:15-17:30. Commuters can engage in additional savings when loading *travel packages* onto their smartcard, as presented in Figure 2-2.

Distance	Standard Peak	Standard Off-peak	Mover Peak	Mover Off-Peak
0-5 kms	R11.50	R7.80	R8.20	R5.50
5-10 kms	R13.30	R9.80	R9.40	R6.90
10 – 20 kms	R17.80	R12.50	R12.60	R8.80
20 – 30 kms	R19.80	R14.80	R13.90	R10.40
30 – 40 kms	R21.00	R16.50	R14.80	R11.60
40 – 50 kms	R24.60	R19.40	R17.40	R13.70
50 – 60 kms	R27.70	R22.00	R19.50	R15.50
60 kms plus	R30.20	R24.10	R21.30	R17.00
*Airport premium	R61.40	R61.40	R50.00	R44.20

\*The Airport premium is charged in addition to the distance-based fare when you tap in or out at the Airport station.

Figure 2-1: MyCiTi IRT service Standard and Mover fares during peak and off-peak periods for November 2015 (City of Cape Town, 2020).

	REGULAR USE			OCCASIONAL USE	
	Standard	Mover	Monthly Pass	Off-Peak Travel	Day Pass
<b>Ideal for</b>	Fares and making small purchases	Cost-effective, regular travel	Cost-effective, regular travel over long distances	Exploring the city on weekends and public holidays	Exploring at any time, on any day
<b>Load</b>	Any amount (load fees apply)	Mover packages (R35, R50, R60, R80, R100, R150, R200, R300, R400, R600)	Monthly Pass (R850)	OPT1 (R41) OPT3 (R118) OPT7 (R221)	One-day (R97) Three-day (R243) Seven-day (R533)
<b>Valid for</b>	3 years	3 years	1 month from a date of your choice	1, 3 or 7 consecutive calendar days	1, 3 or 7 consecutive calendar days
<b>Fares</b>	Standard fares apply	Mover fares apply (save up to 30%)	Unlimited travel anywhere, at any time	Unlimited travel (except Airport) during the off-peak*	Unlimited travel (except Airport) at any time*
<b>Get it at</b>	Station kiosks, retailers, Absa cash-accepting ATMs	Station kiosks, retailers, Absa cash-accepting ATMs	Station kiosks	Station kiosks	Station kiosks

Figure 2-2: MyCiTi service travel packages (The Transport and Urban Development Authority, 2017).

The MyCiTi smartcard is explained as a debit card system that transforms Rands value into MyCiTi IRT bus travel; different products can be loaded simultaneously and used as

required. The MyCiTi bus route map is presented in Appendix A with every route numbered. A commuter may need to travel two or more routes to reach a destination. Every MyCiTi IRT system stop and station is named. Commuters can change between routes at the IRT stops and stations. A *Trip Planner* is available to commuters to calculate the optimal required route and bus times (MyCiTi, 2018).

When entering a MyCiTi bus station, the commuter must hold their *myconnect* smartcard against a validator. This procedure is referred to as a *tap-in*. When the commuter accesses the MyCiTi system from a bus stop, the same *tap-in* procedure must be followed upon entering the bus. When a commuter exits the MyCiTi system, a *tap-out* is required by following the same procedure. However, when a commuter exists the MyCiTi system at a bus station, they do not *tap-out* when exiting the bus but do so when departing from the station. It is in the commuter's interest to *tap-in* and *tap-out* as obligated to avoid penalties being charged to their smartcard (MyCiTi, 2018).

Commuters changing from one route to another will only pay one transport fare. When a commuter *tap-out* at and *tap-in* again within 45 minutes, their journey will be continued without additional fare charges. The commuter will proceed from one bus to another without any *tap* procedure to change busses within a station. After a *tap* procedure, a green light shining around the validator screen with one beep confirms that the transaction was successful. A yellow light shining around the validator screen with two beeps states that the transaction was successful but warns the commuter that their smartcard has less than R20 funds left and that they should recharge their *myconnect* cards. A red light shining around the validator screen with five beeps indicates that the transaction was unsuccessful. This informs the commuter that there were not sufficient funds available on the smartcard or that there might be an additional error. When the commuter *tap-in*, the system registers that the commuter has entered the MyCiTi system. The origin 1<sup>st</sup> boarding stop is recorded. Only on *tap-out* does the system calculate the respective fare and deducts it from the Rands value found on the smartcard in either money value or *mover points*. The destination alighting stop is subsequently recorded. The system is programmed to register and apply special packages automatically. Penalties will be charged when insufficient money value is available on the smartcard upon trip completion, when a commuter fails to *tap* in or out or when a commuter *tap* the wrong validator. First two penalties are charged at R15 each, after that R30. A penalty on the Airport route costs R117. Information terminals are located at specific stations where *myconnect* balances can be checked, and statements can be enquired. There are assistants on duty for commuter support at the Transport Information Centre (TIC) (The Transport and Urban Development Authority, 2017).

This thorough introduction into the MyCiTi IRT system's operational workings gives insight into the system characteristics and automatic fare collection (AFC) process. This AFC process captured the MyCiTi commuter specific data discussed in the succeeding chapters and will serve as input to the destination choice models explored.

## 2.7 Choice Modelling

To understand why an individual behaves in a certain way, Louviere et al. (2003) assert that an understanding is required of the reasoning behind the individual's behaviour. Individual behaviour holds the key to understanding the need that exists and can guide in addressing an underlying demand (Louviere, et al., 2003). Addressing a demand can be economically beneficial, as expressed in Section 2.3. Understanding and predicting individual behaviour can therefore unfold significant economic value. Louviere et al. (2003) describe individual behaviour as a result of the individual's choices. Choice making is a universal activity that can be simplified in the statement of supporting one outcome and rejecting others (Louviere, et al., 2003)

Nobel Laureate Daniel McFadden (2000) discussed that choice survey data and the availability thereof has been increasingly available from the 1960s with the evolution of the digital age. With the technology available to analyse surveyed data, a need was identified to interpret and explain the reasoning behind this accessible data (McFadden, 2000). The necessity to interpret and explain individual choices led to the development of discrete choice models. In 1912, American economist and educator Frank Taussig declared an object as valueless, unless this object consisted of a utility giving weight to the statement that this object will maximise the consumer's self-interest (McFadden, 2000).

McFadden (2000) further explored this self-interest theory in various choice behavioural studies, where he stated that similarities exist between the demand for travel and applications such as location choices, demand for goods and education. These studies led to the adoption of the Random Utility Maximization (RUM), Independence of Irrelevant Alternatives (IIA) and the Multinomial Logit (MNL) models and the application thereof in choice behaviour studies (McFadden, 2000).

The concept of choice in behavioural modelling stems from this theory of Random Utility Maximisation which proposes that an individual would choose an alternative that provides the highest form of satisfaction (McFadden, 2000). This theory is known as the Random Utility Theory (RUT) and led to the development of random utility models. Discrete choice models are derived from these random utility models (Cascetta, 2001).

Casetta (2001) explored the evaluation of transport systems and stated that the demand for transportation results from the collection of individual commuter trips. Each trip made by a commuter is stated as the result of several choices. Each choice is defined by the availability of alternatives, decision procedures and evaluation factors, known as the choice dimension (Cascetta, 2001). It is further stated that choices concerning transport demand are, in most cases, made among a finite number of discrete alternatives. Mathematical models derived from the Random Utility Theory is the most widely used and richest theoretical paradigm to simulate transport choices and, therefore, choices among discrete alternatives (Cascetta, 2001).

### 2.7.1 Random Utility Theory

Choice theory dictates that an individual will make a decision based on whichever alternative gives them the most significant benefit. The benefit to the individual is explored as a utility, and this theory is known as the Random Utility Theory (RUT). The hypothesis of the Random Utility Theory states that an individual is a rational decision-maker who will maximise the utility, and therefore benefit, relative to their choices (Cascetta, 2001).

The Random Utility Theory forms the fundamental basis of discrete choice modelling as utility is based on attributes that impact behaviour, i.e. choice. Cascetta (2001) notes that the popularity of the RUT results from allowing negative attributes to be compensated by positive ones. It is further stated that this theory enables the specification of various models with broad functional forms to be applied to various contexts. An adequately specified random utility model has proven to accurately approximate the choice probabilities obtained with non-compensatory models (Cascetta, 2001).

This study directly references the Random Utility Theory as explored by Hess et al. (2018), where the theory's basic properties were reviewed to explain the pre-eminence of utility maximisation (Hess, et al., 2018).

An individual  $n$  assigns to each alternative  $j$  (with  $j = 1, \dots, J$ ) from the choice set a utility,  $U_{j,n}$ . The alternative selected is the one that yields the utility maximised.

The utility of a choice cannot be observed but comprises two elements. The first component is deterministic and a direct function of the alternative's attributes and the individual's characteristics. The second component is the unobserved random error term.

The general utility function for an alternative in a binary choice situation  $t$  is given by Equation 2-1:

$$U_{j,n,t} = V_{j,n,t} + \varepsilon_{j,n,t}$$

Equation 2-1

Where:

$V_{j,n,t}$  is the observed deterministic characteristics of the attributes relative to individual  $n$  and alternative  $j$  for choice situation  $t$  vectorised.

$\varepsilon_{j,n,t}$  is the unobserved, random error function of the utility for choice situation  $t$ .

The observed vector of the utility is further comprised of variables and individual characteristics:

$$V_{j,n,t} = V(X_{j,n,t}, S_{j,n,t})$$

Equation 2-2

With:

$X_{j,n,t}$  the function of the deterministic identified variables of the alternative for choice situation  $t$ .

$S_{j,n,t}$  the characteristics of the individual for choice situation  $t$ .

The density for each unobserved component of utility is expressed (Train, 2003):

$$f(\varepsilon_{j,n,t}) = \exp^{-\varepsilon_{j,n,t}} \exp(-\exp^{-\varepsilon_{j,n,t}})$$

Equation 2-3

With the cumulative distribution:

$$F(\varepsilon_{j,n,t}) = \exp(-\exp^{-\varepsilon_{j,n,t}})$$

Equation 2-4

and the variance of the distribution being  $\frac{\pi^2}{6}$ . By assuming this, we have normalised the utility scale.

If  $\varepsilon_{j,n,t}$  and  $\varepsilon_{i,n,t}$  are independent and identically distributed (IID) values, then

$\Delta\varepsilon_{ji,n,t} = \varepsilon_{j,n,t} - \varepsilon_{i,n,t}$  has a logistic distribution i.e.

$$F(\Delta\varepsilon_{ji,n,t}) = \frac{\exp^{\Delta\varepsilon_{ji,n,t}}}{1 + \exp^{\Delta\varepsilon_{ji,n,t}}}$$

Equation 2-5

It is not possible to predict which alternative will be chosen by an individual in a specific choice situation. It is, however, possible to express the probability of the individual choosing

an alternative for the specific choice situation, as the perceived utility of the chosen alternative is more significant than all other available options. The probability of choosing an alternative directly corresponds to the utility.

From the set of alternatives  $j = 1, \dots, J$ ; the probability of person  $n$  choosing alternative  $i$  in choice situation  $t$  is (Train, 2003):

$$\begin{aligned}
 P_{i,n,t} &= \text{Prob}(U_{i,n,t} > U_{j,n,t} \forall i \neq j) \\
 P_{i,n,t} &= \text{Prob}(V_{i,n,t} + \varepsilon_{i,n,t} > V_{j,n,t} + \varepsilon_{j,n,t} \forall i \neq j) \\
 P_{i,n,t} &= \text{Prob}(\varepsilon_{j,n,t} - \varepsilon_{i,n,t} < V_{i,n,t} - V_{j,n,t} \forall i \neq j) \\
 P_{i,n,t} | \varepsilon_{i,n,t} &= \prod_{j \neq i} \exp^{-\exp^{-(\varepsilon_{i,n,t} + V_{i,n,t} - V_{j,n,t})}} \\
 P_{i,n,t} | \varepsilon_{i,n,t} &= \int \left( \prod_{j \neq i} \exp^{-e^{-(\varepsilon_{i,n,t} + V_{i,n,t} - V_{j,n,t})}} \right) \exp^{-\varepsilon_{i,n,t}} \exp^{-\exp^{-\varepsilon_{i,n,t}}} d\varepsilon_{i,n,t}
 \end{aligned}$$

Equation 2-6

### 2.7.2 The Multinomial Logit Model

The multinomial logit (MNL) model is a basic random utility model first derived in 1959 by McFadden (McFadden, 2000). The multinomial distribution is stated as a generalisation of the binomial distribution. McFadden started investigating the specification of choice behaviour in 1962, with a focus on production functions. In 1965 his applications broadened into the economic decision making in the setting of a transport freeway system. McFadden aimed to devise a model that yielded choice probabilities for alternatives in a feasible finite set. These early works supported the further development of the MNL model with random utility maximization foundations (McFadden, 2000).

If the random error functions are distributed independently and identically (IID) and follow the Gumbel distribution, the multinomial logit (MNL) model proposed by McFadden (McFadden, 1974) is obtained. In the MNL choice model, the probability of choice for alternative  $i$  can be expressed as (Hess & Palma, 2019):

$$P_{i,n,t} = \frac{\exp^{V_{i,n,t}}}{\sum_{j=1}^J \exp^{V_{j,n,t}}}$$

Equation 2-7

In discrete choice models, the level of utility is unobserved and therefore irrelevant to the individual decision-maker and the analyst. Adding a constant to the utility of all alternatives will not change the outcome of which alternative retains the highest utility. The significance of choice modelling is found in the *change* defined as the differential analysis of the utility. Only parameters that can be estimated can therefore capture the differences across alternatives (Hess & Palma, 2019).

By specifying various attributes, the individual's indirect utility for a choice alternative can be modelled. Alternative-specific constants (ASC) can be applied to specify labelled choice attributes. The ASC is generally added to utility equations to represent the average effect of all factors that influence the choice which has not been included in the base utility function

(Koppelman & Bhat, 2006). The inclusion of the alternative specific constant in Equation 2-1 can be defined as:

$$U_{j,n,t} = ASC + V_{j,n,t} + \varepsilon_{j,n,t}$$

Equation 2-8

Equation 2-8 results in the model specification of the attributes relative to individual  $n$  and alternative  $j$  for choice situation  $t$ .

As only differences in utility matter, the same applies to the ASC's. For every alternative in a specific choice situation, the ASC represents the mean of the difference between the unobserved factors in the error term of one alternative and that of a randomly selected base case (Hensher, 1987). Huybers (2004) states that incorporating ASCs in model specification can help achieve compliance with the assumption of independence of irrelevant alternatives (IIA) in the MNL model. The IIA property, which is associated with the independence characteristic of the IID assumption, implies that the relative choice probabilities between any two alternatives of a specific choice set are not affected by the inclusion or exclusion of other alternatives in that set (Huybers, 2004).

The estimation of a discrete choice model outputs the estimated effects of attributes on the utility of the alternatives and, therefore, on the probability of choice. The model results can subsequently be used to interpret the marginal rate of substitution between attributes (Huybers, 2004). Disaggregate choice models are commonly MNL models, which predict the shares of the specified alternatives (Hensher, et al., 2005).

Three primary assumptions dictate the application of MNL models. The first assumption is that the random elements of the alternatives' utilities are independent and identically distributed (IID) with a Type I extreme value (Gumbel) distribution (Train, 2003). This independence states that no unobserved factors are dictating the utilities of the alternatives. If an unobserved factor exists, it is assumed that the effect on utility is the same across all alternatives. It is assumed that the error for one alternative provides no information about the error of another alternative (Train, 2003). Train (2003) states that the aim is to have the utility well specified so that the logit model is appropriate. As stated, by incorporating ASCs in the model specification where labelled alternatives are present can assist in achieving compliance with the assumption of independence of irrelevant alternatives (IIA) in the MNL model (Huybers, 2004).

The second assumption is that the MNL model does not allow for preference to an alternative due to unobserved individual characteristics. All individuals maintain homogeneity in responsiveness to the attributes in the alternatives (Bhat, 2002).

The MNL model's third assumption dictates that the error variance-covariance structure of alternatives is identical across all individuals (Koppelman & Bhat, 2006). This is an assumption of error variance-covariance homogeneity. It is assumed that there is no unobserved variable between alternatives.

## 2.8 Revealed and Stated Preference Data

The majority of discrete choice applications is currently based on stated preference (SP) or stated choice (SC) data (McFadden, 2000). The stated data can include hypothetical choice scenarios. Respondents are faced with multiple choice situations, and more information is acquired from the respondent. The analyst can, therefore, specify attributes and attribute levels (McFadden, 2000). Stated preference surveys can be less expensive than the collection of actual data. McFadden (2000) states that the advantages of stated choice surveys lie in the inclusion of alternatives that do not exist yet, and personal information on

a choice situation. Due to the hypothetical contexts, disadvantages of stated preference include realism and the limitation of attributes (McFadden, 2000).

McFadden (2000) noted that revealed preference (RP) data is primarily applied in the application of transport systems and is obtained from observed choices. Revealed preference data can be automatically captured by means of smartcard, GPS and camera systems. Advantages of RP data includes that it contains actual data, i.e. real choices made. The disadvantages of RP data consists of the unstudied choice context. Limited information may be present on the choice availabilities, unchosen alternatives and responded characteristics (McFadden, 2000). The unstudied choice context can be captured with SC surveys.

Revealed preference observational surveys represent factual travel and demographic attitudes and opinions (Stopher & Banister, 1985). Stopher & Banister (1985) noted trip logs to be the best means for obtaining travel information, as commuters do not give personal input that might recall typical behaviour rather than an accurate record of data. The use of existing revealed preference survey data allows the application of the most cost-effective, unbiased quality data.

The application of SC surveys is popular in the transportation and planning sector. These surveys lead to the capturing of valuable data to assess choice behaviour when a new development is introduced or when a substantial change in attributes are found (Louviere, et al., 2003). The results of SP surveys are popularly used to build models aimed at predicting future travel behaviour and tend to be multinomial or nested logit models, which can be based on the economic theory of individual utility maximization (Hensher, et al., 2005).

Hensher et al. (2015) state that a combination of revealed and stated preference data is more commonly used in recent years (Hensher, et al., 2015). It is worthy to note that a study based only on the analysis of RP data will limit the application thereof for future planning purposes.

## **2.9 Geospatial Influence on Travel Behaviour**

Hammadou et al. state that the analysis of travel demand is intrinsically spatial and that the spatial separation of activities forms the essence of this demand (Hammadou, et al., 2008). Although this statement is self-evident, incorporating the effects of geospatial properties in travel behaviour modelling studies has only been formally considered in recent years.

Axhausen and Gärling reviewed the conceptualisations of activity scheduling and activity-based models to analyse travel behaviour (Axhausen & Gärling, 1992). The principles of utility maximization were applied to investigate travel behaviour. Badoe and Miller (2000) reviewed the impact of land use policies and urban densities on the transportation system in North America. They found that data and methodological limitations led to mixed conclusions (Badoe & Miller, 2000).

Ewing and Cervero found trip lengths to be a primary function of the built environment, with the built environment referring to land use activities (Ewing & Cervero, 2001). Handy et al. (2005) queried if cities can use land use policies to bring residents closer to destinations and subsequently provide viable, sustainable alternatives to personal vehicle usage. They found that travel behaviour and the built environment showed significant associations (Handy, et al., 2005).

Stead stated that land use planning might have a significant impact on travel patterns, although these patterns often owe more to socioeconomic reasons than to land-use characteristics (Stead, 2001). Bhat and Zhao noted that travel demand analysis is fundamentally spatial, yet spatial analysis considerations are rarely recognised or included in travel modelling (Bhat & Zhao, 2002). Hammadou et al. explored the incorporation of the

spatial dimension on destination choice models with a focus on Antwerp (Hammadou, et al., 2008).

In the stated research, a trend is noted where the conclusions of the studies align in proposing that built environment properties such as land use can have an impact on travel behaviour. These built environment properties are redefined as geospatial properties. The need to investigate the effect of geospatial properties on travel behaviour is highlighted and encouraged. With travel behaviour the result of commuter choices, a choice modelling study is motivated for the geospatial investigation of destination choice for the MyCiTi IRT system in Cape Town. Understanding commuters of the MyCiTi IRT system's travel behaviour and the effect geospatial properties have on this behaviour can unfold significant economic, environmental and social value for the City of Cape Town.

### 3. THE DATA

This chapter introduces the data analysed to investigate the effect of geospatial properties on travel behaviour. Actual commuter data from the Cape Town MyCiTi IRT system was acquired for this study. The automatic fare collected data was in itself inadequate to form a modelling study and was therefore expanded with complementary geospatial datasets to create a substantial set of data, satisfactory for a choice modelling study. The various geospatial properties investigated in this study as applicable to the introduced MyCiTi IRT system are presented. The combination of multiple data sources allows an unbiased analysis and adds credibility to this study and the future application thereof.

#### 3.1 MyCiTi IRT Data

A trip is defined as movement from a point of origin to a point of destination (de Dios Ortúzar & Willumsen, 2011). A trip can have one or more legs (segments), defined as the movement between different trip routes. 1st boarding (the origin) is defined as where the trip begins, alighting (the destination) as to where the trip ends (Munizaga & Palma, 2012). For the MyCiTi Integrated Rapid Transit (IRT) bus system introduced in Section 2.6, a connection is defined as a transfer between two bus routes, i.e. two trip legs.

The City of Cape Town has been collecting smartcard data from the MyCiTi IRT system since introducing its busses in 2011 through automatic fare collection (AFC). This AFC data is classified as revealed preference data. The MyCiTi system is classified as a trunk-feeder system as presented in Figure 3-1, comprising of 42 routes, each serving a specific part of the city. As discussed previously in Section 2.6, the system comprises only of bus transportation with fares collected through smartcard payment. When a commuter *tap*-in, a maximum transit period of 2.5 hours is allowed (MyCiTi, 2018). Upon *tap*-out, the alighting point and respective transfer cost are calculated and deducted from the *myconnect* smartcard.

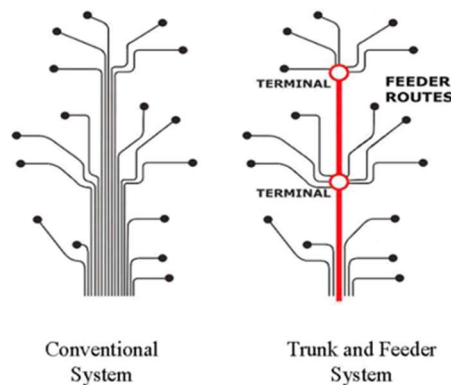


Figure 3-1: Differentiating between Conventional and Trunk and Feeder Systems (Asian Development Bank, 2008).

Actual automatic fare collection (AFC) smartcard data from the MyCiTi Integrated Rapid Transit system for the fiscal years of 2015 and 2016 was accrued from the City of Cape Town for this study. The dataset contained specific information of individually recorded smartcard (also referred to and discussed in Section 2.6 as *tap*) transactions, including<sup>1</sup>:

- the commuter's unique smartcard number;
- *tap* device identification number;
- the MyCiTi stop name and identification number;

<sup>1</sup> For ethical transparency it should be noted that no personal information from any commuter using the MyCiTi IRT system was revealed in the data obtained.

- the transaction type ranging between 1<sup>st</sup> boarding, connection or alighting transactions;
- the upload and reporting date;
- the amount charged per transaction type;
- the number of times the *tap* transaction was processed (stated as 1, assumed used for accurate fare collection purposes of negating double charging on erroneously double-*tap* transactions);
- the recorded time of the *tap* transaction.

From the AFC data, it was determined that the reporting date referred to the date of the actual *tap* transaction while the upload date was assigned to the date the transaction was recorded in the MyCiTi database. To accurately represent commuter travel patterns, the reporting date was therefore referenced in the application of the data.

Studies on the analysis of travel demand have mainly focused on modelling behaviour observed during workdays, i.e. weekdays. This focus is motivated by high commuter volumes found with the associated travel journeys to and from work. Transportation planning and policymaking respond to travel demands forecasted on weekday travel behaviour (Agarwal, 2004). Travel behaviour over weekends is expected to be substantially different from weekday behaviour as erratic, changing travel demands are expected when compared to the more routine weekday schedules of commuters (Transport for Cape Town, 2016). With less commuter travelling occurring over weekends (Statistics South Africa, 2013), the selection criteria for isolating data representing typical weekly commuter travel behaviour was dictated by selecting a week with no public holidays present. AFC smartcard data from the Cape Town IRT system was extracted for a randomly selected week adhering to this specification. Daily reported AFC transactions from the MyCiTi IRT system are presented in Figure 3-2 for a randomly selected week not dated near any South African public holidays in November 2015. The presented commuter behaviour patterns confirmed, as expected, that commuters' choice patterns do not vary between typical workdays.

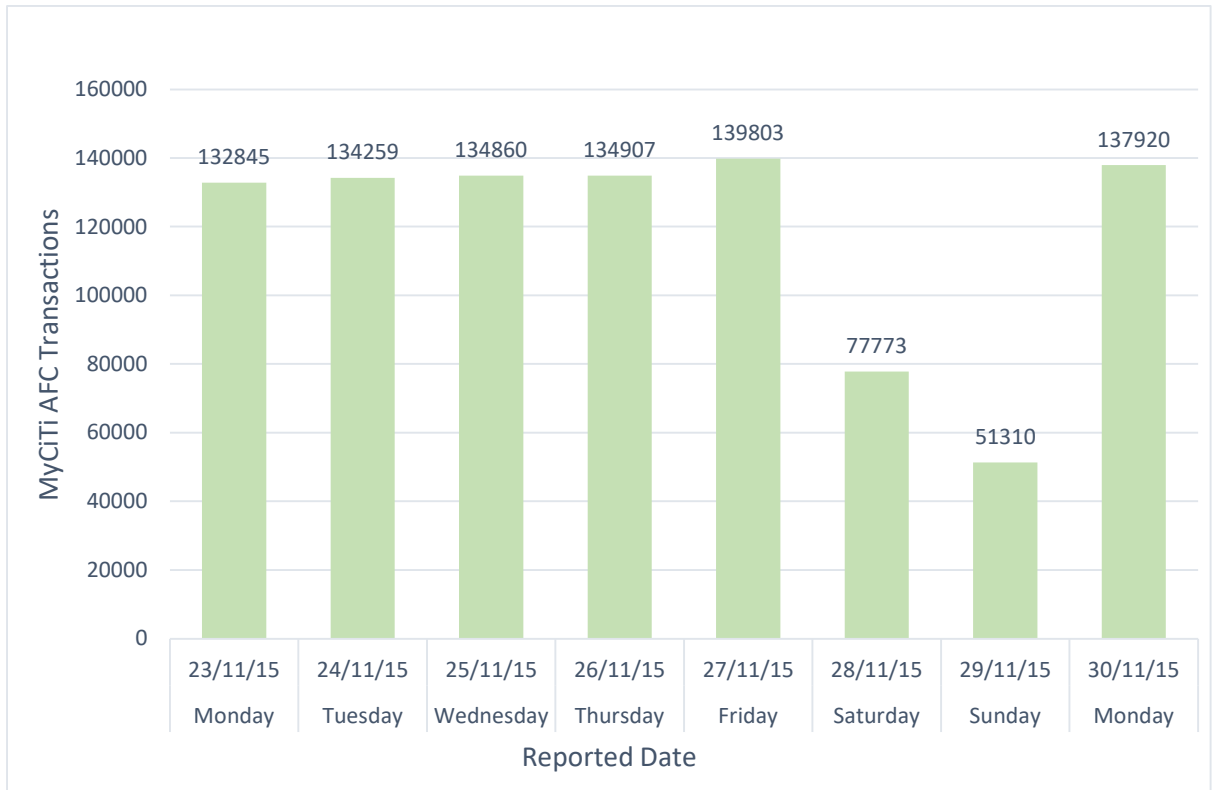


Figure 3-2: Daily recorded AFC transactions for the MyCiTi IRT system in November 2015.

From Figure 3-2, it is seen that travel patterns for the MyCiTi IRT system during weekdays present higher, constant volumes when compared to weekend days. It confirms the assumption that commuters' choice patterns do not vary between typical workdays under the criteria of no public holidays present. This study's target population is the unbiased and all-inclusive (referring to regular and guest) commuter of the MyCiTi IRT system.

To model commuter choices requires the accurate application of the available data. It is therefore introduced that the data analysis of a single random weekday will allow the accurate representation of the choices made by commuters of the MyCiTi IRT system on a daily scale. A one-day data model will set the basis model for the versatile choice modelling application of weekly, monthly and yearly data models and can, therefore, be applied to future continued studies.

From the data represented in Figure 3-2, Wednesday 25/11/2015 was selected as the unbiased random weekday representing the daily choices made by commuters of the MyCiTi IRT system. The sampling unit of this model covers all smartcard *tap* transactions recorded in the sampling frame of the 25/11/2015 weekday. This date reported 134,860 smartcard *tap* transactions.

The filtering of useful data is an essential step in choice modelling, as irrelevant data can cause unusable model noise. Model noise was removed by condensing the one-day data to include only useful, fundamental information level per *tap* transaction for the reporting date of 25/11/2015. The condensed data included per *tap* transaction:

- identifier of choice individual (per commuter's unique smartcard number);
- the MyCiTi stop name and the type of transaction;
- the amount charged;
- the recorded time.

### 3.2 Origin-Destination Classification

The trip destination is defined as a place where a person goes to conduct an activity (Cai, et al., 2015). Cai et al. (2015) define the origin-destination (OD) flow distribution as the aggregated expression of an individual's destination choice result. As per the study done by Munizaga & Palma (Munizaga & Palma, 2012), the trip-chains of the MyCiTi *myconnect* smartcards required reconstruction to estimate the choice destination points from the available data. Reconstruction of the trip-chain would allow the accurate identification of origin-destination transactions required to analyse commuter choice behaviour.

To accurately model the destination choice, it is critical to identify the point of origin for the decision or choice. We cannot model and investigate the factors influencing decision choice if we do not understand the individual choice maker's reasoning and motivation at the origin of their trip to reach the specific destination chosen.

Smartcard *tap* transactions made on the reporting date was sorted in 1<sup>st</sup> boarding (origin) and alighting (destination) data sets, as presented in Figure 3-3.

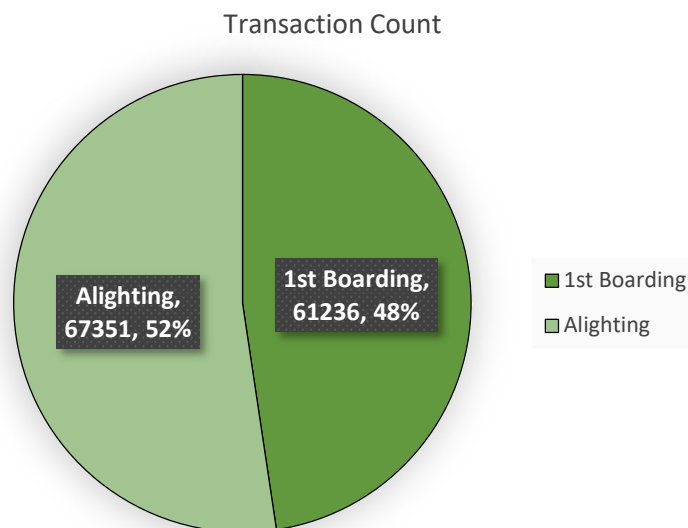


Figure 3-3: AFC Transaction Sorting.

From the 134,860 *tap* transactions reported on 25/11/2015, 61,236 were identified as 1<sup>st</sup> boarding origin transactions and 67,351 identified as alighting destination transactions. This, therefore, left a selection of 6,273 connection transactions. A connection transaction is defined as a route change transaction made by a commuter between their origin and destination. An interesting observation is noted- where substantially fewer connection transactions are recorded. This gives meaningful insight into commuter choice and shows a significantly higher preference towards direct transit routes than connecting routes where commuters undertake a linking course transaction and possibly a route change. Connection transactions, however, do not influence or alter the destination choice but provide the means of reaching the destination. With these mid-route transactions not affecting the origin-destination pairing of transactions, the incorporation of connection transactions was excluded from the scope of this study. It is also noted that no amount was charged on connection transactions; the exclusion of these transactions, therefore, does not affect the origin-destination total trip cost.

In a non-erroneous data set, every journey with a starting point will have an ending point. The count of 1<sup>st</sup> boarding transactions should equal alighting transactions. The higher

percentage of alighting transactions than 1<sup>st</sup> boarding transactions seen in Figure 3-3 indicates incompleteness of the survey data (Richardson, et al., 1995). 1<sup>st</sup> boarding transactions are missing, or erroneous alighting transactions were recorded.

Fare evasion could also contribute to the unbalanced origin and destination transactions. Fare evasion is not homogeneous, and apart from underestimating the origin-destination data, it could encourage biases (Munizaga & Palma, 2012). In the case of Munizaga & Palma (2012) analysing Transantiago in Chile, two types of fare evaders were found. The casual evader, who does not validate in the first stage of the trip because of the lack of charge points, but does charge the trips in the next stage; and the hard evader who will not validate any of the trip segments (Munizaga & Palma, 2012). Both types of evasion described imply different biases. The first type of evasion will contribute to erroneous origin data. The latter would contribute to an underestimation of trips in services that operate in high evasion areas. It is recommended that the effect of trip evaders of the MyCiTi system be investigated in further studies.

Although an error in the data is observed, it should be noted that the sound and precise recording of commuter data is essential for accurate modelling. It will be assumed that the MyCiTi IRT system has boarding validation only with an estimate on the alighting point to be done following the transactions sequence. Each *myconnect* smartcard corresponds to a commuter so that the smartcard will be used by the commuter indistinctively. The basic principles proposed are the same as those assumed by Barry et al. (2002), Zhao et al. (2007) and Trépanier et al. (2007), but additional constraints are recommended (Munizaga & Palma, 2012). For unbiased analysis, the case of only one origin-destination trip per *myconnect* card will be allowed for the one-day analysis.

An interesting observation is made where the transactions presented in Figure 3-3 see a slight increase to the stated average of 59,184 commuters using the MyCiTi IRT system reported by the City of Cape Town in 2015 (City of Cape Town, 2015).

A count of 366 MyCiTi IRT transaction stops was identified in the unfiltered November 2015 monthly dataset. Ben-Akiva & Lerman proved that in a large choice set, consistency is found when model parameters were calibrated with a subset of alternatives (Ben-Akiva & Lerman, 1985). As derived from the application by Cai et al. (Cai, et al., 2015) where the choice-based sampling method was applied, the set of destination alternatives for this study was therefore altered to only include the actual chosen destination alternatives. Therefore, the count of MyCiTi choice alternatives was reduced to 346 as identified as the chosen alternatives in the dataset. This was done to reduce the complexity of the model and to ensure the accuracy of parameter calibration.

The 346 MyCiTi stops were identified as the possible trip origin and destination nodes. It is emphasised that the origin and destination nodes reflect the MyCiTi IRT system data and not the complete trip origin-destination data (e.g. from home to place of work). IRT stop access and egress modes to the IRT system could result in the trip origins and destinations being different to the IRT stop origin-destination.

It should be noted that the comprehensive monthly November 2015 dataset was utilised to identify the designated MyCiTi stops as opposed to only using the one-day dataset. This utilisation was done to ensure that bus stops not selected as choice destinations in the one-day dataset was still included in the impartial choice analysis.

The higher count destination transactions were paired to origin transactions based on the identification of the choice individual and the reporting date. The reporting date was included for the future application of a broader dataset where various reporting dates could be present. The merging of the larger count of destination transactions with the lesser origin transactions resulted in the exclusion of alighting transactions where a 1<sup>st</sup> boarding transaction could not be matched. This origin-destination pairing approach also resulted in

the duplication of origin transactions where multiple destination transactions were matched. With the over-specification of origin-destination pairing present, a verification filtering process commenced.

For a multimodal network such as the MyCiTi IRT system, Munizaga & Palma propose that the time (instead of distance) as a function should be minimised for accurate alighting estimation (Munizaga & Palma, 2012). A time window was defined for the trip trajectory from the instant when the commuter boards the MyCiTi system. With cost and recorded time available for every origin and destination transaction, the total travel time and total travel cost were calculated for each origin-designation paired transaction. OD paired transactions where no trip cost or travel time was incurred or where the total trip duration exceeded 2.5 hours, noted as the maximum transfer period in Section 3.1 (MyCiTi, 2018), was unfeasible and excluded.

For qualitative analysis, accurate data representation is essential. Any erroneous pairing transactions should be excluded. The filtering of accurate origin-destination transactions was sensitised to the level of compliance to the time and cost dictation of the 2015 MyCiTi IRT system fee structure discussed in Section 2.6.

Only the rational argument of one 1<sup>st</sup> boarding and one alighting transaction was allowed per individual per recorded time moment of the *tap* transaction. Out of a maximum 61,236 origin-destination pairing possibilities demonstrated in Figure 3-3, a count of 45,970 origin-destination trips was verified to adhere to the rationalised guidelines dictated by the operation of the MyCiTi IRT system discussed in Section 2.6.

As applied by Cai et al. (2015), origin-destination pairing is based on the concept of the representative individual, in which commuters with the same origin and destination are recognised to make the same destination choice. With homogeneous personalised attributes, this transforms the aggregate OD trip data into disaggregate data (Cai, et al., 2015). The verified origin-destination trips of the MyCiTi IRT system are, therefore, stated as disaggregated data.

### 3.3 Geospatial Data Extension

Although origin-destination pairing was achieved on the automatic fare collected data of the MyCiTi IRT system, the paired data itself was inadequate to form a choice modelling study. The origin-destination dataset was therefore expanded with complementary external datasets to include the aimed geospatial properties of this study.

The incorporation of GIS data is widely found in studies investigating destination choice behaviour. Vega and Reynolds-Feighan incorporated geographic information system (GIS) visualisations and network analysis to generate a choice dataset based on the definition of spatially aggregated alternatives (Vega & Reynolds-Feighan, 2009). Munizaga and Palma applied the geocoded definition of the public transport network in their origin-destination study (Munizaga & Palma, 2012).

The exact geographical location of the MyCiTi IRT stops was accrued from the City of Cape Town in shapefile (*shp*) format (City of Cape Town, 2018). A shapefile is defined as an accessible, geospatial dataset in vector format extracted from geographic information system (GIS) software. This geospatial dataset was imported and analysed in the QGIS software program (QGIS.org, 2019) to extract exact coordinates of all MyCiTi stops included in this study, as presented in Section 3.1.

A discrepancy was noted when the MyCiTi IRT stop names of the coordinated dataset were compared to the revealed preference AFC dataset. Additional stop names were listed in the coordinated data. It was determined that a variety of human spelling errors were captured in both datasets. A sample of the errors identified includes the spelling variation of *Langeberg* and *Langberg*, *Oscar Mpetha* and *Oscar Mpethu*, *Sandrift* and *Sanddrift*,

*Braselton* and *Braseltown* MyCiTi IRT stops. An evaluation process followed where slight spelling errors were rectified. Invalid entries that cannot be verified to represent official MyCiTi stops for this study indicate an incompleteness deficiency in the sampling frame (Richardson, et al., 1995). Where listed IRT stops could not be verified and/or coordinated, it was noted as inadequate data and excluded from the study.

Another discrepancy was noted where certain individual MyCiTi IRT stops within the coordinated dataset were given different coordinates. It was found that this discrepancy arose where an IRT stop had two access points on either side of a road as influenced by the direction of travel.

The revealed preference AFC dataset however only referenced the specific IRT stop name and does not specify from which roadside the commuter accessed the stop or the direction of travel. The coordination of the AFC dataset necessitated the allocation of one coordinate to every IRT stop. Where two coordinates arose for an individual IRT stop name, the selection of either coordinate was deemed an inaccurate geographical representation. A centroid coordinate was generated to represent the midpoint between the two listed coordinates. This is deemed an acceptable assumption in the application of the geographical location between various origin and destination MyCiTi IRT stops.

The fundamentals of the same scenario were raised by Munizaga and Palma (Munizaga & Palma, 2012) as depicted in Figure 3-4.

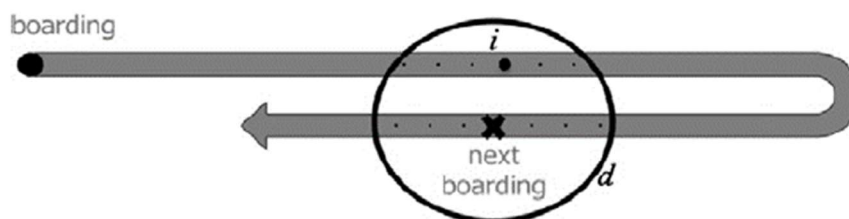


Figure 3-4: Search procedure of distance  $d$  (Munizaga & Palma, 2012).

An explanation of Figure 3-4 follows as presented by Munizaga and Palma (2012). Assume a commuter board a bus route that goes from left to right. This route goes up to a certain point to the right and continues to return to the left. If the route continues in both directions along the same street, or streets that are located close to each other, a commuter whose destination is the point designated with X in the figure will not remain in the bus along the entire route but is assumed to alight at the closest point to their next boarding. The commuter is assumed to more likely alight at the most convenient point ( $i$ ) because travel and walking time is taken into consideration. The generalised time point is used to avoid potential bias (Munizaga & Palma, 2012).

A time point could not be generated in this study. However, following the same principle, the coordinated dataset was revised using the QGIS software, and a centroid coordinate was generated for the MyCiTi IRT stops found to have two original geographical locations. It is noted that the maximum distance between two same-named IRT stops was found to be 50 meters. This dataset, therefore, has a 25-meter geographical location accuracy. The 346 MyCiTi IRT stops noted in the AFC dataset was uniquely coordinated, and a single numeric identifier ranging from 1 to 346 was assigned to each. For each named MyCiTi IRT stop there, therefore, exists one coordinate.

A visual representation of the coordinated IRT stops is presented in Figure 3-5.

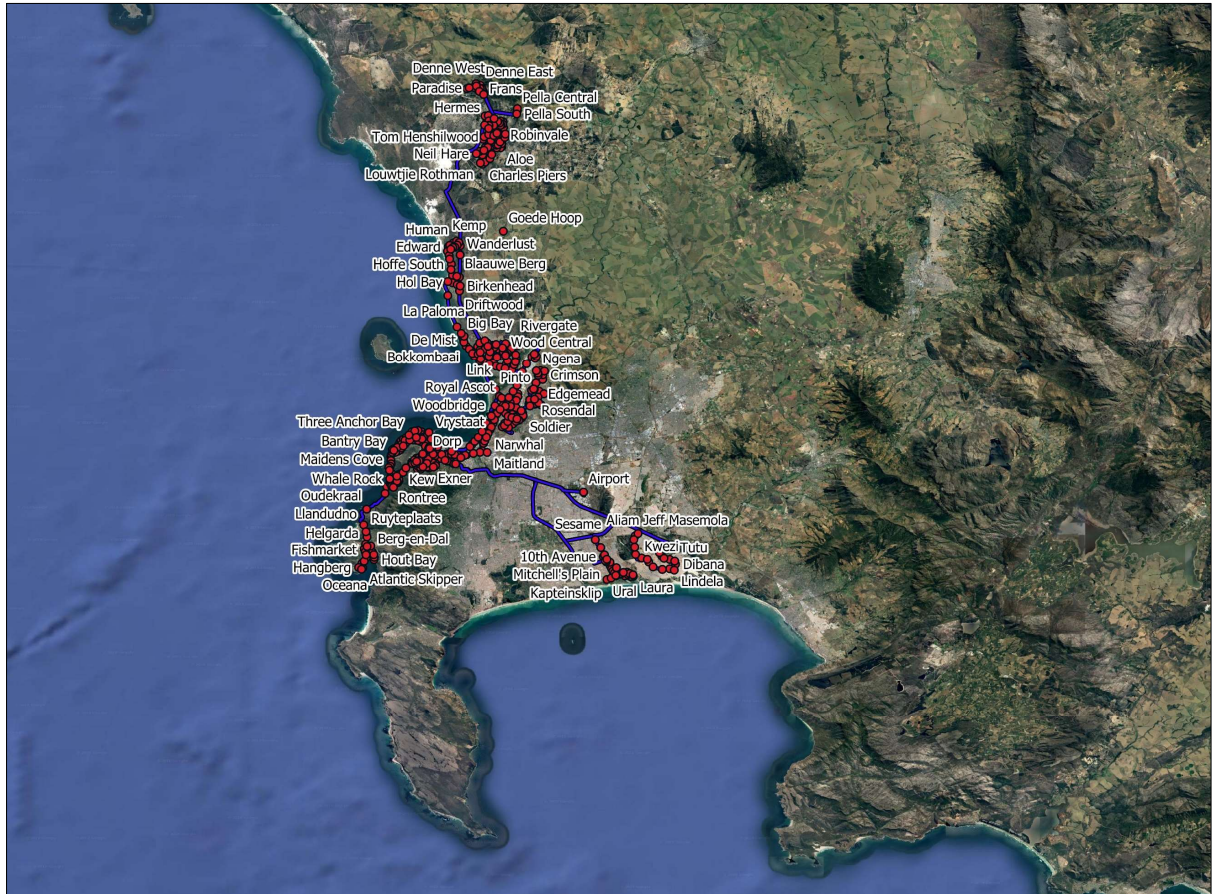


Figure 3-5: MyCiTi IRT stops (Google Earth, 2019).

### 3.3.1 Geographical Distance

It is proposed that the geographical distance between origin and destination gives insight into the choice decision. Coordination of the MyCiTi IRT stops was utilised to extract the geographical distance between each possible origin and destination transaction. This geographical distance is known as displacement (Kenney, 2017) and is illustrated in Figure 3-6.

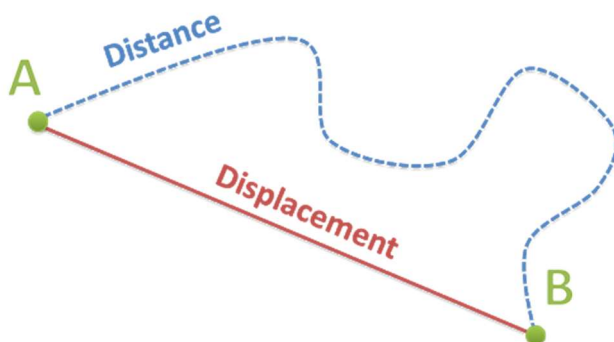


Figure 3-6: Distance versus displacement (Kenney, 2017).

The geographical distance gives valuable insight into the physical displacement need of the individual when making a destination choice selection. Displacement is deemed a critical factor in destination choice modelling, and the dataset was subsequently expanded for this study. A matrix was constructed to present the displacement (geographical distance) in kilometres from each of the 346 origin MyCiTi IRT stops to the possible IRT destinations. This matrix is included in Appendix B. When applying the illustration in Figure 3-6, no displacement will exist where origin A and destination B are the same MyCiTi IRT stop; the displacement will be 0 km. Note that this is only for explanatory purposes as such a validated origin-destination transaction pair will not exist. The trip origin and destination cannot constitute the same MyCiTi IRT stop. For every choice destination there will therefore exist a displacement. This distance matrix expanded the dataset by including the kilometre distance measured from the origin to every alternative choice destination.

### 3.3.2 IRT Stop Density

It is proposed that the density of the IRT stops in a destination area provides insight into the underlying IRT system demand, and therefore, the commuter choice decision. The conglomerate of a higher IRT stop density should signify high commuter demand expected and is therefore proposed as a measurement of attractiveness for destination choice. The dataset was subsequently expanded with MyCiTi IRT stop density data.

A density count is presented for each MyCiTi IRT stop. Referencing the Department of Transport's vision to implement a system that aims to allow the population of a metropolitan city access within 1 km to an Integrated Rapid Public Transport Network (Department of Transport, 2007), a 1 km radius perimeter surrounding each individual MyCiTi IRT stop was created. The subsequent IRT stops located within this perimeter were counted. It should be noted that included in the count is the centroid MyCiTi IRT stop from which the density perimeter was buffered. If an IRT stop exists with no other stops within a 1 km radius, for example, presented in Figure 3-7 for the Airport MyCiTi IRT stop, the density count would be 1.



Figure 3-7: Visual representation of the density count perimeter for the Airport IRT stop (Google Earth, 2019).

With the MyCiTi IRT stops coordinated, the QGIS software was utilised to extract the density count within the perimeter of each IRT stop (QGIS.org, 2019). The dataset was expanded by including this density count for every choice destination as visually represented in Figure 3-8.

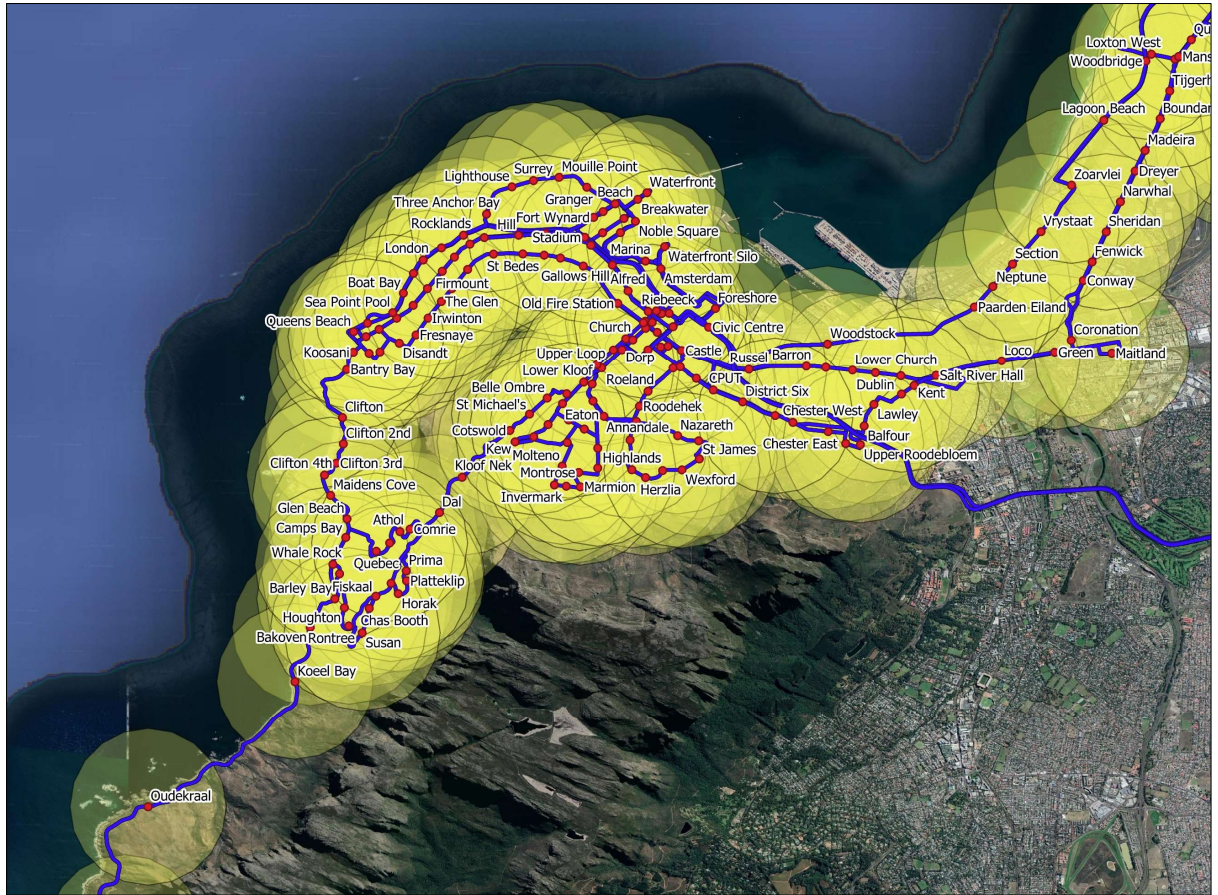


Figure 3-8: Visual representation of the density count perimeters for the various MyCiTi IRT destinations (Google Earth, 2019).

A matrix was constructed to present the density count for each of the 346 origin MyCiTi IRT destinations, referenced to all possible IRT trip origins. This matrix is included in Appendix C. The dataset was expanded by including the density count for every MyCiTi choice destination. It should be noted that the density count is fixed for the destination IRT stop, regardless of the origin.

### 3.3.3 Land Use Rating Classification

Land use activities can influence travel behaviour, as discussed by the various studies in Section 2.9. Ewing and Cervero found land use activities influencing trip lengths (Ewing & Cervero, 2001). Hammadou et al. explored the incorporation of the spatial dimension on destination choice models with a focus on Antwerp (Hammadou, et al., 2008). Bhat et al. analysed destination choice behaviour through the estimation of disaggregate attraction-end choice models. These attraction-end models originated from land use planning (Bhat, et al., 1998). Hong et al. grouped destinations with similar classifications to investigate the roles of categorisation on the decision-making process (Hong, et al., 2006). The results supported the effectiveness of the land use classification concept in the destination choice

process. Handy et al. found that travel behaviour and land use policies showed significant associations (Handy, et al., 2005).

With its importance noted, the destination land use classification was incorporated in this study to investigate its effect on destination choice modelling and therefore, travel behaviour.

Cape Town's land use zoning and classification were accrued from the City of Cape Town in GIS-ready shapefile (*shp*) format (City of Cape Town, 2018). Twenty-seven specified land use classifications were found, including:

- Agricultural;
- Community and Regional;
- General Business 1, General Business 3, General Business 5, General Business 6 and General Business 7;
- Local Business 1;
- General Industrial 1 and General Industrial 2;
- General Residential 1, General Residential 2, General Residential 3, General Residential 4, General Residential 5, Single Residential 1 and Group Housing;
- Mixed Use 1, Mixed Use 2 and Mixed Use 3;
- Public Open Space, Open Space 2 and Open Space 3;
- Rural;
- Utility; and
- Limited Use Zone.

For this study, the official land use zoning was grouped into the ten primary classifications:

1. Agriculture
2. Community and Regional
3. General Business
4. Industrial
5. Residential
6. Limited Use
7. Mixed Use
8. Open Space
9. Rural
10. Utility

The ten grouped land use classifications for the City of Cape Town is presented in Figure 3-9.

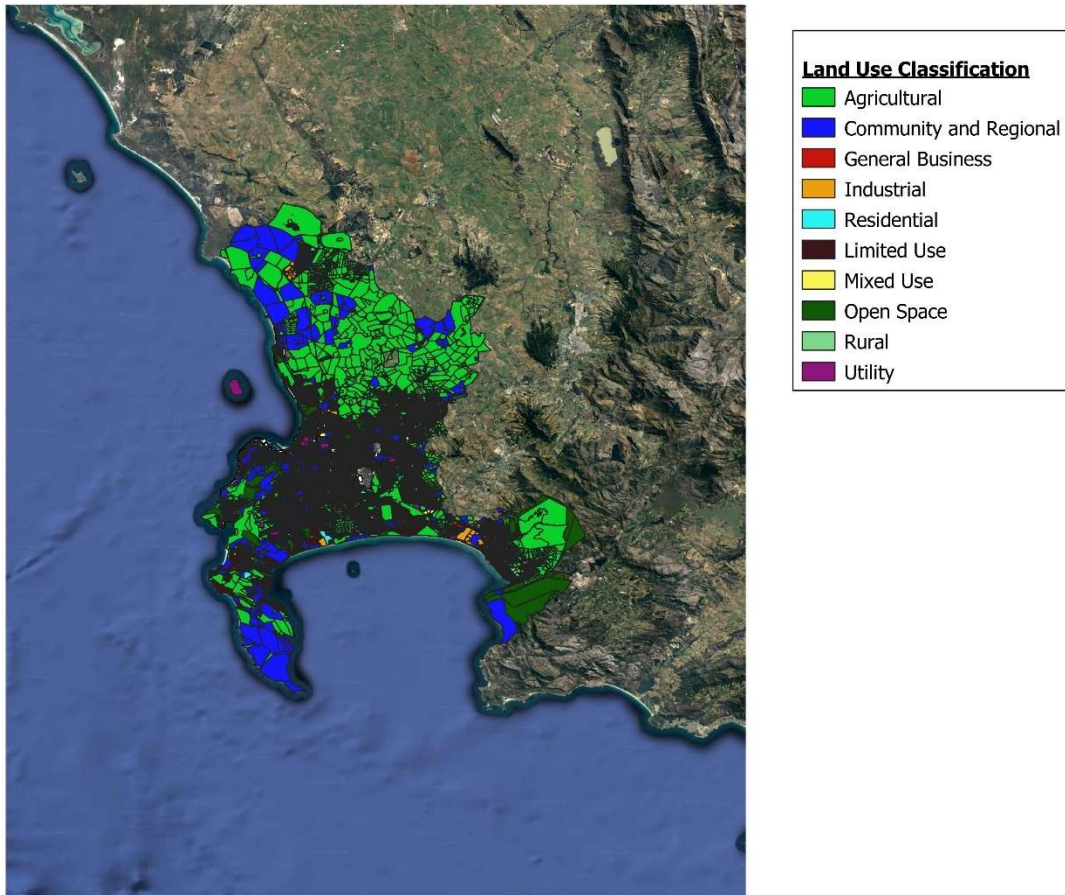


Figure 3-9: Grouped land use classification for the City of Cape Town (Google Earth, 2019).

The grouped resource zoning dataset presented in Figure 3-9 was imported into and analysed in the QGIS software program (QGIS.org, 2019). The coordinated 346 MyCiTi IRT stops, previously discussed in Section 3.3 and presented in Figure 3-5, was projected on the ten primary land use classifications of the City of Cape Town, as seen in Figure 3-10. A specific land use classification was then allocated to each of the 346 MyCiTi IRT stops. Where an IRT stop was located on an unclassified zoning section, the closest land use classification was sought and allocated using the QGIS software program.

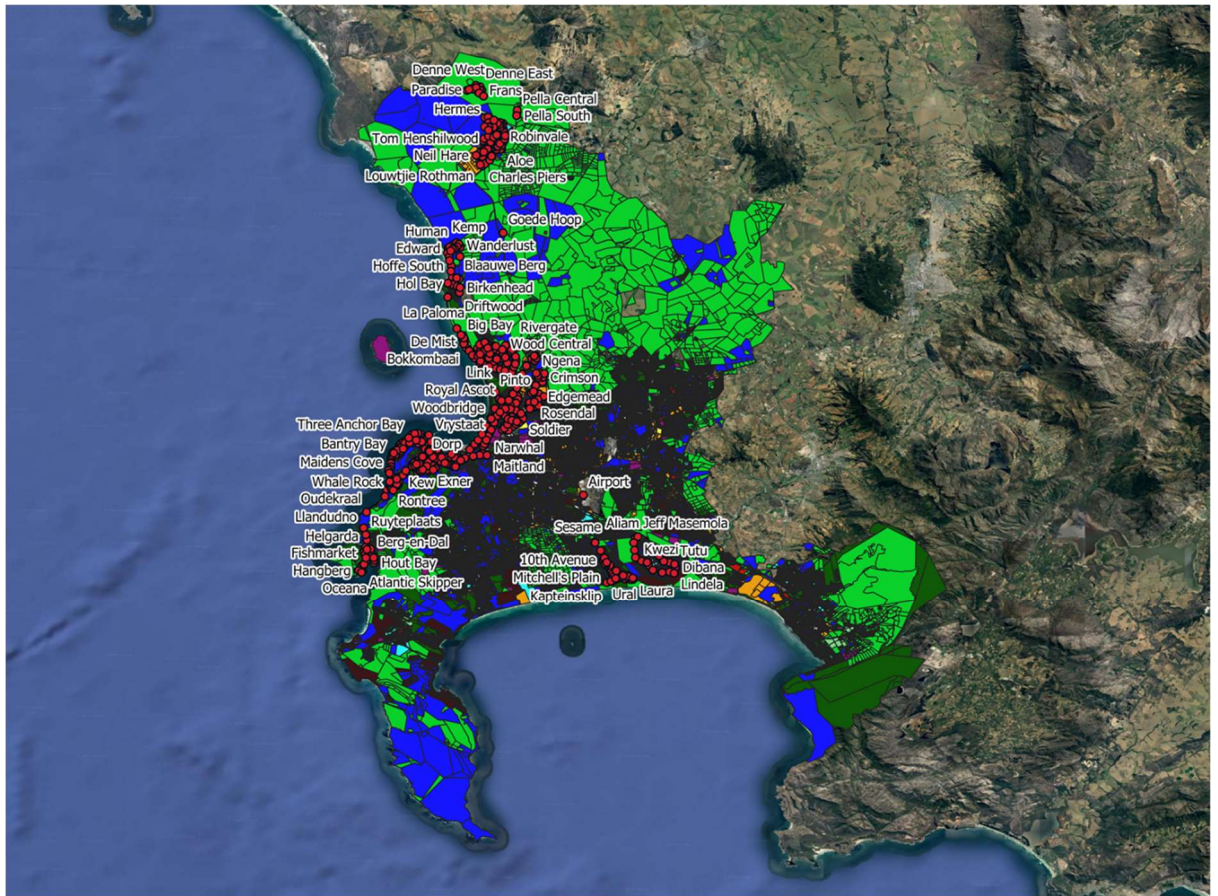


Figure 3-10: MyCiTi IRT stops projected on the land use classification for the City of Cape Town (Google Earth, 2019).

The distribution count of the 346 coordinated MyCiTi IRT stops in terms of grouped land use classification is presented in Figure 3-11.

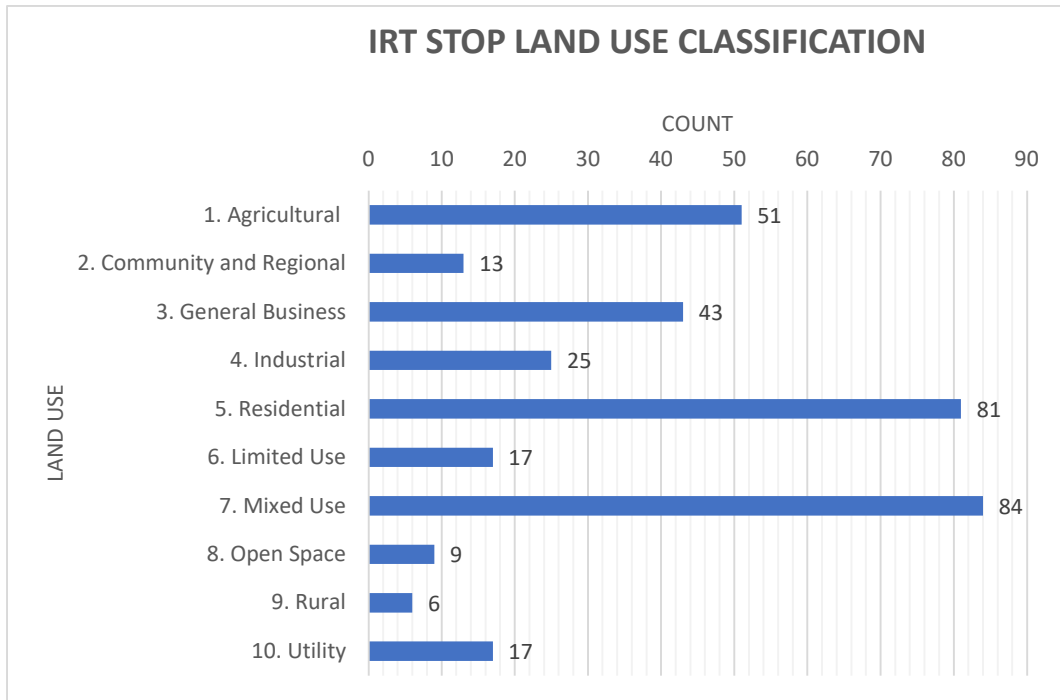


Figure 3-11: MyCiTi IRT Stop Land Use Classification.

An interesting observation is made from Figure 3-11 where the most (84 out of 346) MyCiTi IRT stops are located within the Mixed Use land use classification. The second most MyCiTi IRT stops are located within the Residential land use classification. This Residential land use classification reiterates the distinct general trip pattern reported by The National Household Travel Survey (2013) where a large portion of the Capetonian population heads from the suburbs to the city centre in the mornings and returning in the opposite direction in the evenings (Statistics South Africa, 2013). It is noteworthy that more IRT stops are located within the Agricultural land use classification than in the General Business classification. The least IRT stops are predictably located within the Rural classification.

The land use distribution of the MyCiTi IRT stops in terms of grouped classification is presented in Figure 3-12.

### MYCITI IRT STOP LAND USE CLASSIFICATION

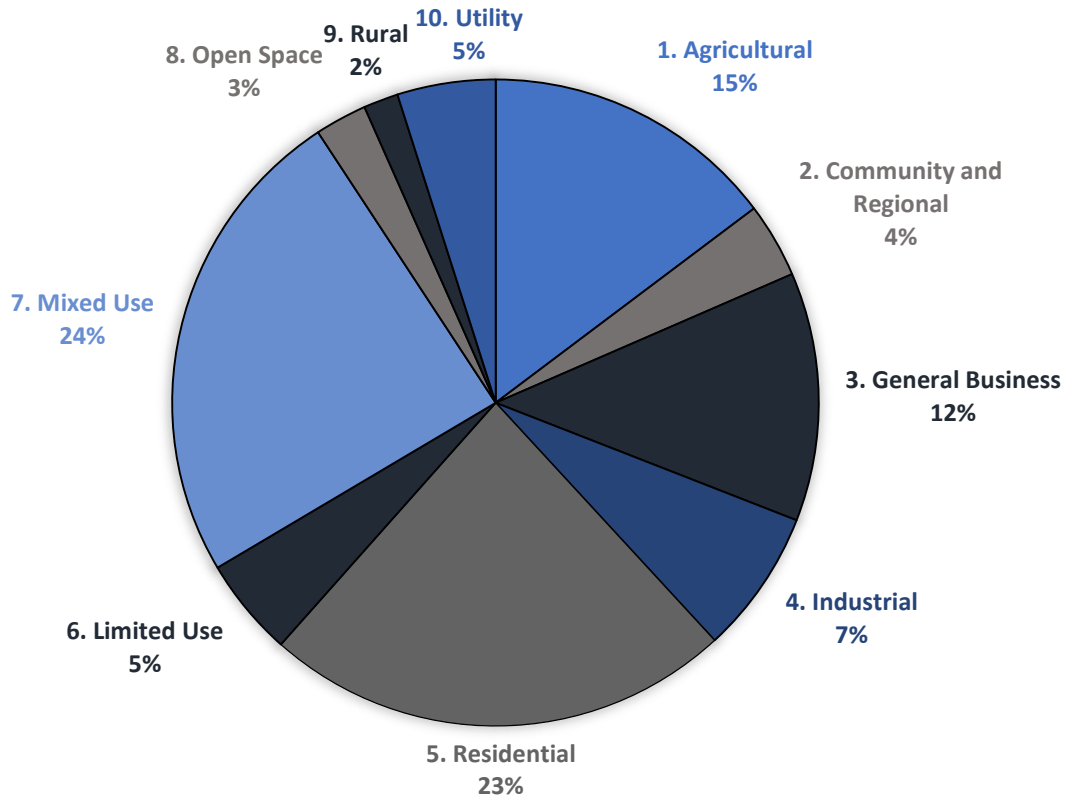


Figure 3-12: IRT stop grouped land use classification percentage distribution.

The percentage distribution of the coordinated MyCiTi IRT stops in terms of grouped land use classification, as presented in Figure 3-12, is summarised as:

- Mixed Use 24.3%
- Residential 23.4%
- Agricultural 14.7%
- General Business 12.4%
- Industrial 7.2%
- Utility 4.9%
- Limited Use 4.9%
- Community and Regional 3.8%
- Open Space 2.6%
- Rural 1.7%

The land use percentage distribution was used to allocate each grouped land use classification a rating from 1 to 10 in increasing order of popularity distribution. A land use rating of 1 was allocated to the land use classification with the least MyCiTi IRT stops found in its spatial classification. Subsequently, a land use rating of 10 was allocated to the land use classification with the most MyCiTi IRT stops found in its spatial classification.

The land use rating allocation in terms of MyCiTi IRT stop distribution is defined:

- Land use rating 1: Rural, 1.7%

- Land use rating 2: Open Space, 2.6%
- Land use rating 3: Community and Regional, 3.8%
- Land use rating 4: Limited Use, 4.9%
- Land use rating 5: Utility, 4.9%
- Land use rating 6: Industrial, 7.2%
- Land use rating 7: General Business, 12.4%
- Land use rating 8: Agricultural, 14.7%
- Land use rating 9: Residential, 23.4%
- Land use rating 10: Mixed Use, 24.3%

The cumulative s-curve presentation of the land use rating allocation is presented in Figure 3-13.

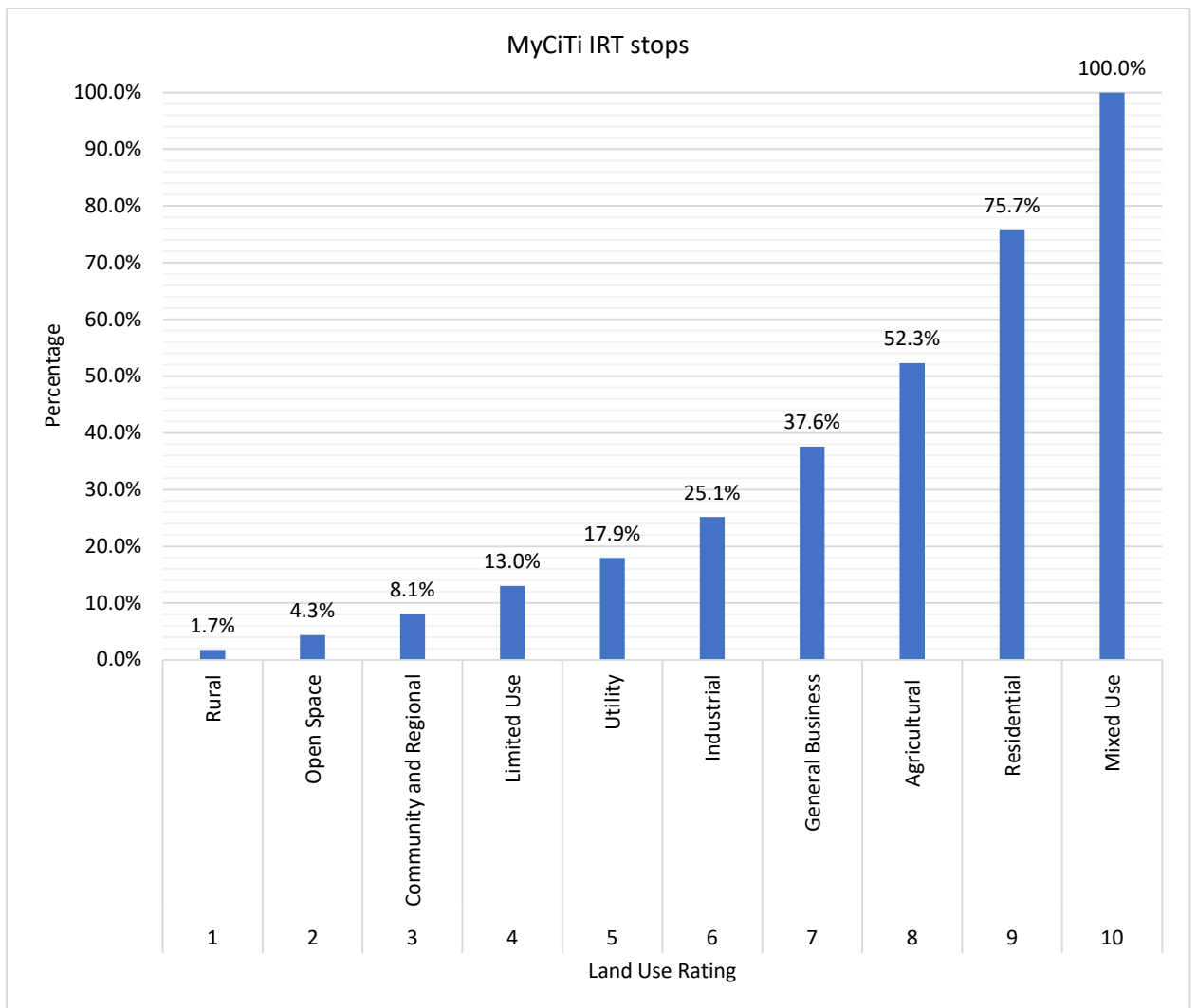


Figure 3-13: Cumulative s-curve presentation of land use rating in terms of the MyCiTi IRT stop distribution.

The land use rating cumulation presented in Figure 3-13 gives insight into the land use utilization of the MyCiTi IRT system. A lesser count of MyCiTi IRT stops are found within

the land use classifications of Rural, Open Space, Community and Regional, Limited Use and Utility as expected. MyCiTi IRT stops are more abundantly found within the land use classifications of Industrial, General Business, Agricultural, Residential and Mixed Use.

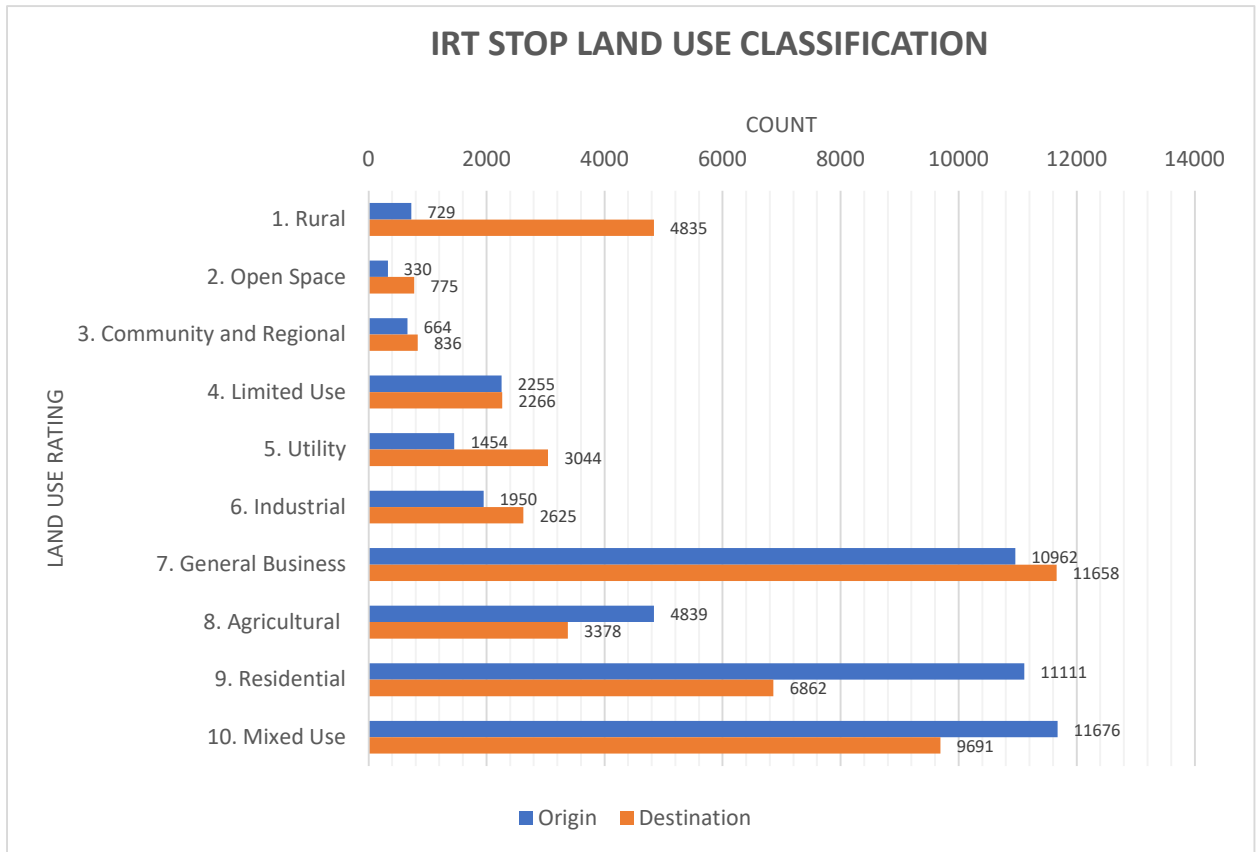


Figure 3-14: Origin and destination distribution per land use classification rating.

The origin and destination distributions of the 45,970 trips per land use rating classification for the MyCiTi IRT system is presented in Figure 3-14. The OD distributions support the land use classification ratings. The higher percentage IRT stops located within the Mixed Use, Residential, Agricultural and General Business land use classifications are popular trip origins and destinations as seen in Figure 3-14. A lesser count of destination trips than origin trips is found for the Residential land use classification. With a higher origin than destination trip count, a possible explanation may be that the data was skewed not to capture the evening peak where commuters tend to depart from places of employment to residential areas. Unskewed data would have indicated a more balanced origin and destination distribution as the residential areas are deemed both popular origin and destination nodes. An explanation could be a delay in reporting commuter trip data. It is worthy to note the popularity of the rural land use classification as a destination.

A matrix was constructed to present the land use rating for each of the 346 origin MyCiTi IRT destinations, referenced to all possible IRT origins. This matrix is included in Appendix D. It should be noted that the land use rating is fixed for the destination IRT stop, regardless of the origin. The dataset was expanded by including the land use rating for every MyCiTi choice destination.

### 3.3.4 CBD Zonification

The zoned Central Business District (CBD) of Cape Town was also accrued from the City of Cape Town in GIS-ready shapefile (*shp*) format (City of Cape Town, 2018). This CBD

zoning dataset was imported into and analysed in the QGIS software program (QGIS.org, 2019). The coordinated 346 MyCiTi IRT stops, previously discussed in Section 3.3 and presented in Figure 3-5, was projected onto the CBD zone of the City of Cape Town. Twenty MyCiTi IRT stops were identified located within the CBD zone. The MyCiTi IRT stops found within the CBD zone include:

1. Adderley
2. Castle
3. Church
4. Civic Centre
5. Darling
6. Dorp
7. Foreshore
8. Grootte Kerk
9. Leeuwen
10. Longmarket
11. Lower Buitenkant
12. Lower Long
13. Lower Loop
14. Mid Long
15. Mid Loop
16. Riebeek
17. Strand
18. Thibault Square
19. Upper Long
20. Upper Loop

The dataset was binary expanded to indicate if destination MyCiTi IRT stops were found within the CBD zone of the City of Cape Town or not. As discussed in Section 2.4, a distinct general trip pattern is reported where a large portion of the population of Cape Town is found heading from the suburbs to the city centre (the CBD) in the mornings and returning in the opposite direction in the evenings (Statistics South Africa, 2013). It is therefore noted that the CBD is a temporal destination attractor during the morning trip peaks. Furthermore, due to the residual segregation of Capetonians, the CBD is found a highly attractive destination.

### **3.4 Personal Characteristics**

It is stated that personal characteristics influence destination choice (Cai, et al., 2015). Destination choice models typically analyse geospatial, trip characteristics and socio-economic utility attributes through the application of stated preference (SP) and revealed preference (RP) data. However, personal characteristics from the commuter (the individual decisionmaker), known as stated preference data, were not captured in the AFC data obtained from the MyCiTi IRT system. This study, therefore, excludes any personal commuter characteristics as in similar modelling studies with the application of AFC data. It is recommended that future studies expand the revealed preference choice data of the MyCiTi IRT system with the inclusion of stated preference data to capture the individual variance. It is worthy to note that a study excluding stated preferences will limit the application thereof for future planning purposes.

### **3.5 Data Summary**

The application of accurate data is essential to execute a valid choice modelling study. AFC smartcard data from the MyCiTi Integrated Rapid Transit system was accrued from the City of Cape Town. This data was filtered to limit unuseful model noise. Erroneous data entries

were identified and excluded from the dataset. Origin-destination trip pairing was executed, and calibration. Auditing was done to ensure an accurate presentation of the MyCiTi trip data. The inclusion of geospatial properties in the origin-destination paired dataset expanded the original dataset substantially and to a satisfactory level to be applied a choice modelling study. The expanded geospatial properties included the geographical distance between trip origin and destination, IRT stop density, land use classification and rating, and the central business zoning classification of identified MyCiTi IRT stops. This choice modelling study is based on the collected and expanded revealed preference AFC data representing factual and verified travel behaviour. The application of revealed preference data from the MyCiTi IRT system enables this study to be cost-effective. The combination of multiple data sources will allow for an unbiased analysis which adds credibility to this study for the future application thereof.

## **4. THE CHOICE MODEL**

Understanding a commuter's behavioural response can greatly influence transportation planning and operational policies, and play a vital role in optimising transport systems. As discussed in Section 2.7 and demonstrated by previous research studies, discrete choice models are fundamentally significant to model and provide insight into commuter decisions within the field of transportation engineering.

A vital component for understanding the operational functionality of a public transport system lies in the accurate modelling of its commuter choices. Destination choice modelling can provide insight into the factors influencing commuter choice. The spatial separation of activities is stated to form the essence of travel demand and travel patterns. A trend is reported where it is proposed that geospatial properties can impact destination choice and travel behaviour. The need to investigate this geospatial effect on destination choice is highlighted and encouraged.

This chapter presents and defines the choice model developed in this study to investigate the effect of geospatial properties on travel behaviour. Understanding commuters of the MyCiTi IRT system's travel behaviour and the effect geospatial properties have on this behaviour can unfold significant economic, environmental and social value for the City of Cape Town.

### **4.1 The Objective**

An introduction was made in Section 2.7 to the application of choice modelling in transport systems. The literature review provided valuable insight into studies linking to the investigation of geospatial properties in destination choice modelling. The City of Cape Town, with a primary focus on the MyCiTi Integrated Rapid Transit system, was defined as the study area in Section 2.4. This IRT system forms a crucial component of the city's transportation network. The AFC dataset was defined in Section 3 and expanded to include the built environment properties required for this geospatial investigation. The objective of this choice modelling study is to identify and investigate geospatial properties that influence commuter destination choice in the MyCiTi IRT system. The estimation of the various destination choice models developed for this study is presented and discussed.

### **4.2 Model Specification**

This study focuses on travel behaviour in the context of commuter destination choice using RP data from AFC. Modelling destination choice directly implies the development of a discrete choice model. Discrete choice models were introduced in Section 2.7. The multinomial logit (MNL) model is the most widely used discrete choice model (Hammadou, et al., 2008). As explored in Section 2.7.2, the MNL model is a basic random utility model first derived by Nobel Laureate Daniel McFadden (McFadden, 1974). The multinomial distribution is stated as a generalisation of the binomial distribution. This study aims to apply the MNL model to effectively present the influence geospatial properties have on destination choice within the MyCiTi IRT system.

As identified in Section 2.7.2, three primary assumptions dictate the application of the MNL model. The first assumption states that the random elements of the alternatives' utilities are independent and identically distributed (Train, 2003). This independence maintains that no unobserved factors should dictate the utilities of the choice alternatives. The choice alternatives of this study are the MyCiTi Integrated Rapid Transit alighting (destination) stops. These stops form part of the same MyCiTi IRT transport bus network system. It is assumed that the effect on utility is the same across all MyCiTi IRT destination alternatives. The random elements of the alternatives' utilities are therefore independent and identically distributed. As stated in Section 2.7.2, the incorporation of alternative specific constants (ASCs) in model specification can assist in achieving compliance with the assumption of

independence in the MNL model (Huybers, 2004). However, this study did not explore the inclusion of ASCs in model development, with the alternative MyCiTi IRT choice destinations unlabelled.

The second assumption states that the MNL model does not allow for preference to an alternative due to unobserved individual characteristics (Bhat, 2002). It is assumed in this study that individual commuters of the MyCiTi IRT system maintain consistency in responsiveness to the attributes in the destination alternatives.

The MNL model's third assumption dictates that the error variance-covariance structure of alternatives is identical across all individuals (Koppelman & Bhat, 2006). It is assumed that there is no unobserved variable between the MyCiTi IRT destination alternatives.

The MNL model's application in this choice modelling study based on the MyCiTi IRT system is deemed appropriate with the three primary assumptions addressed.

### 4.3 Defining the Attributes

A count of 346 MyCiTi IRT bus stops was identified in Section 3.2 as possible commuter choice destinations. These destinations will therefore constitute the choice alternatives in the model. The choice decision for a commuter to select a destination bus stop is dependent on the selection probability. We aim to investigate the geospatial attributes influencing this probability and therefore, the decision choice.

This study's model development will explore the subsequent development of various utility functions incorporating the geospatial variables introduced in Section 3.3. The most critical step in a choice modelling analysis is the identification of the attributes. These attributes aim to capture the characteristics of the deterministic variables that influence the choice probability.

The attributes included in this choice modelling study are geospatially focused, as defined in the aim of this study and introduced in Section 3.3. It includes the origin-destination displacement, destination IRT stop density, destination land use rating classification and the central business district (CBD) zonification. These geospatial attributes are aimed to capture the built environment influences on commuter decision choice in the MyCiTi IRT system.

The trip origin-destination displacement is defined as the geographical distance between a commuter's 1<sup>st</sup> boarding and alighting MyCiTi IRT stops, as detailed in Section 3.3.1. This is characterized as an accessibility variable. The closer a destination is to an origin, the more accessible the destination is to the commuter.

The IRT stop density is defined as the count of IRT stops located within a 1 km radius perimeter surrounding each individual MyCiTi IRT destination stop, as detailed in Section 3.3.2. This density is defined as an attractiveness variable. The higher the IRT stop density, the higher the commuter demand and therefore, the destination's attractiveness.

The land use rating classification (ranging from 1 to 10) allocated to each of the MyCiTi IRT destination stops is defined as a land use variable and a function of the spatial policies of the City of Cape Town, as detailed in Section 3.3.3. A higher rating defines that a MyCiTi IRT stop is located within a land use classification popular to the MyCiTi IRT network distribution as presented in Figure 3-13.

The CBD zonification of a MyCiTi IRT destination stop is defined as both a land use and attractiveness variable and a function of the City of Cape Town's spatial policies, as discussed in Section 3.3.4. Due to the reported residual segregation found in the city where a large portion of the population of Cape Town heads from the suburbs to the city centre (the CBD) in the mornings and returning in the opposite direction in the evenings, the CBD zone in Cape Town is seen as a highly attractive temporal destination.

#### 4.4 Computational Implementation

The multinomial logit models developed in this study were defined and estimated using *Apollo* (Hess & Palma, 2019), a software package developed by Hess & Palma for choice model estimation. Version 0.1.0 of *Apollo* was applied (Hess & Palma, 2019). Coding was executed in R, a software used for scientific computing. RStudio is the integrated development environment to code a model in R. The expanded dataset, defined in Section 3, was imported in csv format.

*Apollo* achieves minimisation of the negative of the log-likelihood for parameter estimation, equivalent to the maximization of the log-likelihood (Hess & Palma, 2019). It also reports the number of estimated parameters, the estimation time and iterations taken, and the eigenvalue of the Hessian that is closest to zero.

#### 4.5 Model Development

A model development approach was presented by Manski (Manski, 2008) and cited by Johnston (Johnston, et al., 2017). The simplest models are estimated first, followed by the subsequential complication thereof. This continuous developmental approach was applied in this study, as presented in Figure 4-1.

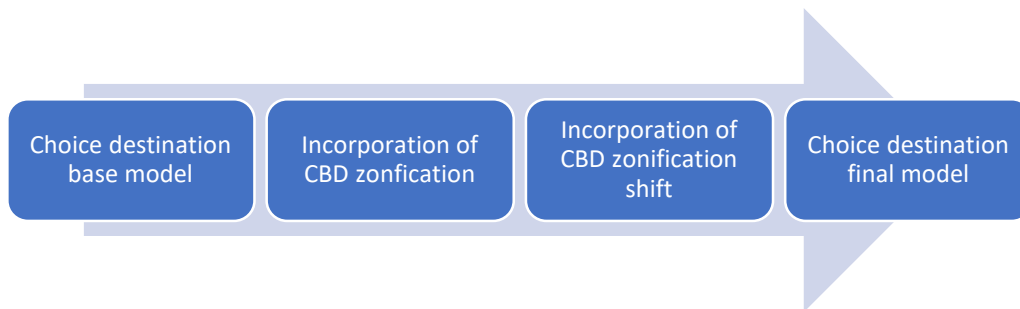


Figure 4-1: Choice destination model development.

A base MNL model is presented incorporating the three primary geospatial variables explored in Section 3.3: the origin-destination displacement, IRT destination density and the destination land use rating attributes. The base model will be further developed to explore the spatial zonification effect of including Cape Town's central business district (CBD) as a geospatial attribute, introduced in Section 3.3.4. The CBD zonification's influence on the primary geospatial variables will furthermore be explored in the subsequent model development and explored as a CBD zonification shift. The model development aims to develop a final choice model that can be applied to identify geospatial properties that influence commuter destination choice in the MyCiTi IRT system.

This study strives to report model improvement with the subsequent choice model development from the base model to the final model. The aim is to develop and present a final model which effectively applies the MNL theory to explore the influence geospatial properties have on destination choice within the MyCiTi IRT system.

#### 4.6 Model Improvement

*Apollo* was used to define and estimate the MNL choice models developed in this study (Hess & Palma, 2019). *Apollo* reports specific goodness of fit statistics with every choice model estimation. The goodness of fit term is used to compare the observed sample distribution with the expected probability distribution. In choice models, the goodness of fit values ascertains how well the statistical methods and analysis fits the model data.

For discrete choice models, *Apollo* reports the log-likelihood (LL), the Pseudo  $R^2$  ( $\rho^2$ ) and adjusted Pseudo  $R^2$  (adjusted  $\rho^2$ ), the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the robust  $t$  ratio.

The Pseudo  $R^2$  ( $\rho^2$ ) is used to evaluate the goodness-of-fit of the estimated models. The Pseudo  $R^2$  is the most common measure of both the overall and relative model fit (Hensher, et al., 2005).

The log-likelihood ratio  $\rho^2$  value is estimated:

$$\rho^2 = 1 - \frac{LL(\hat{\theta})}{LL(0)}$$

Equation 4-1

The adjusted log-likelihood ratio  $\rho^2$  value is estimated:

$$\rho^2 = 1 - \frac{LL(\hat{\theta}) - K}{LL(0)}$$

Equation 4-2

with  $\hat{\theta}$  the set vector of model parameters, LL the log-likelihood and  $K$  the number of estimated parameters.

The Akaike and Bayesian Information Criterion (AIC and BIC) are statistical tests generally applied to higher-order choice models and are calculated to compare two models with different parameters. The AIC is data-dependent and closely relates to the BIC.

The Akaike Information Criterion (AIC) is estimated:

$$AIC = -2LL(\hat{\theta}) + 2K$$

Equation 4-3

with all parameters as previously stated.

The Bayesian Information Criterion (BIC) estimated:

$$BIC = -2LL(\hat{\theta}) + 2 \ln(N)$$

Equation 4-4

with all parameters as previously stated and  $N$  the number of observations in the data.

Despite the various subtle theoretical differences between AIC and BIC, the difference in practice is the size of the penalty. The AIC puts more emphasis on model performance and selects more complex models (Murphy, 2012). BIC penalizes model complexity more heavily (Burnham & Anderson, 2004). Thus, given any two estimated models, the model with the lower AIC and BIC is the one preferred (Louviere, et al., 2003).

The robust  $t$  ratio is estimated by dividing the difference between the parameter estimate and its hypothesised value by the standard estimate error. Low values of the robust  $t$  ratio imply that the parameter does not contribute significantly to the explanatory estimation of the model and should be excluded. Selection of the critical robust  $t$  ratio is dependent on a researcher's judgement and dictates the error allowance the researcher is willing to make (Koppelman & Bhat, 2006). For this study, a confidence level of 95% was applied, noting parameter estimates as statistically significant on account of the robust  $t$  ratio in excess of 1.96.

Estimation of the robust  $t$  ratio will dictate the significance of a parameter for this study. The improvement reported on the log-likelihood (LL), AIC and BIC values will indicate the choice model's improvement. AIC and BIC values are best at lower numbers with the log-likelihood

and adjusted log-likelihood ratios aimed to improve. The model development aims to report that each subsequent model developed constitutes better goodness of fit, therefore reporting the estimations improved.

#### 4.7 Model Estimation and Results

The Random Utility Theory explored by Hess et al. (Hess, et al., 2018) in Section 2.7.1 was applied as defined in Equation 2-1. A destination IRT stop choice decision is therefore made for every MyCiTi origin-destination trip.

With the 346 MyCiTi IRT destination alternatives defined in Section 3.2:

The 1<sup>st</sup> boarding IRT stop, defined as the trip origin is stated,

$$k = 1, \dots, n.$$

The alighting IRT stop, defined as the trip destination is stated,

$$j = 1, \dots, n.$$

The possible IRT origin-destination stops are defined,

$$n = 346; k \neq j.$$

Furthermore, with all MyCiTi IRT stops assumed in operation, full availability was assumed on destination alternatives. The parameters were estimated through Maximum Likelihood Estimation.

##### 4.7.1 Model 1

To generate a base model as starting point, the first model's utility function was specified to incorporate the three primary geospatial variables. As defined in Section 3.3, these variables include the origin-destination displacement, IRT destination density, and the destination land use rating attributes. These attributes were included for base model estimation to test the influence on destination choice. The base utility function for each alternative destination is presented in Equation 4-5.

$$V_{j,n,t} = \beta_{displacement} Displacement_{j,n,t} + \beta_{density} Density_{j,n,t} + \beta_{land\ use} Land\ use_{j,n,t}$$

Equation 4-5

$\beta_{displacement}$  refers to the coefficient of distance measured in kilometres between the trip origin and destination. As stated in Section 4.5, the trip origin and destination cannot constitute the same MyCiTi IRT stop. For every choice destination, there will therefore exist a displacement.

$\beta_{density}$  refers to the coefficient of the density count of alternatives in a 1 km radius from the destination.

$\beta_{land\ use}$  refers to the vector of coefficients for the various land use rating classifications.

With  $Land\ use_{j,n,t}$  a categorical variable with the various classifications underspecified in Equation 4-5, the following output was presented by *Apollo* (Hess & Palma, 2019) upon the first estimation of Model 1:

```
"Testing likelihood function .....Error in apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, :
```

```
Parameter b_landuse does not influence the log-likelihood of your model!"
```

Parameter  $\beta_{land\ use}$  did not influence the log-likelihood of the model, as expected by the underspecified land use variable. This parameter was therefore fixed,  $\beta_{land\ use} = 0$ , for this base estimation. The categorical variable  $Land\ use_{j,n,t}$  shall be defined in the subsequent model development presented in this study.

$Displacement_{j,n,t}$  and  $Density_{j,n,t}$  are continuous variables, not restricted to the refinement of categorical variables and are therefore expected to influence the log-likelihood of the base model. Table 4-1 presents the results of the base model. The full estimation output of Model 1, as provided by *Apollo* (Hess & Palma, 2019) is found in Appendix E.

Table 4-1: Choice Destination Base Model.

<i>Parameter</i>	<i>Estimate</i>	<i>Rob t ratio</i>
$\beta_{displacement}$	-0.0737	-114.1
$\beta_{density}$	0.0127	21.38
$\beta_{land\ use}$	NA	NA

Log-Likelihood (final): -256033.1; AIC: 512070.3; BIC: 512087.7; Adjusted  $\rho^2$ : 0.0473.

The negative coefficient of  $\beta_{displacement}$  indicates that destinations located further from the origin (a larger displacement) are less attractive to individuals than destinations located closer to the origin of the trip. This is expected as the origin-destination displacement is directly associated with travelling time and travel cost, both of which numerous studies have shown commuters of public transport prefer to be kept as low as possible. The positive coefficient of  $\beta_{density}$  indicates that destinations with a higher density count are more attractive to individuals. This attraction highlights that the placement of IRT stops is directly related to the need for commuters to access a specific destination area with the MyCiTi IRT system. It further indicates that the MyCiTi IRT system captures and service its general commuter demand. Another explanation for the higher density count attractiveness was raised by Cai et al., who noted a similar trend and stated that commuters tend to choose destinations that are frequently chosen by other commuters (Cai, et al., 2015).

The parameter estimates indicate that the dislike towards an increased displacement is approximately 6 times greater than the attractiveness of a higher IRT stop density. This result suggests that commuters have a greater preference for minimising displacement (directly related to travel cost and travel time) than accessing multiple IRT stops (increased IRT stop density) at the destination. These results are intuitive as it is expected that the MyCiTi IRT system commuters will strive to reduce travel time and cost and, therefore, displacement when possible. The high-level baseline analysis of Model 1 indicates that if the MyCiTi IRT system identifies an area with a high demand for the system, it will benefit to implement sufficient IRT stops in that specified area to increase the attractiveness to the user to choose these stops as a destination. This general conclusion is further explored in the subsequent model development.

#### 4.7.2 Model 2

The second model's utility function was specified to explore the effect of including Cape Town's central business district (CBD) zone as a geospatial attribute. This led to the addition of the CBD zoning variable to capture the average effect of factors that influence choice with the inclusion of this specific zone, which was not included in the base utility function. The developed utility function is presented in Equation 4-6.

$$V_{j,n,t} = \beta_{CBD} CBD_{j,n,t} + \beta_{displacement} Displacement_{j,n,t} + \beta_{density} Density_{j,n,t} + \beta_{land\ use} Land\ use_{j,n,t}$$

Equation 4-6

$\beta_{displacement}$ ,  $\beta_{density}$  and  $\beta_{land use}$  as previously stated.

$\beta_{CBD}$  refers to the zonification coefficient of the destination alternatives located within the Central Business District of the City of Cape Town. This coefficient was included to capture preferences that are inherent to CBD destination choice and independent to the presented specific attribute values.

With parameter  $\beta_{land use}$  again underspecified in Model 2 and expected not to influence the log-likelihood of the model as presented in Section 4.7.1, this parameter was fixed,  $\beta_{land use} = 0$ , for estimation.

An alternative specification of the utility function stipulated Equation 4-6 with the expanded classification of the land use rating attributes is presented in Equation 4-7.

$$V_{j,n,t} = \beta_{CBD} CBD_{j,n,t} + \beta_{displacement} Displacement_{j,n,t} + \beta_{density} Density_{j,n,t} \\ + \beta_{land use} (Land\ use\ 1_{j,n,t} + Land\ use\ 2_{j,n,t} + Land\ use\ 3_{j,n,t} \\ + Land\ use\ 4_{j,n,t} + Land\ use\ 5_{j,n,t} + Land\ use\ 6_{j,n,t} + Land\ use\ 7_{j,n,t} \\ + Land\ use\ 8_{j,n,t} + Land\ use\ 9_{j,n,t} + Land\ use\ 10_{j,n,t})$$

Equation 4-7

With the quantitative subscript to the land use categorical variable referring to the land use rating classification specified in Section 3.3.3:

- *Land use 1<sub>j,n,t</sub>* classified as Rural,
- *Land use 2<sub>j,n,t</sub>* classified as Open Space,
- *Land use 3<sub>j,n,t</sub>* classified as Community and Regional,
- *Land use 4<sub>j,n,t</sub>* classified as Limited Use,
- *Land use 5<sub>j,n,t</sub>* classified as Utility,
- *Land use 6<sub>j,n,t</sub>* classified as Industrial,
- *Land use 7<sub>j,n,t</sub>* classified as General Business,
- *Land use 8<sub>j,n,t</sub>* classified as Agricultural,
- *Land use 9<sub>j,n,t</sub>* classified as Residential,
- *Land use 10<sub>j,n,t</sub>* classified as Mixed Use.

With  $\beta_{land use} = 0$ , Equation 4-6 and Equation 4-7 will result in the same model estimation.

Table 4-2 presents the results of this model. The full estimation output of Model 2, as provided by *Apollo* (Hess & Palma, 2019) is found in Appendix F.

Table 4-2: Choice Destination Model, CBD zonification incorporated.

<i>Parameter</i>	<i>Estimate</i>	<i>Rob t ratio</i>
$\beta_{CBD}$	1.4605	74.78
$\beta_{displacement}$	-0.0745	-114.7
$\beta_{density}$	-0.0226	-27.08

$\beta_{land\ use}$	NA	NA
---------------------	----	----

Log-Likelihood (final): -252690.6; AIC: 505387.2; BIC: 505413.4; Adjusted  $\rho^2$ : 0.0598.

All of the parameter estimates are statistically significant at the 95% level on account of the robust  $t$  ratio of the variables in excess of 1.96. The positive coefficient and estimate of  $\beta_{CBD}$  indicates the high attractiveness of the central business district in Cape Town as a choice destination. This highlights the statement of residual segregation found in the City of Cape Town, where a need exist for a large portion of the population to head from the outskirts of the city to the city centre (the CBD). The negative coefficient of  $\beta_{displacement}$  was retained and a slightly lesser attractiveness in the destination is captured when the displacement between origin and destination increases. The parameter estimates indicate that the dislike towards displacement is approximately 3 times greater than the dislike of a higher IRT stop density, again noting that commuters place a greater emphasis on minimising displacement, directly related to minimised travel cost and travel time.

A notable change is captured in  $\beta_{density}$  from Model 1 to the inclusion of the CBD zonification parameter in Model 2. A slightly higher parameter estimate is found with a changed coefficient. Hammadou et al. (2008) noted that particular attention should be paid to incorporate the effects of the spatial dimension in the utility expression due to the difficulty of associating complex spatial realities with simplified quantitative measurements. Furthermore, they stated that there is importance in illustrating 'space' in a choice model (Hammadou, et al., 2008). It is presented that this outcome captures the phenomenon where the definition of the spatial dimension can influence the behaviour of coefficients in geospatial choice models.

#### The definition of the spatial dimension

The definition of 'dimension' in Model 1 and Model 2 is explored. In Model 1, the  $\beta_{density}$  parameter is estimated with a positive coefficient. This choice model is illustrated in Figure 4-2. The origin is noted as MyCiTi IRT stop A and the destination as MyCiTi IRT stop B. The red line connecting A and B illustrates the displacement, the geographical distance, between the origin and the destination. The blue circle depicts the 1 km radius perimeter surrounding the destination IRT stop, as discussed in Section 3.3.2. The blue dots represent the MyCiTi IRT stops surrounding the IRT destination B. The count of blue dots located within the 1 km radius perimeter of B is referred to as the destination density count (as introduced in Section 3.3.2).

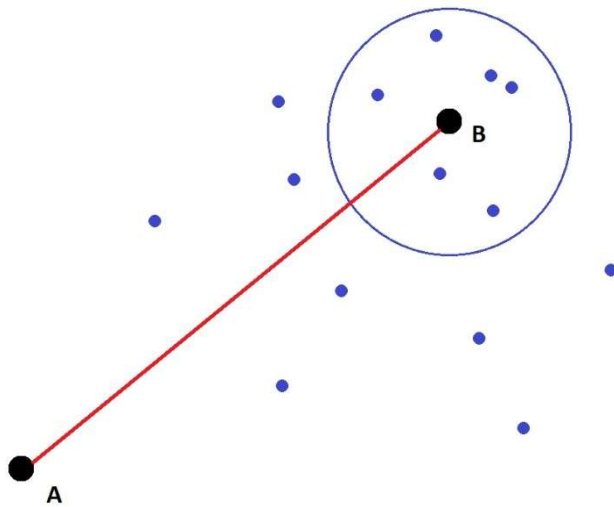


Figure 4-2: Model 1 spatial dimension illustration.

IRT stops are geographically located due to an identified demand. A higher density of IRT stops within the spatial dimension illustrated in Figure 4-2 indicates the higher demand for commuters to access the destination area. The positive coefficient of the density parameter estimated in Model 1 indicates that choice destinations within this spatial dimension, with a higher density count, are more attractive to individuals. This dimension is presented as the inter-densified zoning dimension.

In Model 2, the  $\beta_{density}$  parameter is estimated with a negative coefficient with the inclusion of the  $\beta_{CBD}$  coefficient in the utility function. It is proposed that the inclusion of the zonification parameter for destination alternatives changes the definition of the spatial, and therefore density, dimension. Collinearity is noted between the destination IRT stop density and the central business district zone. Choice Model 2 is illustrated in Figure 4-3 as an extension of Figure 4-2, with all representations as previously stated. Additional to Figure 4-2, within this spatial dimension, the CBD zone is included and schematically depicted by the green square in Figure 4-3.

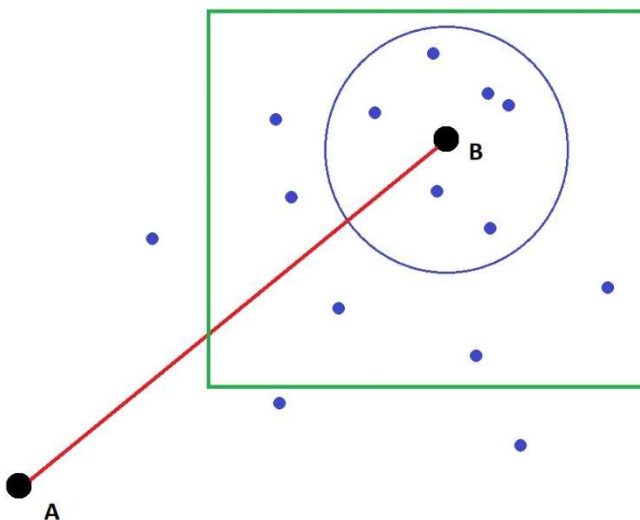


Figure 4-3: Model 2 spatial dimension illustration.

The negative coefficient of the density parameter  $\beta_{density}$  estimated in Model 2 indicates that choice destinations within the spatial dimension of the CBD zonification, are more attractive to individuals when a lesser density count is present. Within this spatial dimension, an individual has a higher preference for less MyCiTi IRT stops to be present in close surround when choosing a destination. The probability of an individual choosing a destination IRT stop destination is therefore increased when there are lesser MyCiTi IRT stops in the immediate surround. This outcome captures the competitiveness between IRT stops within this spatial dimension. This dimension, as illustrated in Figure 4-3, is presented as the intra-densified zoning dimension.

With the destination zoning specified with the inclusion of the zoning parameter, model development following Model 2 in this study will successively estimate choice models within the intra-densified zoning dimension.

It is proposed by the author that various geospatial dimensions exist in the modelling of destination choice and that the estimation of attribute parameters of choice models can differ between geospatial dimensions, as illustrated in this study. Specification of the geospatial dimension is therefore critical in the destination choice modelling process. To further evaluate the impact of the CBD zonification and IRT stop density on destination choice, both attributes were included in the successive developed models presented in this study.

#### 4.7.3 Model 3

The second utility function, presented in Equation 4-6, was expanded in Model 3 to explore the effect of the central business district zone inclusion. As noted, this study estimates choice models within the intra-densified zoning dimension. This model's utility function was expanded to investigate the impact of CBD zone inclusion on the choice utility. The utility function integrating this zone trends to a nested model and is presented in Equation 4-8.

$$\begin{aligned}
 V_{j,n,t} = & \beta_{CBD} CBD_{j,n,t} + \left( \beta_{displacement} + \beta_{displacement_{CBD\ shift}} CBD_{j,n,t} \right) * Displacement_{j,n,t} \\
 & + \left( \beta_{density} + \beta_{density_{CBD\ shift}} CBD_{j,n,t} \right) * Density_{j,n,t} \\
 & + \left( \beta_{land\ use} + \beta_{land\ use_{CBD\ shift}} CBD_{j,n,t} \right) * (Land\ use\ 1_{j,n,t} + Land\ use\ 2_{j,n,t} \\
 & + Land\ use\ 3_{j,n,t} + Land\ use\ 4_{j,n,t} + Land\ use\ 5_{j,n,t} + Land\ use\ 6_{j,n,t} \\
 & + Land\ use\ 7_{j,n,t} + Land\ use\ 8_{j,n,t} + Land\ use\ 9_{j,n,t} + Land\ use\ 10_{j,n,t})
 \end{aligned}$$

Equation 4-8

$\beta_{displacement_{CBD\ shift}}$  refers to the coefficient shift the origin-destination displacement parameter will encounter when the destination is located within the CBD zone.

$\beta_{density_{CBD\ shift}}$  refers to the coefficient shift the destination density parameter will experience when the destination is located within the CBD zone.

$\beta_{landuse_{CBD\ shift}}$  refers to the coefficient shift the destination landuse parameter will encounter when the destination is located within the CBD zone.

$\beta_{CBD}$ ,  $\beta_{displacement}$ ,  $\beta_{density}$  and  $\beta_{land\ use}$  as previously stated.

Parameter  $\beta_{land\ use}$  did not influence the log-likelihood of the model, as presented in Section 4.7.1 for Model 1 in due to the under specification of this parameter even with respect to the various categorical land use variables defined as  $Land\ use\ 1_{j,n,t}$ ,  $Land\ use\ 2_{j,n,t}$ ,

*Land use*  $3_{j,n,t}$ , *Land use*  $4_{j,n,t}$ , *Land use*  $5_{j,n,t}$ , *Land use*  $6_{j,n,t}$ , *Land use*  $7_{j,n,t}$ , *Land use*  $8_{j,n,t}$ , *Land use*  $9_{j,n,t}$  and *Land use*  $10_{j,n,t}$ . Parameters  $\beta_{land\ use}$  and  $\beta_{land\ use_{CBD\ shift}}$  were therefore fixed:  $\beta_{land\ use} = 0$ ;  $\beta_{land\ use_{CBD\ shift}} = 0$ .

The land use parameters shall be further defined in the subsequent model development presented in this study.

Table 4-3 presents the results of Model 3. The full estimation output of Model 3, as provided by *Apollo* (Hess & Palma, 2019) is found in Appendix G.

Table 4-3: Choice Destination Model, CBD zonification shift incorporated.

<i>Parameter</i>	<i>Estimate</i>	<i>Rob t ratio</i>
$\beta_{CBD}$	5.9854	114.24
$\beta_{displacement}$	-0.0795	-110.81
$\beta_{displacement_{CBD\ shift}}$	0.0289	26.58
$\beta_{density}$	-0.0117	-14.40
$\beta_{density_{CBD\ shift}}$	-0.1751	-87.38
$\beta_{land\ use}$	NA	NA
$\beta_{land\ use_{CBD\ shift}}$	NA	NA

*Log-Likelihood (final): -250246.4; AIC: 500502.7; BIC: 500546.4; Adjusted  $\rho^2$ : 0.0689.*

All of the parameter estimates are statistically significant at the 95% level on account of the robust  $t$  ratio of the variables in excess of 1.96. The notable positive coefficient of  $\beta_{CBD}$  was retained, indicating the high attractiveness of the central business district in Cape Town. The negative coefficient of  $\beta_{displacement}$  was maintained with the destination again noted as less attractive when the displacement between the origin and destination increase. This noted disfavour is however reduced when the destination is located within the CBD zone as seen by the positive coefficient of  $\beta_{displacement_{CBD\ shift}}$ . This indicates that although destinations located further away from the origin is less attractive, the attractiveness increase when the destination is located within the CBD zone.

The negative coefficient of  $\beta_{density}$  was maintained, but the preference of lesser MyCiTi IRT stops increase when the destination is located within the CBD zone as seen by the negative coefficient of  $\beta_{density_{CBD\ shift}}$ . This highlights the phenomena proposed in this study, where the spatial dimension can influence choice behaviour and contribute to the author's statement that competitiveness is found between IRT stops within the intra-densified zoning dimension.

When the destination is located outside the CBD zone, the parameter estimates indicate that the dislike towards displacement is approximately 7 times greater than the dislike of a higher IRT stop density. Again, this outcome notes that commuters strive to minimise displacement when considering a destination choice outside of the CBD zone. When the destination is located in the CBD zone, however, the parameter estimates indicate that the dislike towards a higher IRT stop density is approximately 4 times greater than the dislike towards the displacement. This outcome indicates that less IRT stops within the CBD zone greatly increase the attractiveness of an individual stop. Commuters have a lesser disutility to displacement when the destination is located within the CBD zone. These outcomes highlight the attraction of the CBD zone as a choice destination.

#### 4.7.4 Model 4

Equation 4-8 was further developed in Model 4 to specify and include the destination land use rating classification parameters in the utility function. This developed utility function is presented in Equation 4-9.

$$\begin{aligned}
 V_{j,n,t} = & \beta_{CBD} CBD_{j,n,t} + \left( \beta_{displacement} + \beta_{displacement_{CBD\ shift}} CBD_{j,n,t} \right) * Displacement_{j,n,t} \\
 & + \left( \beta_{density} + \beta_{density_{CBD\ shi}} CBD_{j,n,t} \right) * Density_{j,n,t} \\
 & + \beta_{land\ use\ 1} * Land\ use\ 1_{j,n,t} + \beta_{land\ use\ 2} * Land\ use\ 2_{j,n,t} + \beta_{land\ use\ 3} \\
 & * Land\ use\ 3_{j,n,t} + \beta_{land\ use\ 4} * Land\ use\ 4_{j,n,t} + \beta_{land\ use\ 5} * Land\ use\ 5_{j,n,t} \\
 & + \beta_{land\ use\ 6} * Land\ use\ 6_{j,n,t} + \beta_{land\ use\ 7} * Land\ use\ 7_{j,n,t} + \beta_{land\ use\ 8} \\
 & * Land\ use\ 8_{j,n,t} + \beta_{land\ use\ 9} * Land\ use\ 9_{j,n,t} + \beta_{land\ use\ 10} * Land\ use\ 10_{j,n,t}
 \end{aligned}$$

Equation 4-9

All previously introduced parameters as formerly stated, and with the quantitative subscript to the land use variables referencing the land use rating classification specified in Section 3.3.3:

- $\beta_{land\ use\ 1}$  refers to the coefficient of the Rural destination land use rating parameter.
- $\beta_{land\ use\ 2}$  refers to the coefficient of the Open Space destination land use rating parameter.
- $\beta_{land\ use\ 3}$  refers to the coefficient of the Community and Regional destination land use rating parameter.
- $\beta_{land\ use\ 4}$  refers to the coefficient of the Limited Use destination land use rating parameter.
- $\beta_{land\ use\ 5}$  refers to the coefficient of the Utility destination land use rating parameter.
- $\beta_{land\ use\ 6}$  refers to the coefficient of the Industrial destination land use rating parameter.
- $\beta_{land\ use\ 7}$  refers to the coefficient of the General Business destination land use rating parameter.
- $\beta_{land\ use\ 8}$  refers to the coefficient of the Agricultural destination land use rating parameter.
- $\beta_{land\ use\ 9}$  refers to the coefficient of the Residential destination land use rating parameter.
- $\beta_{land\ use\ 10}$  refers to the coefficient of the Mixed Use destination land use rating parameter.

None of the land use parameters was fixed for the first estimation of Model 4. Although a high-level outcome was expected, this was done to establish an unbiased estimate of the influence of the various land use ratings on destination choice. The first estimate resulted in a minimum absolute eigenvalue of the hessian close to zero, which indicated a convergence problem. This first estimate was deemed over-parametrized but did report the insignificance of  $\beta_{land\ use\ 2}$  and therefore the land use rating classification 2. The Open Space land use classification is therefore not significant in the calculation of the utility of a destination.

The insignificant land use parameter was fixed for the second estimation of Model 4,  $\beta_{land\ use\ 2} = 0$ . Table 4-4 presents the results. The full estimation output of Model 4, as provided by *Apollo* (Hess & Palma, 2019) is found in Appendix H.

Table 4-4: Choice Destination Model, land use classification specified.

<i>Parameter</i>	<i>Estimate</i>	<i>Rob t ratio</i>
$\beta_{CBD}$	5.6246	93.35
$\beta_{displacement}$	-0.0781	-107.59
$\beta_{displacement_{CBD\ shift}}$	0.0325	29.77
$\beta_{density}$	-0.0145	-15.70
$\beta_{density_{CBD\ shift}}$	-0.1799	-76.03
$\beta_{land\ use\ 1}$ (Rural)	1.0769	28.01
$\beta_{land\ use\ 2}$ (Open Space)	NA	NA
$\beta_{land\ use\ 3}$ (Community and Regional)	-0.3346	-6.60
$\beta_{land\ use\ 4}$ (Limited Use)	-0.2196	-5.07
$\beta_{land\ use\ 5}$ (Utility)	0.4879	11.70
$\beta_{land\ use\ 6}$ (Industrial)	-0.2251	-5.31
$\beta_{land\ use\ 7}$ (General Business)	0.6067	15.66
$\beta_{land\ use\ 8}$ (Agriculture)	-0.4329	-10.27
$\beta_{land\ use\ 9}$ (Residential)	-0.5144	-12.99
$\beta_{land\ use\ 10}$ (Mixed Use)	-0.307	-7.87

*Log-Likelihood (final): -244789.7; AIC: 489607.4; BIC: 489729.7; Adjusted  $\rho^2$ : 0.0891.*

The notable positive coefficient of  $\beta_{CBD}$  maintains the high attractiveness of the central business district in Cape Town. Coefficients  $\beta_{displacement}$ ,  $\beta_{displacement_{CBD\ shift}}$ ,  $\beta_{density}$  and  $\beta_{density_{CBD\ shift}}$  behaved as presented in Section 4.7.3. When the destination is located outside the CBD zone, the parameter estimates indicate that the dislike towards displacement is approximately 5 times greater than the dislike of a higher IRT stop density, noting that commuters strive to minimise displacement when considering a destination choice outside of the CBD zone. With a destination located in the CBD zone, the parameter estimates indicate that the dislike towards a higher IRT stop density is approximately 4 times greater than the dislike towards the displacement as reported in Model 3. This again motivates that lesser IRT stops within the CBD zone greatly increase the attractiveness of an individual stop. It is noted that planners should be aware of IRT stop densification leading to overcrowded and ineffective public transport systems. All of the parameter estimates are statistically significant at the 95% level on account of the robust  $t$  ratio of the variables in excess of 1.96.

A higher preference is indicated towards the land use classifications of Utility, General Business and Rural, in order of increasing preference. This correlates with the destination trip data presented per land use classification in Figure 3-14. With only 1.7% of MyCiTi IRT stops located in a Rural land use classification, it is counter-intuitively noted that these stops feature as highly favoured destinations. The high preference shown towards the General Business land use classification was expected, as 21.1% of the South African population stated the use of commuter bus services for their daily commute (Statistics South Africa, 2013). It is expected that the high preference noted towards the Utility land use classification may link to the daily commute of Capetonians towards places of employment or places of residence where high utility services are expected.

A lesser preference is shown towards the land use classifications of Limited Use, Industrial, Mixed Use, Community and Regional, Agriculture and Residential, in order of

increasing disfavour. The lesser preference indicated to the land use classifications of Residential and Mixed Use is counter-intuitively, as both serve as popular commuter trip destinations indicated in Figure 3-14.

The disfavour towards Limited Use land use classification is intuitive as limited economic opportunities are expected to be present at such a destination classification. Community and Regional land use classifications are ordinarily accessible to the communities it serves, and it is therefore expected that public transport should not always be required to access these facilities. Notably, the Industrial and Mixed Use land use classifications are not favoured as destinations for the MyCiTi IRT system.

The Agriculture sector is one of the most essential components of Cape Town's economy (Invest Cape Town, 2020); it is therefore surprising that the Agriculture land use classification does not attract a high preference as a choice destination. Thus, the MyCiTi IRT system is not serving as access to this crucial economic component. It is recommended that this outcome be investigated for planning strategies of the future MyCiTi IRT system. If the reasoning of this result can be identified and resolved, the MyCiTi IRT system can be utilized to attract and possibly capture the economic opportunities found within the agricultural sector of Cape Town.

The reported dislike towards the Mixed Use land use classification is counter-intuitive as this land use classification attracts high destination trip volumes, as presented in Figure 3-14. The *Apollo* output for Model 4, found in Appendix H, includes a robust correlation matrix of all attributes. It is worth noting that a higher than 60% correlation is found between all land use classifications.  $\beta_{land\ use\ 10}$  (Mixed Use) is found highly correlated to  $\beta_{land\ use\ 9}$  (Residential) with a correlation of 91%,  $\beta_{land\ use\ 1}$  (Rural) with a correlation of 91%, and  $\beta_{land\ use\ 7}$  (General Business) with a correlation of 93%. The Mixed Use land use classification is a conglomerate of various land uses combined. The correlations reported suggest that the attractiveness of this land use classification is related to the behaviour of the parameters of other land use classifications, with an extremely high influence noted by land use classifications of Residential, Rural and General Business with correlations of higher than 90% as noted. Without more information available on the Mixed Use land use classification for this study, it is challenging to interpret the noted dislike and magnitude of the estimation outcome reported in Table 4-4. The author suggests that additional descriptive data on the Mixed Use land use classification be obtained, i.e. the various land use distributions of the Mixed Use classification, for this land use classification to be considered in further geospatial studies.

A noted dislike is shown towards the Residential land use classifications as a choice destination. The National Household Travel Survey (2013) reported a distinct general trip pattern found where a large portion of the Capetonian population heads from the suburbs to the city centre in the mornings and returning in the opposite direction in the evenings (Statistics South Africa, 2013). This pattern is also indicated in the trip data presented in Figure 3-14. The *Apollo* output robust correlation matrix of all attributes for Model 4, found in Appendix H, indicates that  $\beta_{land\ use\ 7}$  (General Business) is highly correlated to  $\beta_{land\ use\ 9}$  (Residential) with a correlation of 92%. It is expected that the majority of IRT commuters, on a stop-to-stop basis, go to work and return home from the same stop without deviation. Therefore, it is expected that Residential land use classification would be preferred as a destination choice for the returning evening commuters on a one-day dataset. An explanation of this counter-intuitive outcome might lie in skewed data. A skewed dataset may be present if the evening peak trip data is not captured where commuters tend to depart from places of employment to residential areas, as discussed in Section 3.3.3. Unskewed data would indicate a more balanced origin and destination distribution as the Residential land use areas are deemed both popular origin and destination nodes.

#### 4.7.5 Model 5

With the attractiveness of the land use classifications analysed in Model 4 as presented in Section 4.7.4, an investigation towards the CBD zonification influence on the desirability of these categorical variables as choice destinations followed. A review of the dataset found that only one land use rating classification had significant dominance in the CBD zone of Cape Town. The majority of MyCiTi IRT stops located within the CBD had a land use rating classification of General Business. Equation 4-9 was further developed to capture the influence on the utility when the land use rating classification (7) for General Business was located within the CBD zone. This developed utility function is presented in Equation 4-10.

$$\begin{aligned}
 V_{j,n,t} = & \beta_{CBD} CBD_{j,n,t} + \left( \beta_{displacement} + \beta_{displacement_{CBD\ shift}} CBD_{j,n,t} \right) * Displacement_{j,n,t} \\
 & + \left( \beta_{density} + \beta_{density_{CBD\ shift}} CBD_{j,n,t} \right) * Density_{j,n,t} \\
 & + \beta_{land\ use\ 1} * Land\ use\ 1_{j,n,t} + \beta_{land\ use\ 2} * Land\ use\ 2_{j,n,t} + \beta_{land\ use\ 3} \\
 & * Land\ use\ 3_{j,n,t} + \beta_{land\ use\ 4} * Land\ use\ 4_{j,n,t} + \beta_{land\ use\ 5} * Land\ use\ 5_{j,n,t} \\
 & + \beta_{land\ use\ 6} * Land\ use\ 6_{j,n,t} + \left( \beta_{land\ use\ 7} + \beta_{land\ use\ 7_{CBD\ shift}} CBD_{j,n,t} \right) \\
 & * Land\ use\ 7_{j,n,t} + \beta_{land\ use\ 8} * Land\ use\ 8_{j,n,t} + \beta_{land\ use\ 9} * Land\ use\ 9_{j,n,t} \\
 & + \beta_{land\ use\ 10} * Land\ use\ 10_{j,n,t}
 \end{aligned}$$

Equation 4-10

All parameters as previously stated in Sections 4.7.1 to 4.7.4, and with:

$\beta_{land\ use\ 7}$  and  $\beta_{land\ use\ 7_{CBD\ shift}}$  referring to the coefficient of the General Business destination land use parameter and coefficient shift the parameter will experience when the destination is located within the CBD zone subsequently.

As presented in Section 4.7.4, the insignificant parameter of Open Use land use classification was fixed:  $\beta_{land\ use\ 2} = 0$ . Table 4-5 presents the results. The full estimation output of Model 5, as provided by *Apollo* (Hess & Palma, 2019) is found in Appendix I.

Table 4-5: Choice Destination Model, land use specified, and CBD zonification shift included for General Business.

<i>Parameter</i>	<i>Estimate</i>	<i>Rob t ratio</i>
$\beta_{CBD}$	6.9499	74.41
$\beta_{displacement}$	-0.078	-108.21
$\beta_{displacement_{CBD\ shift}}$	0.0322	29.41
$\beta_{density}$	-0.0153	-16.66
$\beta_{density_{CBD\ shift}}$	-0.2401	-59.45
$\beta_{land\ use\ 1}$ (Rural)	1.1072	28.88
$\beta_{land\ use\ 2}$ (Open Space)	NA	NA
$\beta_{land\ use\ 3}$ (Community and Regional)	-0.3394	-6.7
$\beta_{land\ use\ 4}$ (Limited Use)	-0.0425	-0.98
$\beta_{land\ use\ 5}$ (Utility)	0.5836	13.98
$\beta_{land\ use\ 6}$ (Industrial)	-0.2351	-5.55
$\beta_{land\ use\ 7}$ (General Business)	0.5348	13.71
$\beta_{land\ use\ 7_{CBD\ shift}}$	0.7978	18.58

$\beta_{land\ use\ 8}$ (Agriculture)	-0.4444	-10.55
$\beta_{land\ use\ 9}$ (Residential)	-0.5198	-13.13
$\beta_{land\ use\ 10}$ (Mixed Use)	-0.3176	-8.14

*Log-Likelihood (final): -244572.8; AIC: 489175.5; BIC: 489306.5; Adjusted  $\rho^2$ : 0.0899.*

The estimated coefficients seen in Table 4-5 for the proposed model are consistent with their explored and hypothesized effects on the utility presented in this study. The notable positive coefficient of  $\beta_{CBD}$  indicates the very high attractiveness of the central business district in Cape Town being maintained. Coefficients  $\beta_{displacement}$ ,  $\beta_{displacement_{CBD\ shift}}$ ,  $\beta_{density}$  and  $\beta_{density_{CBD\ shift}}$  behaved as presented in Section 4.7.3.

The higher preference shown towards the land use classifications of General Business, Utility and Rural is maintained as presented in Section 4.7.4. Interestingly a slightly higher preference is displayed towards the Utility land use classification in Model 5, than what was previously presented.

The lesser preference shown towards the land use classifications of Limited Use, Industrial, Mixed Use, Community and Regional, Agriculture and Residential, in order of increasing disfavour, is also maintained presented in Section 4.7.4.

The positive coefficient of  $\beta_{land\ use\ 7}$  (General Business) was maintained and it is presented by the notable positive coefficient of  $\beta_{land\ use\ 7_{CBD\ shift}}$  that the preference for choosing a destination with this land use classification is notably increased when the destination is located within the CBD zone. The CBD zone and General Business land use classification are correlated; a change in either variable is therefore parallel to a change in the other. This correlation is expected and reflects that commuters' preferences for the CBD zone are related to the General Business land use classification preferences. This outcome highlights the economic opportunity captured within this zone and the CBD zone's influence on attracting users to the MyCiTi IRT system for business commute.

All of the parameter estimates except the land use parameter of Limited Use are statistically significant at the 95% level on account of the robust  $t$  ratio of the variables in excess of 1.96.

The *Apollo* output for Model 5, found in Appendix I, includes a robust correlation matrix of all attributes. It is worthy to note that all land use classifications have a higher than 60% correlation, as also presented by the outcomes of Model 4 in Section 4.7.4.  $\beta_{land\ use\ 10}$  (Mixed Use) is found highly correlated to  $\beta_{land\ use\ 9}$  (Residential) with a correlation of 91%,  $\beta_{land\ use\ 1}$  (Rural) with a correlation of 91%, and  $\beta_{land\ use\ 7}$  (General Business) with a correlation of 92%.  $\beta_{land\ use\ 7}$  (General Business) is found highly correlated to  $\beta_{land\ use\ 9}$  (Residential) with a correlation of 92%. The high correlation noted between the land use parameters could explain the counter-intuitive outcomes of the Mixed Use and Residential land use classifications presented in Table 4-5 as discussed in Section 4.7.4.

A MyCiTi IRT stop located within the CBD zone of Cape Town, with less surrounding IRT stops present (a low IRT stop density), located the closest distance from the point of trip origin and with a land use classification of General Business is expected to maximise the choice individual's utility. The attractiveness of a destination is therefore closely related to the land use type surrounding the IRT stops as also determined by Cai et al. (Cai, et al., 2015).

#### 4.7.6 Goodness of Fit

As introduced in Section 4.6, several tests are conducted to ascertain the goodness of fit of choice models. In choice models, the goodness of fit dictates how well the statistical

methods and analysis fits the model data. The aim of the model development is to report that each subsequent model constitutes better goodness of fit, therefore reporting the developed model improved.

*Apollo* reported the following goodness of fit statistics for each model developed in Sections 4.7.1 to 4.7.5: the log-likelihood (LL), the adjusted Pseudo  $R^2$  (adjusted  $\rho^2$ ), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). AIC and BIC values are aimed to be minimised with the log-likelihood and adjusted Pseudo  $R^2$  ratios aimed to be improved following the subsequent model development.

The goodness of fit tests are summarised in Table 4-6 for the subsequent model development from the base model (Model 1) to the final model (Model 5) as reported.

Table 4-6: Model Development Summary.

<i>Goodness of fit</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>	<i>Model 5</i>
<i>Log – likelihood (final)</i>	-256033.1	-252690.6	-250246.4	-244789.7	-244572.8
<i>AIC</i>	512070.3	505387.2	500502.7	489607.4	489175.5
<i>BIC</i>	512087.7	505413.4	500546.4	489729.7	489306.5
<i>Adjusted <math>\rho^2</math></i>	0.0473	0.0598	0.0689	0.0891	0.0899

From Table 4-6 it is seen that the log-likelihood improves from Model 1 to Model 5 with the subsequent model development.

The information criterion indices AIC and BIC are used to compare models, with the lowest value of a given index indicating the best model fit (Nylund, et al., 2007). Burnham and Anderson (2004) defined model equivalency as *substantial* for an AIC difference of 0 – 2, *weak* for an AIC difference of 4 – 7 and *none* for an AIC difference of > 10 (Burnham & Anderson, 2004). Raftery (1995) stated the difference between models as *weak* for a BIC difference of 0 – 2, *positive* for a BIC difference of 2 – 6, *strong* for a BIC difference of 6 – 10 and *very strong* for a BIC difference of > 10 (Raftery, 1995).

The AIC difference in succeeding models from Model 1 to Model 5 results in a difference >10, which supports equivalency between none of the models. The BIC difference in succeeding models from Model 1 to Model 5 results in a difference of >10, which supports the development of the subsequent models. The AIC and BIC values become less for each subsequent model developed, with Model 1 reporting higher values than Model 5, indicating model improvement.

Pseudo  $R^2$  ( $\rho^2$ ) is the most general measure of both the overall and relative model fit (goodness of fit). It is an indication of how well the model fits the data and is used to compare multiple models' fit to the same dataset. In regression analysis, the output from the regression model is aimed to have significant variables and to produce a high  $\rho^2$  value. Significant variables were found in the model development of this study, as discussed in Sections 4.7.1 to 4.7.5.

The log-likelihood is a non-linear function, and therefore adjusted  $\rho^2$  values cannot be interpreted in linear terms. A model with no predictive ability will allow the ratio of the two log-likelihoods presented in Equation 4-1 to be close to 1, and  $\rho^2$  to be close to zero. A highly predictive model will result in a  $\rho^2$  value close to 1. A Pseudo  $R^2$  value exceeding 0.2 typically indicates goodness of fit for the linear regression model estimation (Frost, 2020). A  $\rho^2$  value exceeding 0.3 generally indicates goodness of fit of the logistic non-linear regression model (i.e. MNL model) estimation (Hensher, et al., 2015). The adjusted  $\rho^2$  value considers the number of variables in the model. Its value only increases when a

newly included variable improves the model fit more than when compared to the model excluding this addition (Frost, 2021).

The adjusted  $\rho^2$  values increased from 0.0473 in Model 1 to 0.0899 in Model 5 with the subsequent model development. With the continuous introduction of geospatial properties, the adjusted  $\rho^2$  values increased, indicating an improved fit of the models. It also confirms that the included variables in the subsequent model development improved the model fit. The increase of  $\rho^2$  reported with every model estimation states that the subsequent model is superior, with Model 5 showcasing the better fit.

Although the adjusted  $\rho^2$  values increased with the subsequent model development from Model 1 to Model 5, very low adjusted  $\rho^2$  values were estimated, as presented in Table 4-6. As stated, an adjusted  $\rho^2$  value of less than 0.3 indicates that the models presented in this study do not fit the dataset well (Hensher, et al., 2015) and indicates the exclusion of important explanatory variables. Caution is raised on the application of models with adjusted  $\rho^2$  values lower than 0.1, but models estimating large datasets with these low values can still indicate significance (Miller & Falk, 1992). Therefore, although Model 5 is the superior model developed, it has a low predictive ability. From this result, it can be concluded that not all relevant variables explaining the choice outcome were included in the model specification. It is therefore recommended that studies on destination modelling with a geospatial focus be complemented with the inclusion of trip and user-specific variables.

Although the low  $\rho^2$  values indicate underspecified models, the models still constitute explanatory power. The low  $\rho^2$  values of the estimated Models (i.e. for Model 5,  $\rho^2 = 0.0899$ ) and the anomalies reported in the model estimates noted in Sections 4.7.4 and 4.7.5 indicates that the models developed are not fit for application. However, the results from this study provide significant insight into the effects geospatial properties have on destination choice for the case of the MyCiTi IRT system. Further studies into the investigation of the geospatial influence on destination choice supporting application are therefore motivated.

The improvement reported in the Log-likelihood, AIC and BIC values additionally indicate that each following model development presented in this study is subsequently superior. Therefore, Model 5 presents the most accurate utility function to investigate the geospatial influence on destination choice in this study.

#### 4.7.7 Model Application in Transportation Planning and Policy Strategies

As discussed in Section 2.4, the City of Cape Town's Municipal Spatial Development Framework highlights the need to connect the city's citizens to economic opportunities. The existing MyCiTi Integrated Rapid Transit (IRT) system will be used as the basis of the Transit-Oriented Development philosophy, with the City of Cape Town's future urban form and function to be structured around this IRT system (City of Cape Town, 2017). The application of the results presented in this study can therefore hold value to the transportation planning and policy strategies of the City of Cape Town on the factors that can influence it reaching its aimed development goals and targeted urban form.

The results from this destination choice modelling study support the noted trend proposing that geospatial properties can influence travel behaviour. The multinomial logit choice models presented and discussed in this study showcased goodness of fit to provide insight into the influence geospatial properties have on destination choice for the case of the MyCiTi IRT system as presented in Section 4.7.6.

A significantly higher preference is displayed by commuters to select direct transit routes. Destinations that result in a higher displacement were found less attractive to commuters than destinations located closer to the trip origin. A very high attraction to the Central Business District as destination in Cape Town was found as expected. This zoned attraction highlights the phenomenon of residual segregation found in the City of Cape Town. Although a destination's attractiveness decreases with an increase in displacement, a lesser dislike was presented towards destinations located further from the origin but located within the CBD.

It is proposed that various geospatial dimensions exist in the modelling of destination choice. The estimation of attribute parameters in choice models can differ between geospatial dimensions, as illustrated in this study. Transport planners should note that the geospatial dimension specification is deemed a critical step in the destination choice process for parameter estimation. Inter-densified and intra-densified zoning dimensions are introduced as dictated by the geospatial dimension.

Destinations within the intra-densified zoning dimension (where the CBD zonification is specified) were more attractive to commuters when fewer MyCiTi IRT stops were present. This outcome iterates the competitiveness between the IRT stops within the CBD of Cape Town. It is noted that transportation planners should be aware that MyCiTi IRT stop densification within the CBD may lead to an overcrowded and ineffective system.

A higher preference was found towards the land use classifications of General Business, Utility and Rural, in order of increasing preference. With only 1.7% of the MyCiTi IRT stops located in a Rural land use classification, it is counter-intuitively noted that these stops feature as highly favoured destinations. It is proposed that transport planners explore the need reported for commuters to access rural destinations.

The high preference shown towards the General Business land use classification as a destination was expected. It was additionally reported that the preference for choosing a destination with General Business land use classification is increased when the destination is located within the CBD. The high preference noted towards the Utility land use classification is expectedly synonymous to places of employment or residence where high utility services are required. Therefore, it is noted for planning policies that the development of utility services can increase a destination's attraction.

It was reported that the Industrial and Mixed Use land use classifications were not favoured as destinations for the MyCiTi IRT system. A high correlation between the Mixed Use and various other land use classifications were found, which might explain the counter-intuitive outcome. Further investigation is recommended to explain why a preference is not captured by the MyCiTi IRT system for commuters to access these destinations, as both these classifications should involve employment opportunities.

The Agriculture land use classification not attracting a high preference was a highlighted outcome, as this sector is an essential component of Cape Town's economy (Invest Cape Town, 2020). It is recommended that this outcome be investigated to resolve and enable the MyCiTi IRT system to be utilised to attract and possibly capture the economic opportunities presented by the agricultural sector of Cape Town.

An unexpected dislike was reported for the Residential land use classifications as a choice destination. The National Household Travel Survey (2013) states a distinct trip pattern where a large percentage of the Capetonian population heads from the suburbs to the city centre in the mornings and returning in the opposite direction in the evenings (Statistics South Africa, 2013). These suburbs are expected to fall within the residential land use classification. It is noted that further investigation is required to confirm if an explanation of this counter-intuitive outcome might lie in the high correlation found between the Residential and General Business land use classifications.

By further exploring the results presented by this study on investigating the effect geospatial properties have on commuter choices, insight can be obtained into how the MyCiTi IRT system can be developed and optimised to meet commuter demand and accelerate the aimed diversification of the City of Cape Town. Understanding travel behaviour and the effect geospatial properties have on the operation of the MyCiTi IRT system can unfold significant value for the City of Cape Town.

## 5. LIMITATIONS AND FUTURE WORK

With ever-changing conditions and data from 2015 applied in this study, the author recommends that the findings of this study be compared to the application of present-day data. This study excludes any personal characteristics. It is recommended that future studies expand the revealed preference data with the inclusion of stated preference data to capture the personal variance and for application in the field of transportation planning.

Automatic fare collected data was applied in this study. Fare evasion is a noted general problem and can contribute to erroneous data or an underestimation of trips in services that operate in high evasion areas. It is recommended that the effect of trip evaders of the MyCiTi IRT system be investigated in further studies.

In a perfect dataset, every journey with a starting point will have an ending point. The count of 1<sup>st</sup> boarding transactions not equalling the alighting transactions in the dataset indicated an incompleteness of the survey data (Richardson, et al., 1995). Transactions were therefore missing, or it is proposed that erroneous transactions were recorded.

Connection transactions were noted not to affect the origin-destination pairing of transactions required for this study and were therefore excluded. This study is based on one-day data analysis; the author recommends this study to be compared with a weekly or monthly expanded analysis to support the findings made in this study.

A discrepancy was noted when the MyCiTi IRT stop names of the coordinated dataset were compared to the names of the automatic fare collected dataset. Additional names were listed in the coordinated data. It was determined that a variety of human spelling errors were captured in *both* datasets. A sample of the errors identified includes the spelling variation of *Langeberg* and *Langberg*, *Oscar Mpetha* and *Oscar Mpethu*, *Sandrift* and *Sanddrift*, *Braselton* and *Braseltown* IRT stops as noted. The invalid entries indicated an incompleteness deficiency in the sampling frame (Richardson, et al., 1995). Where the listed MyCiTi IRT stop names could not be verified, it was excluded from the study.

A discrepancy was noted where certain individual MyCiTi IRT stops within the coordinated dataset were given two coordinates. It was stated that this discrepancy arose where an IRT stop had two access points on either side of a road as influenced by the direction of travel.

The combination of multiple data sources allowed for an unbiased analysis and added credibility to this study and the future application thereof. As noted with the modelling execution of this study, the computational implementation of a major dataset of multiple data sources is prone to limitations. Should this study be expanded or further explored, it is recommended by the author that computational abilities should be verified.

With the high correlation found between the various land use classifications, the author recommends that the multinomial logit model presented in this study be developed into a nested logit model to address the correlated results and improve the model's specification.

The author suggests that supporting descriptive data on the Mixed Use land use classification be obtained, i.e. the distribution of the various land use definition of the Mixed Use classification. Supporting data will enable the researcher to better interpret the Mixed Use land use classification parameter estimates in further geospatial studies.

The author recommends further studies on the geospatial investigation of destination choice models to include peak hour attributes. It is additionally recommended that trip parameters, including but not limited to commuter fare and trip duration, be incorporated in future geospatial investigations of destination choice models.

This study highlights that geospatial attributes play an important role in destination choice modelling. Further research into destination choice models as an alternative to gravity models are therefore recommended.

## 6. CONCLUSION

Transport systems shape urban growth by guiding spatial diversification and population settlement. An increasing trend was reported by Statistics South Africa, where the South African population preferred road-based transportation for daily commute (Statistics South Africa, 2013). In major urban areas like the City of Cape Town, public transportation is the key to economic connectivity. Public transport systems allow investment due to their environmental, social and economic benefits.

Efficient transport systems are desired to limit substantial losses that might arise from missed economic opportunities. Optimised transport networks and densified transportation infrastructure are identified as the catalyst for economic development. Studies on transport networks and the factors that might lead to the optimisation of these systems are crucial. There is significant value in analysing public transportation systems in South Africa.

The release of the City of Cape Town's Municipal Spatial Development Framework raised the critical need to connect the city's citizens to economic opportunities. The existing MyCiTi Integrated Rapid Transit (IRT) system will be used as the basis of the Transit-Oriented Development philosophy, with the City of Cape Town's future urban form and function to be structured around this IRT system. The study and analysis of the MyCiTi IRT system can provide valuable insight for the City of Cape Town on the factors that can influence it reaching its aimed development goals and targeted urban form.

Although the spatial separation of activities forms the essence of travel demand, the incorporation of the effects of geospatial properties in travel behaviour modelling has only in recent years been formally studied. A trend was noted proposing that geospatial properties can influence travel behaviour. In the stated research, the need to investigate the effect of geospatial properties on travel behaviour was highlighted. With travel behaviour the result of commuter choices, a choice modelling study was conducted to investigate the effect of geospatial properties on the MyCiTi IRT commuter destination choice.

Automatic fare collected smartcard data from the MyCiTi Integrated Rapid Transit system was accrued from the City of Cape Town. Origin-destination trip pairing was executed, and the dataset expanded to include geospatial properties. The included geospatial properties comprised the geographical distance between trip origin and destination, IRT stop density, land use classification rating and the central business zoning classification of the MyCiTi IRT system. This study was based on revealed preference data which represents factual and unbiased travel behaviour cost-effectively. Multiple data sources add credibility to this study and the future application thereof. A one-day data model was presented for the versatile future application of weekly, monthly and yearly choice modelling studies.

An interesting observation was made where notable fewer connection transactions were recorded in the dataset. This observation gives noteworthy insight that a significantly higher preference is displayed by commuters to select direct transit routes.

The multinomial logit model was deemed appropriate to investigate the influence geospatial attributes have on destination choice. The multinomial logit models developed in this study were defined and estimated by using *Apollo* (Hess & Palma, 2019), a software package developed for choice model estimation.

Destinations located further from the origin (a higher displacement) were found less attractive to choice individuals than destinations located closer to the origin. Destinations with a higher IRT density were initially found to be more attractive to choice individuals in Model 1. This outcome, however, changed in Model 2 with the inclusion of the central business district zonification variable. Hammadou et al. (2008) noted that particular attention should be paid to incorporate the effects of the spatial dimension due to the difficulty of understanding spatial realities by simple quantitative measurements. It is

presented that the changed outcome reported in this study captures the phenomenon where the definition of the spatial dimension can influence the behaviour of coefficients in geospatial choice models. The inclusion of the CBD zonification parameter changed the definition of the spatial (and therefore density) dimension. Inter-densified and intra-densified zoning dimensions were introduced in Model 2. With the CBD zone specification and inclusion in the utility function, this study proceeded to estimate choice models within the intra-densified zoning dimension. Choice destinations within the intra-densified zoning dimension, where the CBD zonification is specified, were found to be more attractive to individuals when a lesser IRT density count was present. This outcome captured the competitiveness between the MyCiTi IRT stops within the central business district of Cape Town.

The author proposes that various geospatial dimensions exist in the modelling of destination choice. The estimation of attribute parameters in choice models can differ between geospatial dimensions, as illustrated in this study. Specification of the geospatial dimension is therefore noted as a critical step in the destination choice process.

A very high attraction of the Central Business District as a destination in Cape Town was found. This result highlighted the statement of residual segregation found in the City of Cape Town, where a need exists for a large portion of the population to head from the suburbs to the city centre. Although the attractiveness of a destination decrease with an increase in displacement, a lesser dislike was presented by commuters towards destinations located further from the origin but located within the CBD. A preference of lesser MyCiTi IRT stops (a lower IRT stop density) was reported with the inclusion of this CBD zone. This outcome highlighted the phenomena proposed in this study where the spatial dimension is stated to influence choice behaviour and contribute to the author's statement that competitiveness is found between IRT stops within the intra-densified zoning dimension. It is noted that city planners should be aware that MyCiTi IRT stop densification may lead to an overcrowded and ineffective system.

A higher preference was stated towards the land use classifications of General Business, Utility and Rural, in order of increasing preference. With only 1.7% of the MyCiTi IRT stops located in a Rural land use classification, it was noteworthy that these stops feature as highly favoured destinations. The high preference shown towards the General Business land use classification was expected. It was additionally found that the preference for choosing a destination with General Business land use classification is increased when the destination is located within the CBD of the City of Cape Town. The high preference noted towards the Utility land use classification is expectedly linked to places of employment or residence where high utility services are required.

A lesser preference was reported towards the land use classifications of Limited Use, Industrial, Mixed Use, Community and Regional, Agriculture and Residential, in order of increasing disfavour. It was counter-intuitively noted that the Industrial and Mixed Use land use classifications were not favoured as destinations for the MyCiTi IRT system. The disfavour towards Limited Use and Community and Regional land use classifications were notably expected as discussed. The Agriculture land use classification not attracting a high preference was a surprising outcome, as this sector is stated an essential component of the economy of Cape Town (Invest Cape Town, 2020). It is recommended that this effect be investigated to resolve and enable the MyCiTi IRT system to be utilised to attract and possibly capture the economic opportunities found within the agricultural sector of Cape Town.

An unexpected dislike was shown towards the Residential land use classifications as a choice destination. The National Household Travel Survey (2013) reported a distinct general trip pattern where a large portion of the Capetonian population heads from the suburbs to the city centre in the mornings and returning in the opposite direction in the

evenings (Statistics South Africa, 2013). The author notes that further investigation is required to confirm if an explanation of this counter-intuitive outcome might lie in the high correlation found between the Residential and General Business land use classifications.

The increase of the reported adjusted log-likelihood  $\rho^2$  values with every model estimation state that the subsequent model development was found superior. Model 5 showcased the greatest goodness-of-fit. The low  $\rho^2$  values of the estimated models (i.e. for Model 5,  $\rho^2 = 0.0899$ ) indicates that the choice model presented in this study is not fit for commercial application. The model results, however, still provide significant insight into the influence geospatial properties have on destination choice for the case of the MyCiTi IRT system. The improvements reported in the log-likelihood, AIC and BIC values additionally confirm the improved model development presented in this study. Model 5 presents the best insight into geospatial influence on destination choice for the MyCiTi IRT system analysed in this study.

Public transport plays a vital role in reducing congestion and the carbon emissions footprint, especially in major metropolitan cities. Commuters should be encouraged to select public transport as their preferred mode of choice. It should be a priority for authorities to create attractive, integrated, user-friendly public transport networks. The MyCiTi IRT system can be developed to counter the current segregation found in the City of Cape Town. This study complements the proposal made that geospatial properties impact travel behaviour. Geospatial properties therefore influence commuter choice behaviour in the operation of the MyCiTi IRT system. By further investigating the effect geospatial properties have on commuter choices, insight can be obtained into how the MyCiTi IRT system can be further developed and optimised to meet commuter demand and accelerate the aimed diversification of the City of Cape Town. Further investigations could include mixed logit or nested logit choice models to explore the influence of the spatial dimension on commuter choice as presented in this study. Understanding travel behaviour and the effect geospatial properties have on the operation of the MyCiTi IRT system can unfold significant stated economic, environmental and social value for the City of Cape Town. To harness the full social and economic potential of public transport in South Africa, continuous study and investment into transport infrastructure and systems are required.

## **REFERENCES**

- Agarwal, A., 2004. *A comparison of weekend and weekday travel behavior characteristics in urban areas*. [Online]  
Available at:  
[https://www.researchgate.net/publication/239837014\\_A\\_comparison\\_of\\_weekend\\_and\\_weekday\\_travel\\_behavior\\_characteristics\\_in\\_urban\\_areas](https://www.researchgate.net/publication/239837014_A_comparison_of_weekend_and_weekday_travel_behavior_characteristics_in_urban_areas)  
[Accessed 25 July 2020].
- Asian Development Bank, 2008. *Guidelines and Toolkits for Urban Transport Development in Medium Sized Cities in India*. [Online]  
Available at: <https://sti-india-uttoolkit.adb.org/mod1/se6/010.html>  
[Accessed 01 September 2018].
- Axhausen, K. W. & Gärling, T., 1992. Activity-based approaches to travel analysis: conceptual frameworks, models, and research problems. *Transport Reviews*, 12(4), pp. 323-341.
- Badoe, D. A. & Miller, E. J., 2000. Transportation–land-use interaction: empirical findings in North America, and their implications for modeling. *Transportation Research Part D: Transport and Environment*, 5(4), pp. 235-263.
- Ben-Akiva, M. E. & Lerman, S. R., 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge: MIT Press.
- Bhat, C., Govindarajan, A. & Pulugurta, V., 1998. Disaggregate attraction-end choice modeling formulation and empirical analysis. *Transportation Research Record*, 1645(1), pp. 60-68.
- Bhat, C. R., 2002. *Random Utility-Based Discrete Choice Models for Travel Demand Analysis*. s.l.:The University of Texas at Austin.
- Bhat, C. & Zhao, H., 2002. The spatial analysis of activity stop generation. *Transportation Research Part B: Methodological*, 36(6), pp. 557-575.
- Browning, P., 2017. *The Public Transport Strategy 2007: A Decade of Implementation*. s.l., TransForum Business Development cc, p. 10.
- Burnham, K. P. & Anderson, D. R., 2004. Multimodel Inference Understanding AIC and BIC in Model Selection. *Sociological Methods and Research*, 33(2), pp. 261-304.
- Cai, C.-j. et al., 2015. Holiday Destination Choice Behavior Analysis Based on AFC Data of Urban Rail Transit. *Discrete Dynamics in Nature and Society*, p. 7.
- Cascetta, E., 2001. *Transportation Systems Engineering: Theory and Method*. Dordrecht: Springer Science+Business Media .
- City of Cape Town, 2015. *MyCITI Media Releases*. [Online]  
Available at: <https://www.myciti.org.za/en/contact/media-releases/myciti-commuter-numbers-soaring-on-routes-from-hout-bay-camps-bay-and-along-the-west-coast/>  
[Accessed 21 August 2020].
- City of Cape Town, 2017. *City of Cape Town Municipal Spatial Development Framework*, Cape Town: City of Cape Town.

- City of Cape Town, 2018. *City of Cape Town Open Data Portal*. [Online]  
Available at: <https://web1.capetown.gov.za/web1/OpenDataPortal/AllDatasets>  
[Accessed 7 January 2019].
- City of Cape Town, 2019. *City of Cape Town Transport Network*. [Online]  
Available at: <https://www.tct.gov.za/en/transport/transport-network/>  
[Accessed 07 10 2020].
- City of Cape Town, 2020. *MyCiTi Media Releases*. [Online]  
Available at: <https://www.myciti.org.za/en/contact/media-releases/fare-increase-1-july-2015/>  
[Accessed 6 September 2020].
- City of Cape Town, 2020. *MyCiTi: Use your myconnect card*. [Online]  
Available at: <https://www.myciti.org.za/en/myconnect-fares/use-your-myconnect-card/>  
[Accessed 07 10 2020].
- de Dios Ortúzar, J. & Willumsen, L. G., 2011. *Modelling Transport, 4th Edition*. Chichester: Wiley.
- Department of Transport, 2007. *Public Transport Action Plan; Phase 1 (2007-2010) Catalytic Integrated Rapid Public Transport Network Projects*, Pretoria: Department of Transport.
- Ewing, R. & Cervero, R., 2001. Travel and the Built Environment: A Synthesis. *Transportation Research Record: Journal of the Transportation Research Board*, 1780(1), pp. 97-114.
- Frost, J., 2020. *How To Interpret R-squared in Regression Analysis*. [Online]  
Available at: <https://statisticsbyjim.com/regression/interpret-r-squared-regression/>  
[Accessed 11 10 2020].
- Frost, J., 2021. *Statistics By Jim: Making Statistics Intuitive*. [Online]  
Available at: <https://statisticsbyjim.com/regression/interpret-adjusted-r-squared-predicted-r-squared-regression/>  
[Accessed 17 September 2021].
- Google Earth, 2019. *Google Earth*. [Online]  
Available at: <https://earth.google.com/web/@-33.9147992,18.65606,65.84478413a,308671.31532155d,35y,0h,0t,0r/data=CIeATxJJCiUweDFkY2M1MDBmODgyNmVlZDc6MHg2ODdmZTFmYzI4MjhhYTg3Gd9MTBdi9kDAIQoyXeOOBdJAKg5DaWRhZGUgZG8gQ2FibxgCIAE?EarthFeedSuffix=ttamz>  
[Accessed 7 January 2019].
- Government of South Africa, 2019. *South African Government*. [Online]  
Available at: <https://www.gov.za/about-government/government-system/local-government>  
[Accessed 10 08 2019].
- Hammadou, H., Thomas, I., Verhetsel, A. & Witlox, F., 2008. How to Incorporate the Spatial Dimension in Destination Choice Models: The Case of Antwerp. *Transportation Planning and Technology*, 31(2), pp. 153-181.
- Handy, S., Cao, J. & Mokhtarian, P. L., 2005. Correlation or Causality Between the Built Environment and Travel Behavior? Evidence from Northern California. *Transportation Research Part D Transport and Environment*, 10(6), pp. 427-444.

- Hensher, D. A., 1987. A Practical Concern about the Relevance of Alternative-Specific Constants for New Alternatives in Simple Logit Models. *Transportation Research Part B: Methodological*, 15(6), pp. 407-410.
- Hensher, D. A., Rose, J. & Greene, W. H., 2005. *Applied Choice Analysis: A Primer*. 1 ed. New York: Cambridge University Press .
- Hensher, D. A., Rose, J. & Greene, W. H., 2015. *Applied Choice Analysis*. 2 ed. Cambridge: Cambridge University Press.
- Hess, S., Daly, A. & Batley, R., 2018. Revisiting consistency with random utility maximisation: theory and implications for practical work. *Theory and Decision*, Volume 84, pp. 181-2014.
- Hess, S. & Palma, D., 2019. *Apollo*. [Online]  
Available at: [www.ApolloChoiceModelling.com](http://www.ApolloChoiceModelling.com)
- Hess, S. & Palma, D., 2019. Apollo: A Flexible, Powerful and Customisable Freeware Package for Choice Model Estimation and Application. *Journal of Choice Modelling*, September, Volume 32, p. 201.
- Hong, S. K., Kim, J. H., Jang, H. & Lee, S., 2006. The roles of categorization, affective image and constraints on destination choice: an application of the NMNL model. *Tourism Management*, 27(5), pp. 750-761.
- Huybers, T., 2004. *Destination choice modelling - To label or not to label?*. Cyprus, s.n.
- Invest Cape Town, 2020. *Cape Town's Agricultural Sector*. [Online]  
Available at: <https://www.investcapetown.com/opportunities/agri-business/>  
[Accessed 11 10 2020].
- Johnston, R. J. et al., 2017. Contemporary Guidance for Stated Preference Studies. *Journal of the Association of Environmental and Resource Economists*, 4(2), p. 319–405.
- Kenney, J., 2017. *The Science Classroom*. [Online]  
Available at: <http://thescienceclassroom.org/physics/motion-in-1-d/distance-and-displacement/>  
[Accessed 22 August 2020].
- Koppelman, F. S. & Bhat, C., 2006. *A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models*. s.l.:s.n.
- Louviere, J. J., Hensher, D. A., Swait, J. D. & Adamowicz, W., 2003. *Stated Choice Methods Analysis and Applications*. 3rd ed. Cambridge: The Press Syndicate of the University of Cambridge.
- Manski, C. F., 2008. *Identification for Prediction and Decision*. Cambridge, Massachusetts and London: Harvard University Press.
- McFadden, D., 1974. Conditional Logit Analysis of Qualitative Choice Behavior. In: *Frontiers in Econometrics*. New York: Academic Press, pp. 105-142.
- McFadden, D., 2000. *Economic Choices. Nobel Prize Lecture..* [Online]  
Available at: <https://www.nobelprize.org/uploads/2018/06/mcfadden-lecture.pdf>  
[Accessed 06 08 2019].
- Miller, N. B. & Falk, R. F., 1992. *A Primer for Soft Modeling*. 1 ed. Akron: The University of Akron Press.
- Minitab LLC., 2014. *Minitab Blog*. [Online]  
Available at: <https://blog.minitab.com/en/adventures-in-statistics-2/how-to-interpret-a-regression->

model-with-low-r-squared-and-low-p-values

[Accessed 17 September 2021].

Munizaga, M. & Palma, C., 2012. Estimation of a disaggregate multimodal public transport. *Transportation Research Part C 24 (2012) 9–18*, Part C(24), pp. 9-18.

Murphy, K. P., 2012. *Machine Learning: A Probabilistic Perspective (Adaptive Computation and Machine Learning series)*. 1 ed. Cambridge: The MIT Press.

MyCiTi, 2015. *MyCiTi: New Routes and Changes*. [Online]

Available at: <https://www.myciti.org.za/en/contact/media-releases/new-routes-and-changes-july-august-2015/>

[Accessed 07 10 2020].

MyCiTi, 2018. Your MyCiTi Guide. *MyCiTi System Guides*, 25 June, p. 35.

Nylund, K. L., Asparouhov, T. & Buthen, B. O., 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, 14(4), pp. 535-569.

QGIS.org, 2019. *QGIS Geographic Information System*. [Online]

Available at: <http://qgis.org/>

[Accessed 07 January 2019].

Raftery, A. E., 1995. Bayesian Model Selection in Social Research (With Discussion). *Sociological Methodology*, Volume 25, pp. 111-163.

Richardson, A. J., Ampt, E. S. & Meyburg, A. H., 1995. *Survey Methods for Transport Planning*. Melbourne: Eucalyptus Press.

Rodrigue, J.-P., Comtois, C. & Slack, B., 2017. The Geography of Transport Systems. In: 4th ed. New York: Routledge, p. 440.

Statistics South Africa, 2013. *National Household Travel Survey*, Pretoria: Statistics South Africa.

Stead, D., 2001. Relationships between Land Use, Socioeconomic Factors, and Travel Patterns in Britain. *Environment and Planning B: Planning and Design*, 28(4), pp. 499-528.

Stopher, P. & Banister, D., 1985. *Total Design Concepts*. Utrecht, VNU Science Press.

The Transport and Urban Development Authority, 2017. New User's Guide 2017. *A guide to using the MyCiTi bus system*, p. 15.

The Transport and Urban Development Authority, 2018. [Online]

Available at: <https://myciti.org.za/en/myconnect-fares/get-your-card/>

[Accessed 20 July 2018].

Thompson, A., 2017. *Culture Trip*. [Online]

Available at: <https://theculturetrip.com/africa/south-africa/articles/how-post-apartheid-cape-town-remains-segregated-by-its-infrastructure/>

[Accessed 07 10 2020].

Tourism & Transport Forum Australia, 2010. *The Benefits of Public Transport*. [Online]

Available at: <https://www.ttf.org.au/wp-content/uploads/2016/06/TTF-The-Benefits-Of-Public-Transport->

2010.pdf

[Accessed 09 08 2019].

Train, K. E., 2003. *Discrete choice methods with simulation*. 2nd ed. New York: Cambridge University Press.

Transport for Cape Town, 2016. *MyCiti Stakeholder Guide*. [Online]

Available at: <https://myciti.org.za/docs/categories/3894/Stakeholder%20guide.pdf>

[Accessed 25 July 2020].

United Nations, 2018. *World Urbanization Prospects 2018*. [Online]

Available at: <https://esa.un.org/unpd/wup/>

[Accessed 21 July 2018].

van Ryneveld, H., 2014. *Expenditure and Performance Review of South Africa's Public Transport and Infrastructure System*, s.l.: s.n.

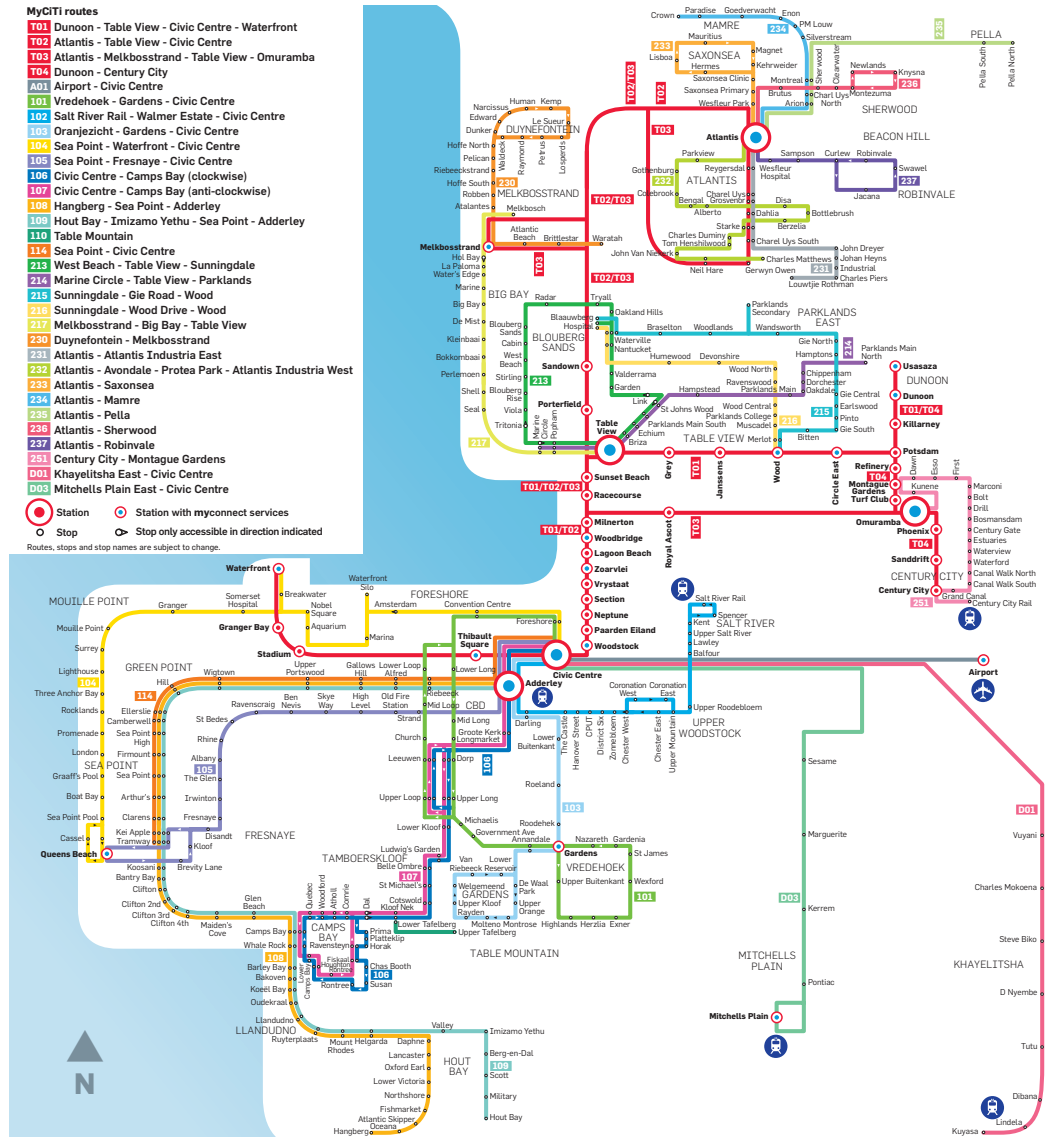
Vega, A. & Reynolds-Feighan, A., 2009. Geographic information system (GIS) visualisations and network analysis are used to generate a choice set based on the definition of spatially aggregated alternatives. *Transportation Research Part A: Policy and Practice*, May, 43(4), pp. 401-419.

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX A**

The MyCiTi Integrated Rapid Transit System Route Map (MyCiTi, 2015)

# MyCiTi services, including routes launching in July and August 2015



# CONNECT WITH THE CITY



## New MyCiTi services in Atlantis

The launch of more MyCiTi services in the Atlantis area will also mean changes to some of the existing routes and current Sibanye/Golden Arrow transport services.

On 4 July 2015 three new MyCiTi bus routes will be launched in the Atlantis area. This will offer passengers more options for travelling, with safe, reliable and affordable transport.

This is how you and your family will be affected by these changes:

- Changes in Atlantis area**
- There are three new MyCiTi routes in the Atlantis area:
- 234 Atlantis - Mamre
  - 235 Atlantis - Pella
  - 237 Atlantis - Robinvale

All these routes connect with the MyCiTi Atlantis station. The Witsand area, as well as Mamre and Pella, will continue to be served by Sibanye/Golden Arrow services travelling along the N7.

**Changes affecting other areas**

One of the biggest changes will be a new T02 route, which is a direct service between Atlantis and central Cape Town via Table View. For passengers travelling between Atlantis and Duynfontein, the journey will be via Melkbosstrand station using 230 and T03 buses.

There are also changes to bus services connecting with Table View, Killarney Gardens, Montague Gardens and central



The centrally located Atlantis station is the hub of MyCiTi services. Passengers making the change from Sibanye buses to MyCiTi can get their myconnect cards from the station kiosk.

Cape Town. Passengers travelling to Maitland and Salt

River will also be affected. For more details on planning

your journey, see page 3.

## Calling all Sibanye passengers

When the changes to MyCiTi services come into effect on 4 July 2015, many of the current Atlantis services offered by Sibanye/Golden Arrow will stop. This particularly affects services along the R27. Passengers who have been using Sibanye/Golden Arrow buses will need to switch to using the MyCiTi service from this date.

between Atlantis and the Koeberg nuclear power station. Passengers using this service will not be affected. Sibanye buses will continue to travel down the N7 from parts of Atlantis, including Mamre, Pella and Witsand. This will be an express service, stopping along Koeberg Road only south of Racecourse Road en route to Maitland and Salt River.

Note: Sibanye/Golden Arrow will continue to run a service

However, some buses will still enter Killarney Gardens.

## How to use MyCiTi

All passengers aged four years and older and under 1m tall need their own myconnect card to travel on MyCiTi buses. These cards are R30, available from MyCiTi stations, including Atlantis and Table View. You can load money on the card or Mover packages to save at least 30% on fares. You cannot pay cash for your fare on the bus. See inside for details.

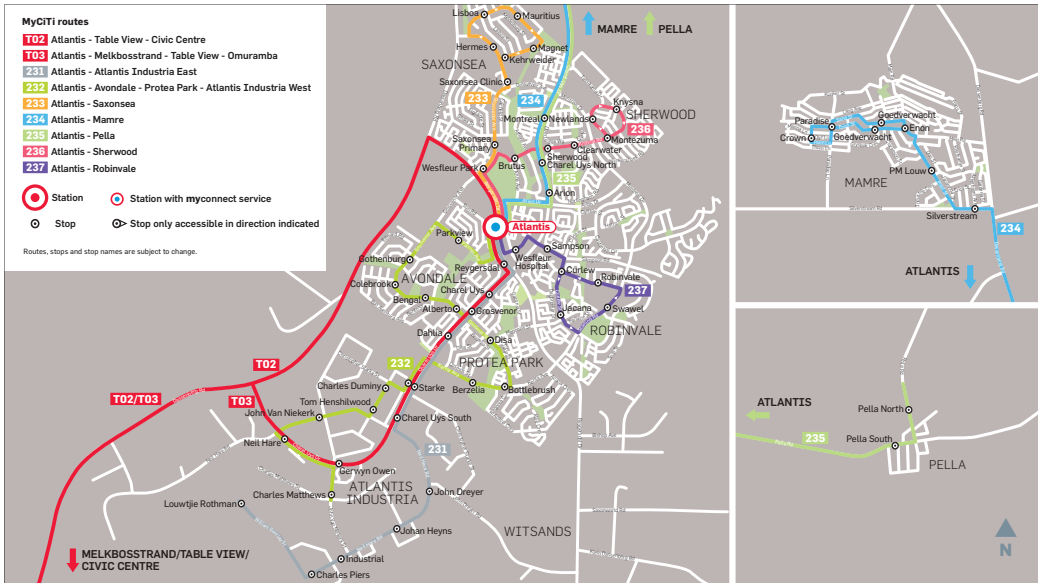


Call the Transport Information Centre (toll-free 24/7) 0800 65 64 63 [www.myciti.org.za](http://www.myciti.org.za) dial \*120\*1040#

MyCiTi - Integrated Rapid Transit System Transport4CapeTown



# Atlantis routes, 4 July 2015



# How to use MyCiTi

Catching a MyCiTi bus is easy once you know how. Follow this step-by-step guide and connect to Cape Town's safe, reliable, scheduled bus service.

## ① Get a myconnect card

Every passenger aged four years and over and under 1m tall needs their own **myconnect** card to use the bus. The smartcard is like a wallet and a travel card in one. Load money as Standard and you can use it like a debit card to pay for purchases up to R200 and pay MyCiTi fares at the Standard rate. You can also load Mover packages from as little as R30 and use the Mover points to pay MyCiTi fares – saving you at least 30%. You can load Standard and Mover at the same time. If you do

the fares are first paid from Mover, and only from Standard if your Mover points are insufficient.

*TIP: With Standard you can pay fares and make purchases, but with Mover you save on fares.*



## ② Tap in and tap out

MyCiTi fares are based on a boarding fare and then how far you travel. When you enter a MyCiTi station or get on a bus you hold your **myconnect** card against the validator and the boarding fare will be deducted from the balance on your card. When you leave the bus or exit the station, tap your card on the validator to end your journey. The system calculates how far you have travelled and deducts the correct fare.

When you transfer to another MyCiTi bus at a station you do not pay the boarding fare again, as it is calculated as one journey. You can also make a



free transfer at a bus stop if you tap in again within 45 minutes and it is not a return journey.

*TIP: The validators on the buses are marked 'in' and 'out'. At station gates you tap on the validator on your right hand side. Make sure you tap on the correct validator to avoid a penalty.*

## ③ Choose the time you travel

The fares are higher when you start your journey (tap in) during the peak period, even if you end your journey in the peak.

*TIP: Plan your journey so you tap in at a MyCiTi station or on the bus outside of these hours and save.*

Peak	06:45 – 08:00 and 16:15 – 17:30 on weekdays only
Saver	All other times and on weekends

## ④ Avoid a penalty!

You may be charged a penalty if you:

- You do not tap in or out of a station or a bus
  - You tap on the wrong validator, or
  - You do not have enough money on your card.
- For the first three times you

make a mistake the penalty is R10, but after that it is R22 or R83 at the Airport station.

*TIP: Check your balance at an information terminal near the entrance to a station to ensure you have enough money on your card.*

# Planning your journey along the new routes

The launch of more MyCiTi services in the Atlantis area will also mean changes to some of the existing routes and current Sibanye/Golden Arrow transport services.

**Travelling to Melkbosstrand**  
From 4 July, route **239**, the direct route from Atlantis to Dufnefontein will be discontinued. Passengers travelling to Dufnefontein and parts of Melkbosstrand must take the main route **T03** from Atlantis and transfer to the **230** Dufnefontein – Melkbosstrand route at Melkbosstrand station.

*Note: The travelling time, including the transfer, will be similar because the larger buses can travel quicker on the R27. The fare will also be the same in most cases.*

**Travelling to central Cape Town**  
A new direct route from Atlantis station, via Table View, to Civic Centre will be launched, giving passengers a quicker route to town. This will also mean easy transfers to other MyCiTi destinations from the Civic Centre station.

Transfer to rail for Wynberg and Claremont.

**Travelling to Killarney Gardens**  
Passengers from Atlantis should catch **T02** or **T03** from Atlantis station to Table View station. At Table View, they should transfer to **T01** travelling along Blaauwberg Road, exiting at the Killarney station and walking to the nearby industrial area.

**Travelling to Montague Gardens, Maitland and Salt River**

The existing **T03** MyCiTi service will take passengers to Omuramba station in Montague Gardens, with a transfer to MyCiTi route **R251** towards Century City. These buses will travel via Table View station. Some buses will short-turn at Table View station and return to Atlantis. They will be designated as **T03a** buses. From August passengers will also be able to connect with **T04** from Dunoon to Century City.

The MyCiTi route to Salt River will be using the new **T02** route from Atlantis to Civic Centre station and then transferring to **T02** route to Salt River rail station via Walmer Estate. Passengers travelling to southern Koeberg Road and Maitland should continue to use Sibanye/Golden Arrow services along the N7.

## Buy a monthly package

If you make a long journey to and from Atlantis every day then you may save with a monthly travel package, available from 1 July 2015.

A monthly travel package is loaded on your **myconnect** card and includes your first two journeys every day, including transfers.

For example, you may get on the **234** bus at Mmamre, transfer to a **T03** bus at Atlantis station, and then transfer at Civic Centre station to a **T07** bus to Camps Bay. This counts as one journey.

The monthly travel packages cost R530 (excluding the Airport) or R780 (including the Airport). Available from MyCiTi station kiosks only.

*TIP: The monthly travel package is valid for 30 days from any day you load it on your card, so you don't have to wait until the end of the month to buy one.*

## ⑤ How much will I pay?

These MyCiTi fares come into effect on 1 July 2015 and are for a one-way journey including transfers.

Distance	Standard Peak	Standard Saver	Mover Peak	Mover Saver
0-5 kms	R11.50	R7.80	R8.20	R5.50
5-10 kms	R13.30	R9.80	R9.40	R6.90
10 – 20 kms	R17.80	R12.50	R12.60	R8.80
20 – 30 kms	R19.80	R14.80	R13.90	R10.40
30 – 40 kms	R21.00	R16.50	R14.80	R11.60
40 – 50 kms	R24.60	R19.40	R17.40	R13.70
50 – 60 kms	R27.70	R22.00	R19.50	R15.50
60 kms plus	R30.20	R24.10	R21.30	R17.00
*Airport premium	R61.40	R61.40	R50.00	R44.20

*\*The Airport premium is charged in addition to the distance-based fare when you tap in or out at the Airport station.*

## What are the fares from Atlantis?

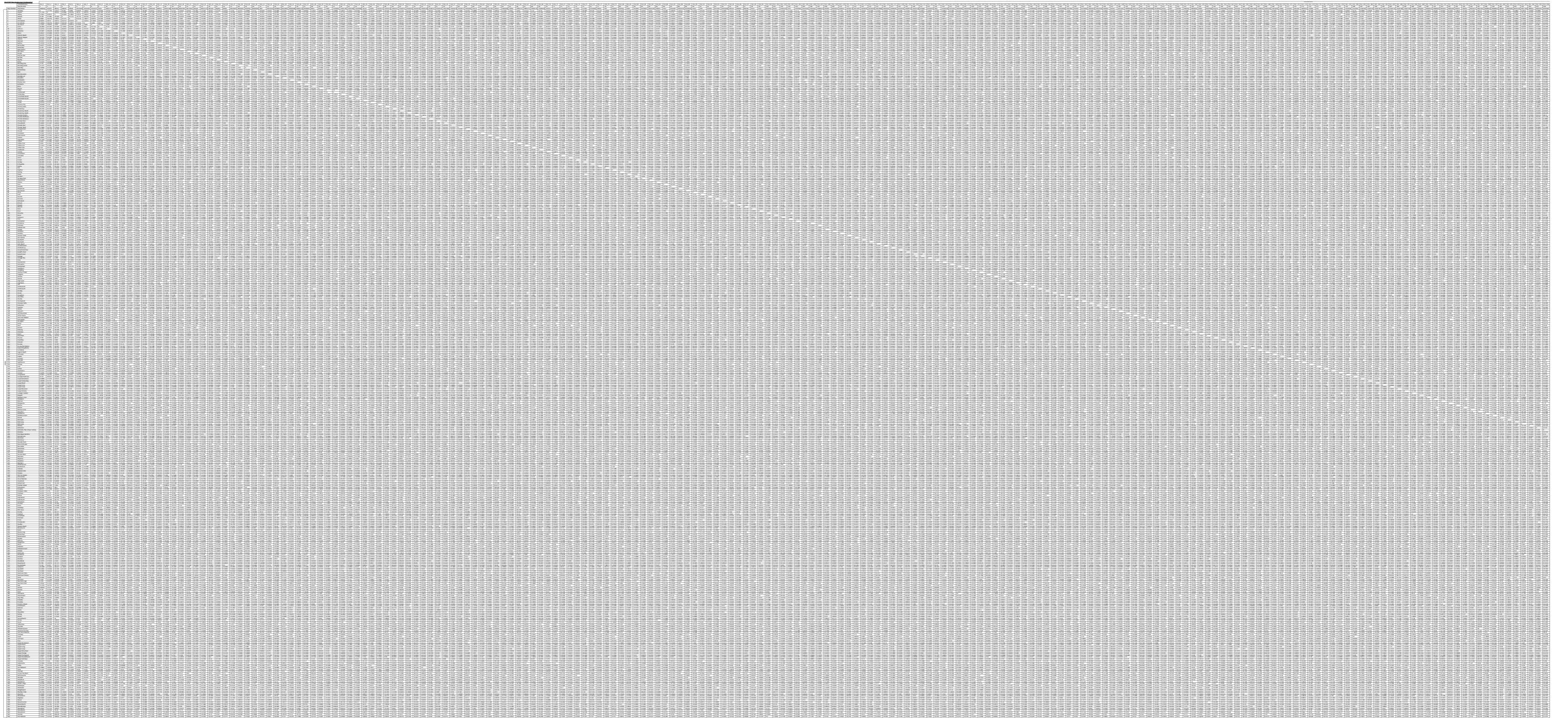
Journey	Standard (Peak) 06:45 – 08:00 16:15 – 17:30	Standard (Saver) All other times	Mover (Peak) 06:45 – 08:00 16:15 – 17:30	Mover (Saver) All other times
Atlantis station – Melkbosstrand station 20 – 30 kms	R19.80	R14.80	R13.90	R10.40
Atlantis station – Table View station 30 – 40 kms	R21.00	R16.50	R14.80	R11.60
Atlantis station – Civic Centre station 50 – 60 kms	R27.70	R22.00	R19.50	R15.50

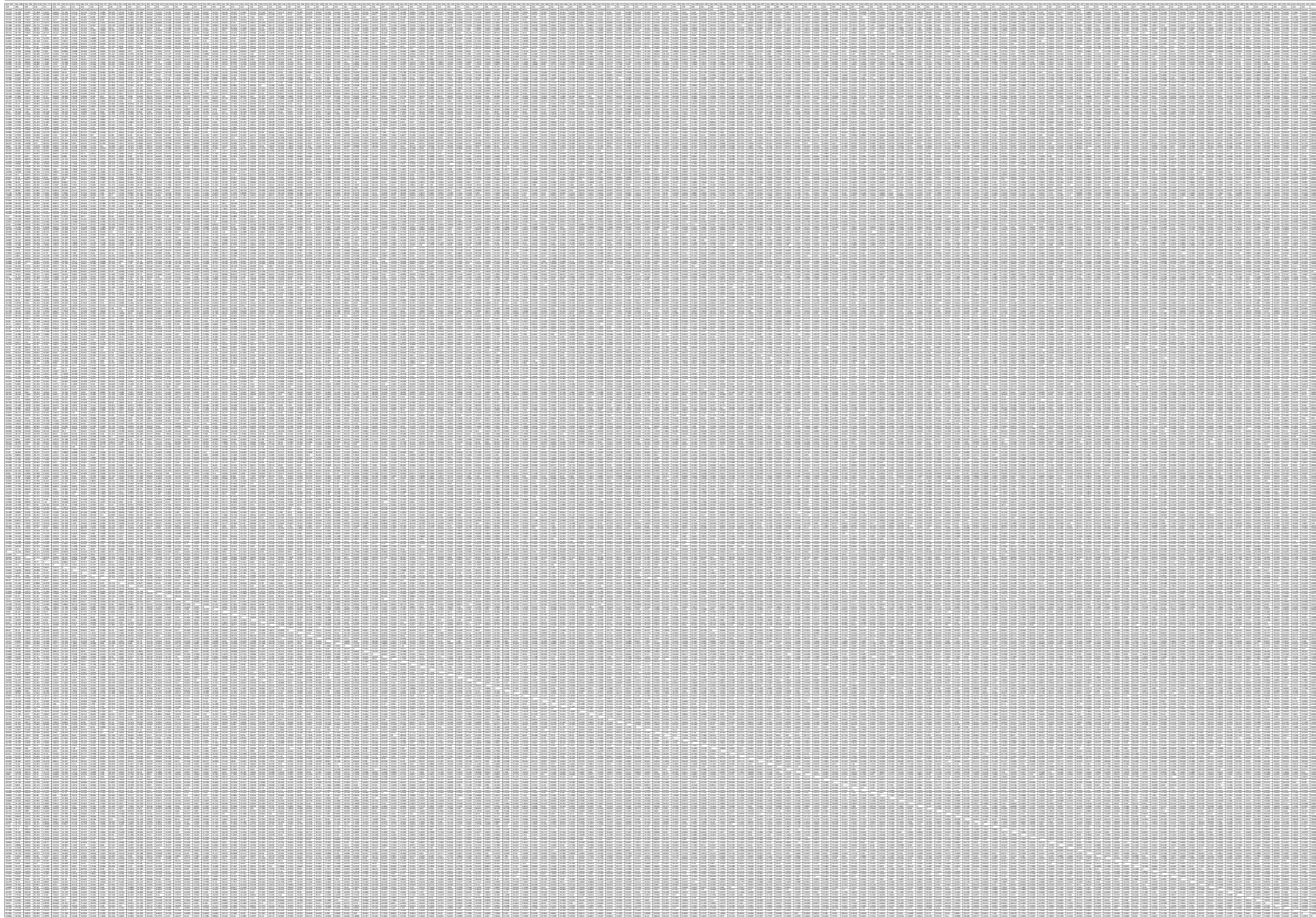
*\*Fares for shorter distances within the Atlantis area are as indicated in the table on the left.*

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX B**

MyCiTi IRT Stop Displacement Matrix (in kilometre)

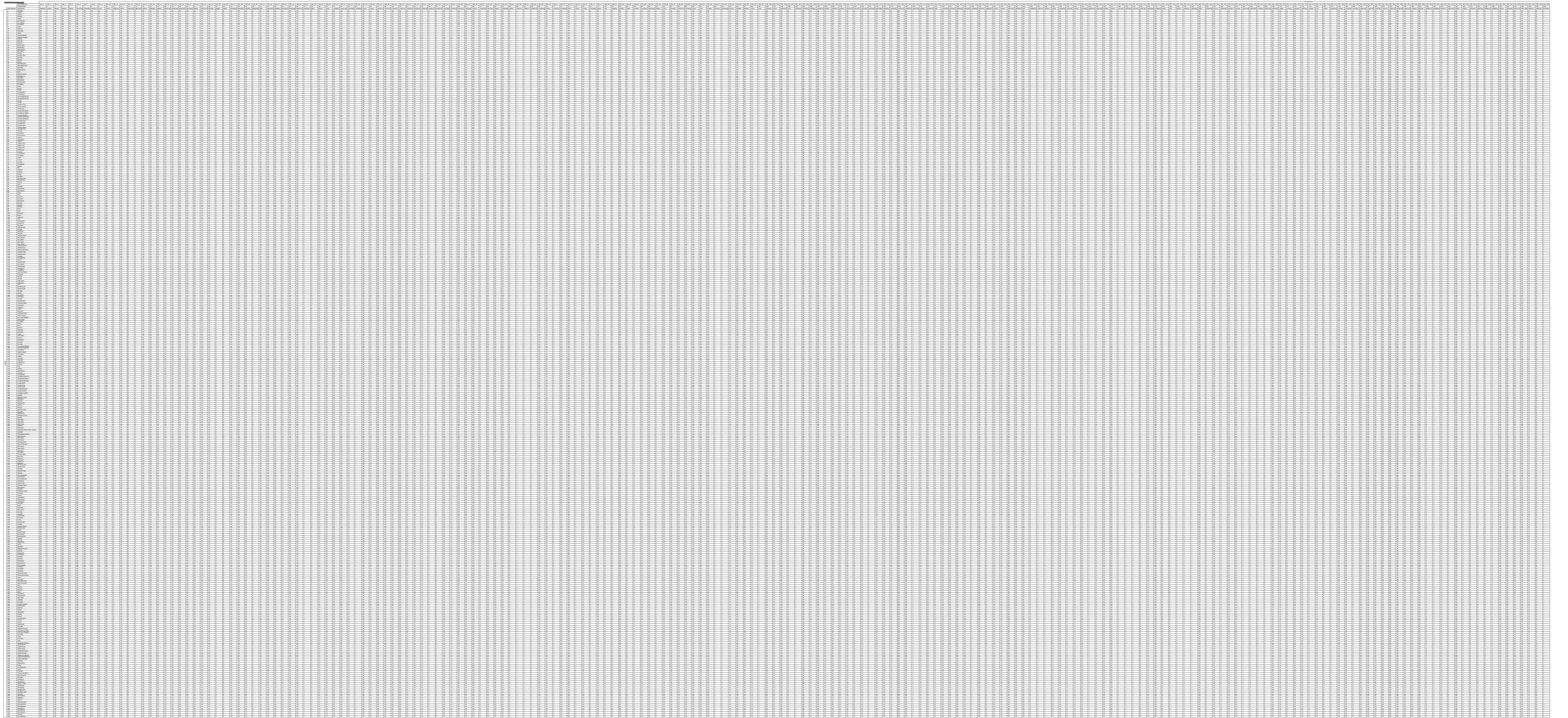


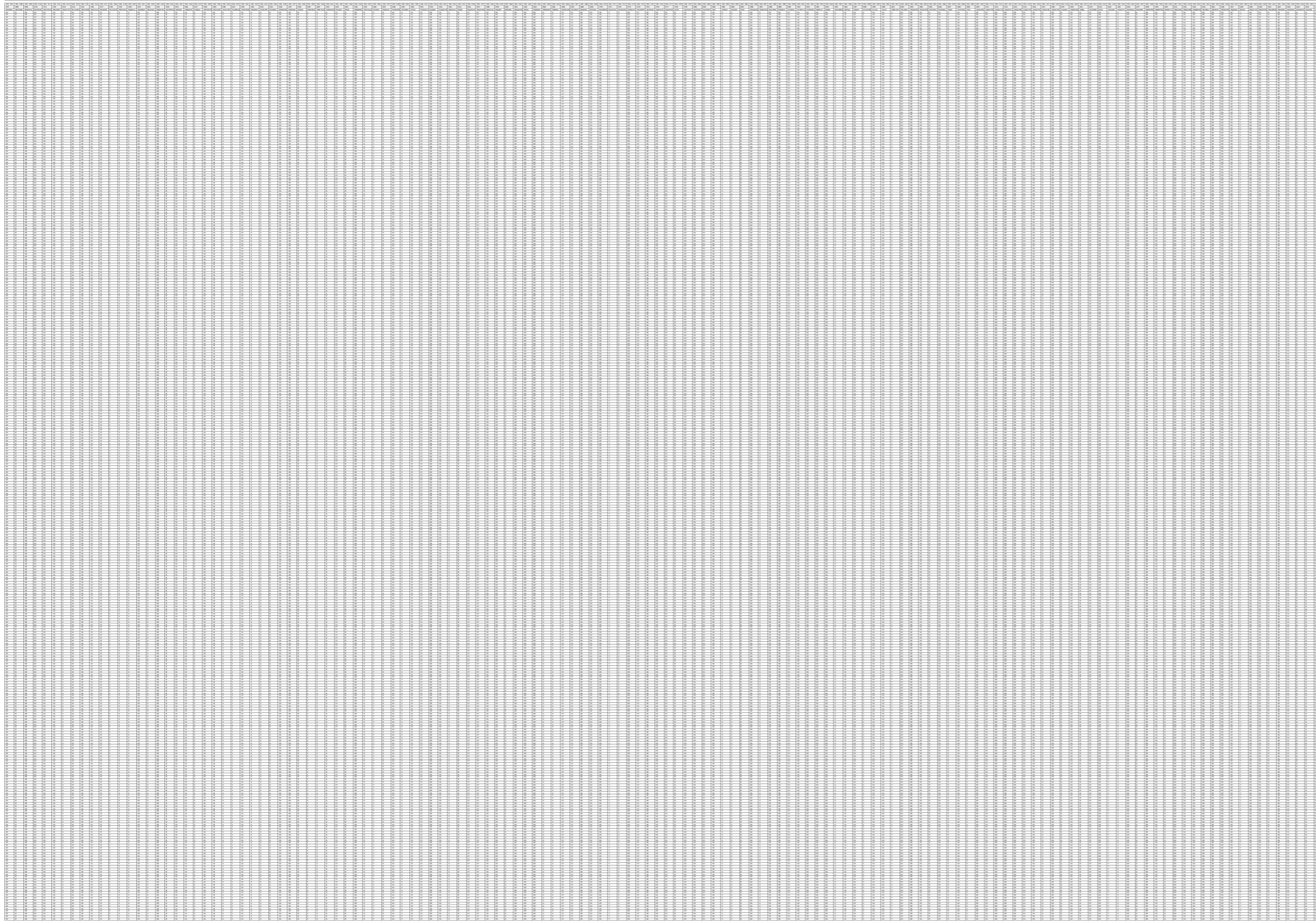


A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX C**

MyCiTi IRT Stop Density Count Matrix

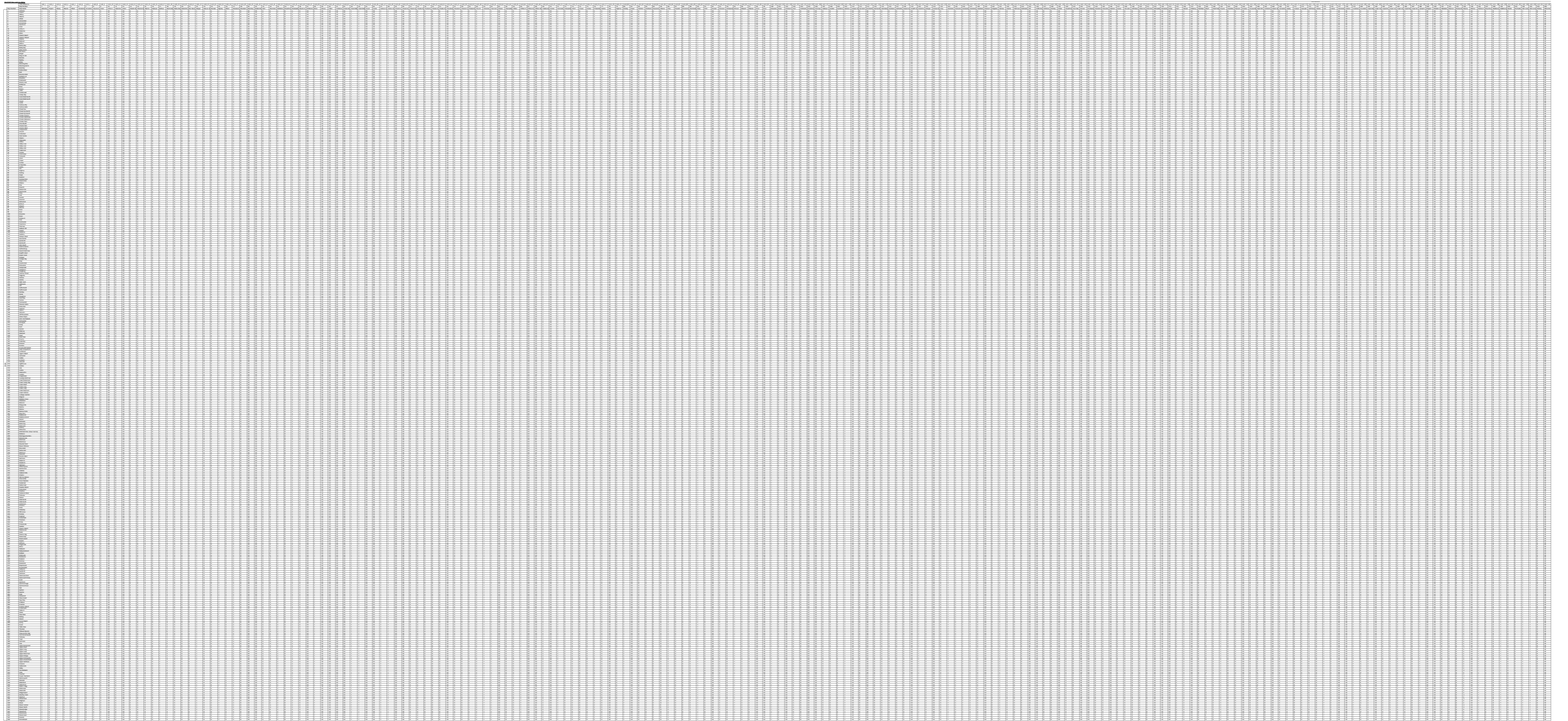


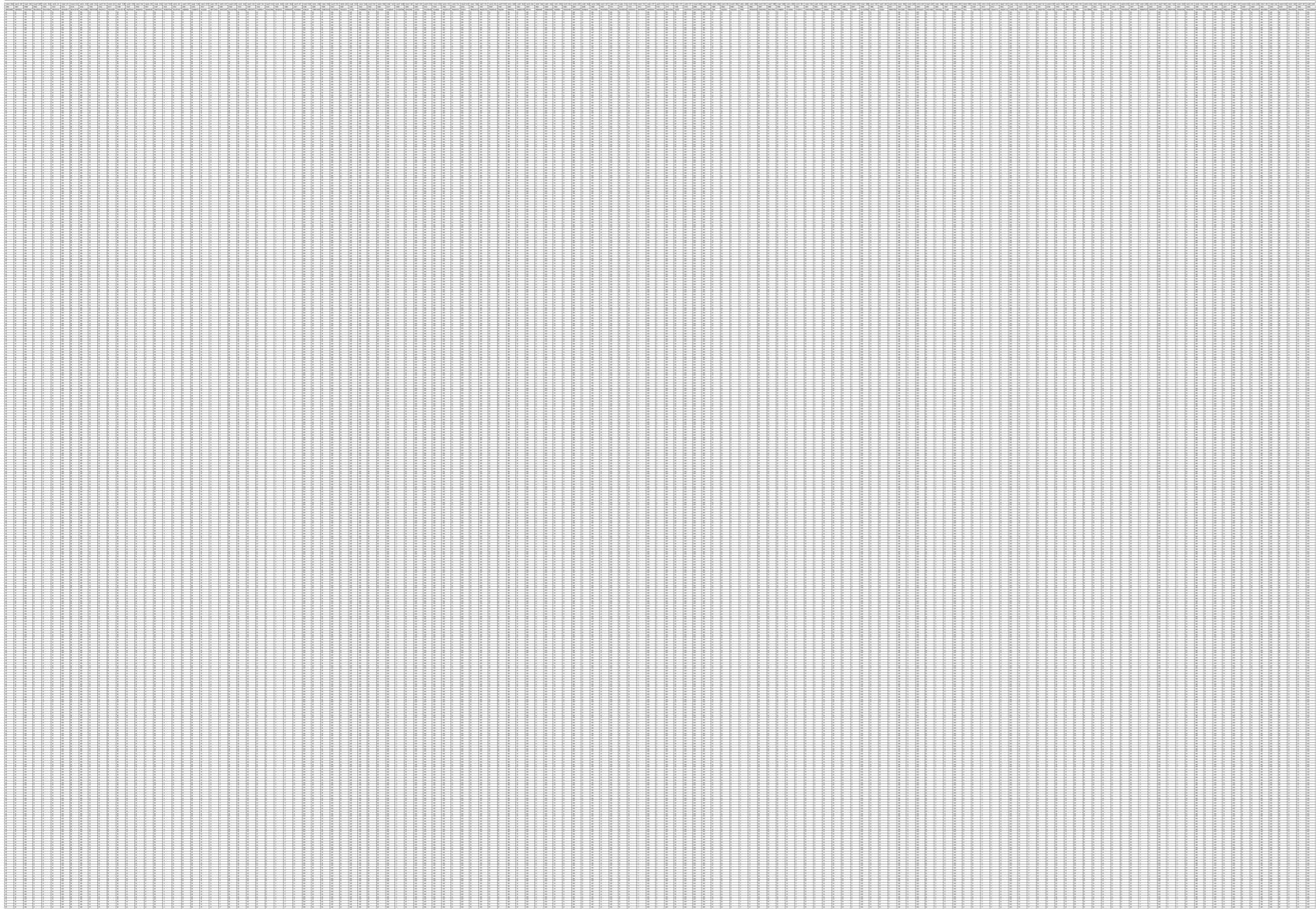


A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX D**

MyCiTi IRT Stop Land Use Rating Matrix





A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX E**

Full estimation output of Model 1



45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				186.0	86.00	26.00	204.00	429.00
72.00	104.00	42.00	255.00	5.00	120.00	96.00	46.0	6.00
				alt57	alt58	alt59	alt60	alt61
alt62	alt63	alt64	alt65	alt66	alt67	alt68	alt69	alt70
Times available				45970.00	45970.00	45970.00	45970.00	45970.0
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				7.00	34.00	289.00	6.00	274.0
3479.00	216.00	81.00	66.00	55.00	22.00	74.00	71.00	227.00
				alt71	alt72	alt73	alt74	alt75
alt76	alt77	alt78	alt79	alt80	alt81	alt82	alt83	alt84
Times available				45970.0	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00
Times chosen				45.0	87.00	83.00	49.00	20.00
42.00	220.00	38.00	9.00	317.00	23.00	48.0	22.00	85.00
				alt85	alt86	alt87	alt88	alt89
alt90	alt91	alt92	alt93	alt94	alt95	alt96	alt97	alt98
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.0
Times chosen				84.00	202.00	51.00	37.00	252.00
113.00	26.00	9.00	1047.00	46.0	154.00	5.00	163.00	90.0
				alt99	alt100	alt101	alt102	alt103
alt104	alt105	alt106	alt107	alt108	alt109	alt110	alt111	alt112
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				21.00	89.00	16.00	235.00	26.00
28.00	1	82.00	180.00	4.00	3.00	310.00	159.00	39.00
				alt113	alt114	alt115	alt116	alt117
alt118	alt119	alt120	alt121	alt122	alt123	alt124	alt125	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				77.00	145.00	69.00	21.00	103.00
38.00	33.00	28.00	22.00	105.00	95.00	430.00	165.00	
				alt126	alt127	alt128	alt129	alt130
alt131	alt132	alt133	alt134	alt135	alt136	alt137	alt138	alt139
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970
Times chosen				58.00	137.0	109.00	59.00	70.00
53.00	57.00	23.00	18.00	151.00	13.00	29.00	29.00	2
				alt140	alt141	alt142	alt143	alt144
alt145	alt146	alt147	alt148	alt149	alt150	alt151	alt152	alt153
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.0	45970.00	45970.00	45970.0	45970.00	45970.00	45970.0	45970	45970.00
Times chosen				14.00	43.00	13.00	33.00	363.00
44.0	28.00	87.00	186.0	5.00	28.00	92.0	1	396.00
				alt154	alt155	alt156	alt157	alt158
alt159	alt160	alt161	alt162	alt163	alt164	alt165	alt166	alt167
Times available				45970.00	45970.00	45970.00	45970.0	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	63.00	80.00	230.0	38.00
12.00	159.00	180.00	4.00	66.00	4.00	148.00	71.00	14.00
				alt168	alt169	alt170	alt171	alt172
alt173	alt174	alt175	alt176	alt177	alt178	alt179	alt180	alt181
Times available				45970.00	45970.00	45970.00	45970.00	45970.00

45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				219.00	18.00	119.00	61.00	28.00
28.00	113.00	60.00	139.0	72.00	34.00	40.00	55.00	167.00
				alt182	alt183	alt184	alt185	alt186
alt187	alt188	alt189	alt190	alt191	alt192	alt193	alt194	alt195
Times available				45970.00	45970.00	45970.00	45970.00	45970
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	221.00	7.00	12.00	2
25.00	62.00	66.00	108.00	6.00	5.00	55.00	15.00	67.00
				alt196	alt197	alt198	alt199	alt200
alt201	alt202	alt203	alt204	alt205	alt206	alt207	alt208	alt209
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				394.00	45.0	118.00	953.00	36.00
185.0	20.00	14.00	54.00	171.00	204.00	17.00	147.00	60.00
				alt210	alt211	alt212	alt213	alt214
alt215	alt216	alt217	alt218	alt219	alt220	alt221	alt222	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				110.00	37.00	27.00	30.00	60.00
43.00	11.00	8.00	39.00	95.00	141.00	86.00	53.00	
				alt223	alt224	alt225	alt226	alt227
alt228	alt229	alt230	alt231	alt232	alt233	alt234	alt235	alt236
Times available				45970.00	45970.00	45970.00	45970	45970.00
45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970	45970.00	45970.00
Times chosen				35.00	11.00	143.00	1	63.00
63.00	481.00	48.0	8.00	86.00	272.00	2	59.00	212.00
				alt237	alt238	alt239	alt240	alt241
alt242	alt243	alt244	alt245	alt246	alt247	alt248	alt249	alt250
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00
Times chosen				52.00	146.00	13.00	60.00	9.00
244.00	128.00	14.00	38.00	65.00	46.0	222.00	180.00	5.00
				alt251	alt252	alt253	alt254	alt255
alt256	alt257	alt258	alt259	alt260	alt261	alt262	alt263	alt264
Times available				45970.00	45970.00	45970.0	45970.00	45970.00
45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				22.00	41.00	92.0	318.00	59.00
29.00	11.00	48.0	34.00	89.00	180.00	61.00	332.00	59.00
				alt265	alt266	alt267	alt268	alt269
alt270	alt271	alt272	alt273	alt274	alt275	alt276	alt277	alt278
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				33.00	117.00	30.00	96.00	8.00
131.00	164.00	34.00	16.00	118.00	667.00	80.00	230.0	17.00
				alt279	alt280	alt281	alt282	alt283
alt284	alt285	alt286	alt287	alt288	alt289	alt290	alt291	alt292
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0
Times chosen				235.00	178.00	39.00	32.00	218.00
114.00	69.00	86.00	65.00	32.00	71.00	15.00	465.00	94.0
				alt293	alt294	alt295	alt296	alt297
alt298	alt299	alt300	alt301	alt302	alt303	alt304	alt305	alt306
Times available				45970.00	45970.00	45970.00	45970.00	45970.00

```

45970.00 45970.00 45970.00 45970.00 45970.00 45970.0 45970.00 45970.00 45970.00
Times chosen                178.00  217.00  100.00  25.00  115.00
253.00   17.00   19.00  2184.00   35.00  690.0  21.00  84.00  258.00
                alt307  alt308  alt309  alt310  alt311
alt312  alt313  alt314  alt315  alt316  alt317  alt318  alt319
Times available                45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00
Times chosen                68.00   34.00  124.00  25.00  43.00
119.00   10.00   66.00   35.00  259.00  59.00  64.00  405.00
                alt320  alt321  alt322  alt323  alt324
alt325  alt326  alt327  alt328  alt329  alt330  alt331  alt332  alt333
Times available                45970.00 45970.0 45970.00 45970.00 45970.00
45970.00 45970.0 45970.00 45970.00 45970.00 45970.00 45970.00 45970.0 45970.00
Times chosen                21.00   48.0  9.00  24.00  290.00
132.00   47.0  16.00  102.00  733.00  176.00  60.00  136.0  12.00
                alt334  alt335  alt336  alt337  alt338
alt339  alt340  alt341  alt342  alt343  alt344  alt345  alt346
Times available                45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00
Times chosen                41.00   98.00  296.00  96.00  860.00
143.00  103.00  272.00  50.00  65.00  546.00  243.00  70.00
[ reached getOption("max.print") -- omitted 2 rows ]

```

WARNING: Availability not provided to 'apollo\_mnl' (or some elements are NA).  
Full availability assumed.

Classical covariance matrix:

	b_displacement	b_density
b_displacement	0	0
b_density	0	0

Robust covariance matrix:

	b_displacement	b_density
b_displacement	0	0
b_density	0	0

Classical correlation matrix:

	b_displacement	b_density
b_displacement	1.0000	0.0855
b_density	0.0855	1.0000

Robust correlation matrix:

	b_displacement	b_density
b_displacement	1.0000	0.1538
b_density	0.1538	1.0000

20 worst outliers in terms of lowest average per choice prediction:

ID	Avg prob per choice
10658552656679172096	0.0002580598
12459102128112312320	0.0002580598
5028398331823306752	0.0002651021
3920273676112835584	0.0002654294
6016488577462255616	0.0002654294

8061079042806119424	0.0002654294
1.0183959020319e+19	0.0002654294
1809392133632938496	0.0002655877
11480148089940199424	0.0002660131
5058522891058887680	0.0002694342
1817022443524843520	0.0002763950
11937965295098773504	0.0002763950
17227586037209133056	0.0002851655
16404170097490569216	0.0002859908
5920585922404176896	0.0002883822
15280816626888587264	0.0002883822
11062249888851384320	0.0002900237
17024257580363632640	0.0002966455
12856729207619379200	0.0002983230
14721042590055723008	0.0003069511

Changes in parameter estimates from starting values:

	Initial	Estimate	Difference
b_displacement	0	-0.0737	-0.0737
b_density	0	0.0127	0.0127
b_landuse	0	0.0000	0.0000

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX F**

Full estimation output of Model 2

Model run using Apollo for R, version 0.1.0  
 www.ApolloChoiceModelling.com

Model name : MNL\_MyCiTi\_Model2  
 Model description : MNL Model of MyCiTi IRT System on RP data  
 Model run at : 2021-01-28 14:25:30  
 Estimation method : bfgs  
 Model diagnosis : successful convergence  
 Number of individuals : 31681  
 Number of observations : 45970

Number of cores used : 1  
 Model without mixing

LL(start) : -268760.8  
 LL(0) : -268760.8  
 LL(final) : -252690.6  
 Rho-square (0) : 0.0598  
 Adj.Rho-square (0) : 0.0598  
 AIC : 505387.2  
 BIC : 505413.4  
 Estimated parameters : 3  
 Time taken (hh:mm:ss) : 00:08:41.2  
 Iterations : 10  
 Min abs eigenvalue of hessian : 3234.718

Estimates:

	Estimate	Std.err.	t.ratio(0)	Rob.std.err.	Rob.t.ratio(0)
b_cbd	1.4605	0.0176	83.10	0.0195	74.78
b_displacement	-0.0745	0.0005	-140.44	0.0006	-114.70
b_density	-0.0226	0.0007	-30.39	0.0008	-27.08
b_landuse	0.0000	NA	NA	NA	NA

Overview of choices for model component "MNL"

	alt1	alt2	alt3	alt4	alt5
alt6	alt7	alt8	alt9	alt10	alt11
alt12	alt13	alt14	alt15	alt16	alt17
alt18	alt19	alt20	alt21	alt22	alt23
alt24	alt25	alt26	alt27	alt28	alt29
alt30	alt31	alt32	alt33	alt34	alt35
alt36	alt37	alt38	alt39	alt40	alt41
alt42	alt43	alt44	alt45	alt46	alt47
alt48	alt49	alt50	alt51	alt52	alt53
alt54	alt55	alt56			

Times available				45970.0	45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				186.0	86.00	26.00	204.00	429.00	
72.00	104.00	42.00	255.00	5.00	120.00	96.00	46.0	6.00	
alt62	alt63	alt64	alt65	alt66	alt67	alt68	alt69	alt70	
Times available				45970.00	45970.00	45970.00	45970.00	45970.0	
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				7.00	34.00	289.00	6.00	274.0	
3479.00	216.00	81.00	66.00	55.00	22.00	74.00	71.00	227.00	
alt76	alt77	alt78	alt79	alt80	alt81	alt82	alt83	alt84	
Times available				45970.0	45970.00	45970.00	45970.00	45970.00	
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	
Times chosen				45.0	87.00	83.00	49.00	20.00	
42.00	220.00	38.00	9.00	317.00	23.00	48.0	22.00	85.00	
alt90	alt91	alt92	alt93	alt94	alt95	alt96	alt97	alt98	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00	
45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.0	
Times chosen				84.00	202.00	51.00	37.00	252.00	
113.00	26.00	9.00	1047.00	46.0	154.00	5.00	163.00	90.0	
alt104	alt105	alt106	alt107	alt108	alt109	alt110	alt111	alt112	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00	
45970.00	45970	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				21.00	89.00	16.00	235.00	26.00	
28.00	1	82.00	180.00	4.00	3.00	310.00	159.00	39.00	
alt118	alt119	alt120	alt121	alt122	alt123	alt124	alt125		
Times available				45970.00	45970.00	45970.00	45970.00	45970.00	
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				77.00	145.00	69.00	21.00	103.00	
38.00	33.00	28.00	22.00	105.00	95.00	430.00	165.00		
alt131	alt132	alt133	alt134	alt135	alt136	alt137	alt138	alt139	
Times available				45970.00	45970.0	45970.00	45970.00	45970.00	
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970	
Times chosen				58.00	137.0	109.00	59.00	70.00	
53.00	57.00	23.00	18.00	151.00	13.00	29.00	29.00	2	
alt145	alt146	alt147	alt148	alt149	alt150	alt151	alt152	alt153	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00	
45970.0	45970.00	45970.00	45970.0	45970.00	45970.00	45970.0	45970	45970.00	
Times chosen				14.00	43.00	13.00	33.00	363.00	
44.0	28.00	87.00	186.0	5.00	28.00	92.0	1	396.00	
alt159	alt160	alt161	alt162	alt163	alt164	alt165	alt166	alt167	
Times available				45970.00	45970.00	45970.00	45970.0	45970.00	
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				11.00	63.00	80.00	230.0	38.00	
12.00	159.00	180.00	4.00	66.00	4.00	148.00	71.00	14.00	
alt173	alt174	alt175	alt176	alt177	alt178	alt179	alt180	alt181	

Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00				
Times chosen									219.00	18.00	119.00	61.00	28.00
28.00	113.00	60.00	139.00	72.00	34.00	40.00	55.00	167.00					
									alt182	alt183	alt184	alt185	alt186
alt187	alt188	alt189	alt190	alt191	alt192	alt193	alt194	alt195					
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00					
Times chosen									11.00	221.00	7.00	12.00	2
25.00	62.00	66.00	108.00	6.00	5.00	55.00	15.00	67.00					
									alt196	alt197	alt198	alt199	alt200
alt201	alt202	alt203	alt204	alt205	alt206	alt207	alt208	alt209					
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00					
Times chosen									394.00	45.00	118.00	953.00	36.00
185.00	20.00	14.00	54.00	171.00	204.00	17.00	147.00	60.00					
									alt210	alt211	alt212	alt213	alt214
alt215	alt216	alt217	alt218	alt219	alt220	alt221	alt222						
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00						
Times chosen									110.00	37.00	27.00	30.00	60.00
43.00	11.00	8.00	39.00	95.00	141.00	86.00	53.00						
									alt223	alt224	alt225	alt226	alt227
alt228	alt229	alt230	alt231	alt232	alt233	alt234	alt235	alt236					
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00					
Times chosen									35.00	11.00	143.00	1	63.00
63.00	481.00	48.00	8.00	86.00	272.00	2	59.00	212.00					
									alt237	alt238	alt239	alt240	alt241
alt242	alt243	alt244	alt245	alt246	alt247	alt248	alt249	alt250					
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00					
Times chosen									52.00	146.00	13.00	60.00	9.00
244.00	128.00	14.00	38.00	65.00	46.00	222.00	180.00	5.00					
									alt251	alt252	alt253	alt254	alt255
alt256	alt257	alt258	alt259	alt260	alt261	alt262	alt263	alt264					
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00					
Times chosen									22.00	41.00	92.00	318.00	59.00
29.00	11.00	48.00	34.00	89.00	180.00	61.00	332.00	59.00					
									alt265	alt266	alt267	alt268	alt269
alt270	alt271	alt272	alt273	alt274	alt275	alt276	alt277	alt278					
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00					
Times chosen									33.00	117.00	30.00	96.00	8.00
131.00	164.00	34.00	16.00	118.00	667.00	80.00	230.00	17.00					
									alt279	alt280	alt281	alt282	alt283
alt284	alt285	alt286	alt287	alt288	alt289	alt290	alt291	alt292					
Times available									45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00					
Times chosen									235.00	178.00	39.00	32.00	218.00
114.00	69.00	86.00	65.00	32.00	71.00	15.00	465.00	94.00					
									alt293	alt294	alt295	alt296	alt297
alt298	alt299	alt300	alt301	alt302	alt303	alt304	alt305	alt306					

```

Times available          45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.0 45970.00 45970.00 45970.00
Times chosen              178.00  217.00  100.00   25.00  115.00
253.00   17.00   19.00 2184.00   35.00  690.0   21.00   84.00  258.00
                    alt307  alt308  alt309  alt310  alt311
alt312  alt313  alt314  alt315  alt316  alt317  alt318  alt319
Times available          45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00
Times chosen              68.00   34.00  124.00   25.00   43.00
119.00   10.00   66.00   35.00  259.00   59.00   64.00  405.00
                    alt320  alt321  alt322  alt323  alt324
alt325  alt326  alt327  alt328  alt329  alt330  alt331  alt332  alt333
Times available          45970.00 45970.0 45970.00 45970.00 45970.00
45970.00 45970.0 45970.00 45970.00 45970.00 45970.00 45970.00 45970.0 45970.00
Times chosen              21.00   48.0   9.00   24.00  290.00
132.00   47.0   16.00  102.00  733.00  176.00   60.00  136.0   12.00
                    alt334  alt335  alt336  alt337  alt338
alt339  alt340  alt341  alt342  alt343  alt344  alt345  alt346
Times available          45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00
Times chosen              41.00   98.00  296.00   96.00  860.00
143.00  103.00  272.00   50.00   65.00  546.00  243.00   70.00
[ reached getOption("max.print") -- omitted 2 rows ]

```

WARNING: Availability not provided to 'apollo\_mnl' (or some elements are NA).  
Full availability assumed.

Classical covariance matrix:

	b_cbd	b_displacement	b_density
b_cbd	3e-04	0	0
b_displacement	0e+00	0	0
b_density	0e+00	0	0

Robust covariance matrix:

	b_cbd	b_displacement	b_density
b_cbd	4e-04	0	0
b_displacement	0e+00	0	0
b_density	0e+00	0	0

Classical correlation matrix:

	b_cbd	b_displacement	b_density
b_cbd	1.0000	-0.0329	-0.7095
b_displacement	-0.0329	1.0000	0.0868
b_density	-0.7095	0.0868	1.0000

Robust correlation matrix:

	b_cbd	b_displacement	b_density
b_cbd	1.0000	0.0646	-0.8149
b_displacement	0.0646	1.0000	0.0527
b_density	-0.8149	0.0527	1.0000

20 worst outliers in terms of lowest average per choice prediction:  
ID Avg prob per choice

2774916347813847552	0.0002107837
15776034442216282112	0.0002319723
16420658169178376192	0.0002319723
3802522546109566464	0.0002328309
15835785591066517504	0.0002328309
7297136756525148160	0.0002332606
13977591018014330880	0.0002359035
13853233355017904128	0.0002380797
14794354505161234432	0.0002380830
5028398331823306752	0.0002438946
3920273676112835584	0.0002441105
6016488577462255616	0.0002441105
8061079042806119424	0.0002441105
1.0183959020319e+19	0.0002441105
61706660413014328	0.0002456308
861729362512641024	0.0002488327
12267183877589512192	0.0002500969
1.8288945217247e+19	0.0002505128
6803533354303611904	0.0002519814
924143177505015296	0.0002533403

Changes in parameter estimates from starting values:

	Initial	Estimate	Difference
b_cbd	0	1.4605	1.4605
b_displacement	0	-0.0745	-0.0745
b_density	0	-0.0226	-0.0226
b_landuse	0	0.0000	0.0000

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX G**

Full estimation output of Model 3



45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				1921.00	72.00	79.00	25.00	23.00
90.0	20.00	108.00	5.00	68.00	208.00	16.00	65.00	5.00
				alt29	alt30	alt31	alt32	alt33
alt34	alt35	alt36	alt37	alt38	alt39	alt40	alt41	alt42
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				27.00	23.00	8.00	35.00	74.00
35.00	139.0	15.00	14.00	230.0	10.00	88.00	218.00	651.00
				alt43	alt44	alt45	alt46	alt47
alt48	alt49	alt50	alt51	alt52	alt53	alt54	alt55	alt56
Times available				45970.0	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				186.0	86.00	26.00	204.00	429.00
72.00	104.00	42.00	255.00	5.00	120.00	96.00	46.0	6.00
				alt57	alt58	alt59	alt60	alt61
alt62	alt63	alt64	alt65	alt66	alt67	alt68	alt69	alt70
Times available				45970.00	45970.00	45970.00	45970.00	45970.0
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				7.00	34.00	289.00	6.00	274.0
3479.00	216.00	81.00	66.00	55.00	22.00	74.00	71.00	227.00
				alt71	alt72	alt73	alt74	alt75
alt76	alt77	alt78	alt79	alt80	alt81	alt82	alt83	alt84
Times available				45970.0	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00
Times chosen				45.0	87.00	83.00	49.00	20.00
42.00	220.00	38.00	9.00	317.00	23.00	48.0	22.00	85.00
				alt85	alt86	alt87	alt88	alt89
alt90	alt91	alt92	alt93	alt94	alt95	alt96	alt97	alt98
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.0
Times chosen				84.00	202.00	51.00	37.00	252.00
113.00	26.00	9.00	1047.00	46.0	154.00	5.00	163.00	90.0
				alt99	alt100	alt101	alt102	alt103
alt104	alt105	alt106	alt107	alt108	alt109	alt110	alt111	alt112
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				21.00	89.00	16.00	235.00	26.00
28.00	1	82.00	180.00	4.00	3.00	310.00	159.00	39.00
				alt113	alt114	alt115	alt116	alt117
alt118	alt119	alt120	alt121	alt122	alt123	alt124	alt125	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				77.00	145.00	69.00	21.00	103.00
38.00	33.00	28.00	22.00	105.00	95.00	430.00	165.00	
				alt126	alt127	alt128	alt129	alt130
alt131	alt132	alt133	alt134	alt135	alt136	alt137	alt138	alt139
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				58.00	137.0	109.00	59.00	70.00
53.00	57.00	23.00	18.00	151.00	13.00	29.00	29.00	2
				alt140	alt141	alt142	alt143	alt144
alt145	alt146	alt147	alt148	alt149	alt150	alt151	alt152	alt153
Times available				45970.00	45970.00	45970.00	45970.00	45970.00

45970.0	45970.00	45970.00	45970.0	45970.00	45970.00	45970.0	45970	45970.00
Times chosen				14.00	43.00	13.00	33.00	363.00
44.0	28.00	87.00	186.0	5.00	28.00	92.0	1	396.00
				alt154	alt155	alt156	alt157	alt158
alt159	alt160	alt161	alt162	alt163	alt164	alt165	alt166	alt167
Times available				45970.00	45970.00	45970.00	45970.0	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	63.00	80.00	230.0	38.00
12.00	159.00	180.00	4.00	66.00	4.00	148.00	71.00	14.00
				alt168	alt169	alt170	alt171	alt172
alt173	alt174	alt175	alt176	alt177	alt178	alt179	alt180	alt181
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				219.00	18.00	119.00	61.00	28.00
28.00	113.00	60.00	139.0	72.00	34.00	40.00	55.00	167.00
				alt182	alt183	alt184	alt185	alt186
alt187	alt188	alt189	alt190	alt191	alt192	alt193	alt194	alt195
Times available				45970.00	45970.00	45970.00	45970.00	45970
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	221.00	7.00	12.00	2
25.00	62.00	66.00	108.00	6.00	5.00	55.00	15.00	67.00
				alt196	alt197	alt198	alt199	alt200
alt201	alt202	alt203	alt204	alt205	alt206	alt207	alt208	alt209
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				394.00	45.0	118.00	953.00	36.00
185.0	20.00	14.00	54.00	171.00	204.00	17.00	147.00	60.00
				alt210	alt211	alt212	alt213	alt214
alt215	alt216	alt217	alt218	alt219	alt220	alt221	alt222	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				110.00	37.00	27.00	30.00	60.00
43.00	11.00	8.00	39.00	95.00	141.00	86.00	53.00	
				alt223	alt224	alt225	alt226	alt227
alt228	alt229	alt230	alt231	alt232	alt233	alt234	alt235	alt236
Times available				45970.00	45970.00	45970.00	45970	45970.00
45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970	45970.00	45970.00
Times chosen				35.00	11.00	143.00	1	63.00
63.00	481.00	48.0	8.00	86.00	272.00	2	59.00	212.00
				alt237	alt238	alt239	alt240	alt241
alt242	alt243	alt244	alt245	alt246	alt247	alt248	alt249	alt250
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00
Times chosen				52.00	146.00	13.00	60.00	9.00
244.00	128.00	14.00	38.00	65.00	46.0	222.00	180.00	5.00
				alt251	alt252	alt253	alt254	alt255
alt256	alt257	alt258	alt259	alt260	alt261	alt262	alt263	alt264
Times available				45970.00	45970.00	45970.0	45970.00	45970.00
45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				22.00	41.00	92.0	318.00	59.00
29.00	11.00	48.0	34.00	89.00	180.00	61.00	332.00	59.00
				alt265	alt266	alt267	alt268	alt269
alt270	alt271	alt272	alt273	alt274	alt275	alt276	alt277	alt278
Times available				45970.00	45970.00	45970.00	45970.00	45970.00

```

45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.0 45970.00
Times chosen                33.00  117.00   30.00   96.00    8.00
131.00  164.00   34.00   16.00  118.00  667.00   80.00  230.0  17.00
                alt279  alt280  alt281  alt282  alt283
alt284  alt285  alt286  alt287  alt288  alt289  alt290  alt291  alt292
Times available            45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.0
Times chosen                235.00  178.00   39.00   32.00  218.00
114.00   69.00   86.00   65.00   32.00   71.00   15.00  465.00   94.0
                alt293  alt294  alt295  alt296  alt297
alt298  alt299  alt300  alt301  alt302  alt303  alt304  alt305  alt306
Times available            45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.0 45970.00 45970.00 45970.00
Times chosen                178.00  217.00  100.00   25.00  115.00
253.00   17.00   19.00  2184.00   35.00  690.0  21.00   84.00  258.00
                alt307  alt308  alt309  alt310  alt311
alt312  alt313  alt314  alt315  alt316  alt317  alt318  alt319
Times available            45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00
Times chosen                68.00   34.00  124.00   25.00   43.00
119.00   10.00   66.00   35.00  259.00   59.00   64.00  405.00
                alt320  alt321  alt322  alt323  alt324
alt325  alt326  alt327  alt328  alt329  alt330  alt331  alt332  alt333
Times available            45970.00 45970.0 45970.00 45970.00 45970.00
45970.00 45970.0 45970.00 45970.00 45970.00 45970.00 45970.00 45970.0 45970.00
Times chosen                21.00   48.0  9.00   24.00  290.00
132.00   47.0  16.00  102.00  733.00  176.00   60.00  136.0  12.00
                alt334  alt335  alt336  alt337  alt338
alt339  alt340  alt341  alt342  alt343  alt344  alt345  alt346
Times available            45970.00 45970.00 45970.00 45970.00 45970.00
45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00 45970.00
Times chosen                41.00   98.00  296.00   96.00  860.00
143.00  103.00  272.00   50.00   65.00  546.00  243.00   70.00
[ reached getOption("max.print") -- omitted 2 rows ]

```

WARNING: Availability not provided to 'apollo\_mnl' (or some elements are NA).  
Full availability assumed.

Classical covariance matrix:

	b_density	b_displacement_cbd_shift	b_cbd	b_displacement
b_cbd	0	0	5e-03	0
b_displacement	0	0	0e+00	-2e-04
b_density	0	0	0e+00	0e+00
b_displacement_cbd_shift	0	0	0e+00	0e+00
b_density_cbd_shift	0	0	-2e-04	0e+00

Robust covariance matrix:

	b_density	b_displacement_cbd_shift	b_cbd	b_displacement
b_cbd			0.0027	0
	0		0	-1e-04
b_displacement			0.0000	0
	0		0	0e+00
b_density			0.0000	0
	0		0	0e+00
b_displacement_cbd_shift			0.0000	0
	0		0	0e+00
b_density_cbd_shift			-0.0001	0
	0		0	0e+00

Classical correlation matrix:

	b_density	b_displacement_cbd_shift	b_cbd	b_displacement
b_cbd			1.0000	0.0697
	0.1592		-0.2833	-0.9587
b_displacement			0.0697	1.0000
	0.1073		-0.3944	-0.0235
b_density			0.1592	0.1073
	1.0000		-0.0839	-0.2966
b_displacement_cbd_shift			-0.2833	-0.3944
	-0.0839		1.0000	0.1134
b_density_cbd_shift			-0.9587	-0.0235
	-0.2966		0.1134	1.0000

Robust correlation matrix:

	b_density	b_displacement_cbd_shift	b_cbd	b_displacement
b_cbd			1.0000	0.1480
	0.1974		-0.1298	-0.9417
b_displacement			0.1480	1.0000
	0.1489		-0.4366	-0.0900
b_density			0.1974	0.1489
	1.0000		-0.1737	-0.3649
b_displacement_cbd_shift			-0.1298	-0.4366
	-0.1737		1.0000	-0.0428
b_density_cbd_shift			-0.9417	-0.0900
	-0.3649		-0.0428	1.0000

20 worst outliers in terms of lowest average per choice prediction:

ID	Avg prob per choice
6803533354303611904	0.0002111446
3920273676112835584	0.0002120875
6016488577462255616	0.0002120875
8061079042806119424	0.0002120875
1.0183959020319e+19	0.0002120875
5028398331823306752	0.0002125771
2774916347813847552	0.0002176244
13977591018014330880	0.0002184004
1817022443524843520	0.0002196254
11937965295098773504	0.0002196254
11480148089940199424	0.0002236423

1809392133632938496	0.0002240699
861729362512641024	0.0002254792
16404170097490569216	0.0002305027
10658552656679172096	0.0002395233
12459102128112312320	0.0002395233
14794354505161234432	0.0002429545
15776034442216282112	0.0002430824
16420658169178376192	0.0002430824
3802522546109566464	0.0002432503

Changes in parameter estimates from starting values:

	Initial	Estimate	Difference
b_cbd	0	5.9854	5.9854
b_displacement	0	-0.0795	-0.0795
b_density	0	-0.0117	-0.0117
b_landuse	0	0.0000	0.0000
b_displacement_cbd_shift	0	0.0289	0.0289
b_density_cbd_shift	0	-0.1751	-0.1751
b_landuse_cbd_shift	0	0.0000	0.0000

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX H**

Full estimation output of Model 4

Model run using Apollo for R, version 0.1.0  
 www.ApolloChoiceModelling.com

Model name : MNL\_MyCiTi\_Model4  
 Model description : MNL Model of MyCiTi IRT System on RP data  
 Model run at : 2021-01-29 20:39:38  
 Estimation method : bfgs  
 Model diagnosis : successful convergence  
 Number of individuals : 31681  
 Number of observations : 45970

Number of cores used : 1  
 Model without mixing

LL(start) : -268760.8  
 LL(0) : -268760.8  
 LL(final) : -244789.7  
 Rho-square (0) : 0.0892  
 Adj.Rho-square (0) : 0.0891  
 AIC : 489607.4  
 BIC : 489729.7  
 Estimated parameters : 14  
 Time taken (hh:mm:ss) : 01:26:55.51  
 Iterations : 24  
 Min abs eigenvalue of hessian : 76.84849

Estimates:

	Estimate	Std.err.	t.ratio(0)	Rob.std.err.
Rob.t.ratio(0)				
b_cbd	5.6246	0.0865	65.02	0.0603
93.35				
b_displacement	-0.0781	0.0006	-132.94	0.0007
-107.59				
b_density	-0.0145	0.0008	-17.22	0.0009
-15.70				
b_landuse1	1.0769	0.0408	26.40	0.0384
28.01				
b_landuse2	0.0000	NA	NA	NA
NA				
b_landuse3	-0.3346	0.0503	-6.65	0.0507
-6.60				
b_landuse4	-0.2196	0.0435	-5.04	0.0433
-5.07				
b_landuse5	0.4879	0.0421	11.60	0.0417
11.70				
b_landuse6	-0.2251	0.0423	-5.32	0.0424
-5.31				
b_landuse7	0.6067	0.0391	15.52	0.0387
15.66				
b_landuse8	-0.4329	0.0423	-10.24	0.0422
-10.27				
b_landuse9	-0.5144	0.0394	-13.07	0.0396
-12.99				
b_landuse10	-0.3070	0.0390	-7.87	0.0390

-7.87

b\_displacement\_cbd\_shift 0.0325 0.0012 26.97 0.0011

29.77

b\_density\_cbd\_shift -0.1799 0.0032 -56.64 0.0024

-76.03

Overview of choices for model component "MNL"

	alt1	alt2	alt3	alt4	alt5
alt6	alt7	alt8	alt9	alt10	alt11
alt12	alt13	alt14	alt15	alt16	alt17
alt18	alt19	alt20	alt21	alt22	alt23
alt24	alt25	alt26	alt27	alt28	alt29
alt30	alt31	alt32	alt33	alt34	alt35
alt36	alt37	alt38	alt39	alt40	alt41
alt42	alt43	alt44	alt45	alt46	alt47
alt48	alt49	alt50	alt51	alt52	alt53
alt54	alt55	alt56	alt57	alt58	alt59
alt60	alt61	alt62	alt63	alt64	alt65
alt66	alt67	alt68	alt69	alt70	alt71
alt72	alt73	alt74	alt75	alt76	alt77
alt78	alt79	alt80	alt81	alt82	alt83
alt84	alt85	alt86	alt87	alt88	alt89
alt90	alt91	alt92	alt93	alt94	alt95
alt96	alt97	alt98	alt99	alt100	alt101
alt102	alt103	alt104	alt105	alt106	alt107
alt108	alt109	alt110	alt111	alt112	

28.00	1	82.00	180.00	4.00	3.00	310.00	159.00	39.00
				alt113	alt114	alt115	alt116	alt117
alt118	alt119	alt120	alt121	alt122	alt123	alt124	alt125	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				77.00	145.00	69.00	21.00	103.00
38.00	33.00	28.00	22.00	105.00	95.00	430.00	165.00	
				alt126	alt127	alt128	alt129	alt130
alt131	alt132	alt133	alt134	alt135	alt136	alt137	alt138	alt139
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				58.00	137.00	109.00	59.00	70.00
53.00	57.00	23.00	18.00	151.00	13.00	29.00	29.00	2
				alt140	alt141	alt142	alt143	alt144
alt145	alt146	alt147	alt148	alt149	alt150	alt151	alt152	alt153
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				14.00	43.00	13.00	33.00	363.00
44.00	28.00	87.00	186.00	5.00	28.00	92.00	1	396.00
				alt154	alt155	alt156	alt157	alt158
alt159	alt160	alt161	alt162	alt163	alt164	alt165	alt166	alt167
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	63.00	80.00	230.00	38.00
12.00	159.00	180.00	4.00	66.00	4.00	148.00	71.00	14.00
				alt168	alt169	alt170	alt171	alt172
alt173	alt174	alt175	alt176	alt177	alt178	alt179	alt180	alt181
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				219.00	18.00	119.00	61.00	28.00
28.00	113.00	60.00	139.00	72.00	34.00	40.00	55.00	167.00
				alt182	alt183	alt184	alt185	alt186
alt187	alt188	alt189	alt190	alt191	alt192	alt193	alt194	alt195
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	221.00	7.00	12.00	2
25.00	62.00	66.00	108.00	6.00	5.00	55.00	15.00	67.00
				alt196	alt197	alt198	alt199	alt200
alt201	alt202	alt203	alt204	alt205	alt206	alt207	alt208	alt209
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				394.00	45.00	118.00	953.00	36.00
185.00	20.00	14.00	54.00	171.00	204.00	17.00	147.00	60.00
				alt210	alt211	alt212	alt213	alt214
alt215	alt216	alt217	alt218	alt219	alt220	alt221	alt222	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				110.00	37.00	27.00	30.00	60.00
43.00	11.00	8.00	39.00	95.00	141.00	86.00	53.00	
				alt223	alt224	alt225	alt226	alt227
alt228	alt229	alt230	alt231	alt232	alt233	alt234	alt235	alt236
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				35.00	11.00	143.00	1	63.00

63.00	481.00	48.0	8.00	86.00	272.00	2	59.00	212.00
				alt237	alt238	alt239	alt240	alt241
alt242	alt243	alt244	alt245	alt246	alt247	alt248	alt249	alt250
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00
Times chosen				52.00	146.00	13.00	60.00	9.00
244.00	128.00	14.00	38.00	65.00	46.0	222.00	180.00	5.00
				alt251	alt252	alt253	alt254	alt255
alt256	alt257	alt258	alt259	alt260	alt261	alt262	alt263	alt264
Times available				45970.00	45970.00	45970.0	45970.00	45970.00
45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				22.00	41.00	92.0	318.00	59.00
29.00	11.00	48.0	34.00	89.00	180.00	61.00	332.00	59.00
				alt265	alt266	alt267	alt268	alt269
alt270	alt271	alt272	alt273	alt274	alt275	alt276	alt277	alt278
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				33.00	117.00	30.00	96.00	8.00
131.00	164.00	34.00	16.00	118.00	667.00	80.00	230.0	17.00
				alt279	alt280	alt281	alt282	alt283
alt284	alt285	alt286	alt287	alt288	alt289	alt290	alt291	alt292
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0
Times chosen				235.00	178.00	39.00	32.00	218.00
114.00	69.00	86.00	65.00	32.00	71.00	15.00	465.00	94.0
				alt293	alt294	alt295	alt296	alt297
alt298	alt299	alt300	alt301	alt302	alt303	alt304	alt305	alt306
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00
Times chosen				178.00	217.00	100.00	25.00	115.00
253.00	17.00	19.00	2184.00	35.00	690.0	21.00	84.00	258.00
				alt307	alt308	alt309	alt310	alt311
alt312	alt313	alt314	alt315	alt316	alt317	alt318	alt319	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				68.00	34.00	124.00	25.00	43.00
119.00	10.00	66.00	35.00	259.00	59.00	64.00	405.00	
				alt320	alt321	alt322	alt323	alt324
alt325	alt326	alt327	alt328	alt329	alt330	alt331	alt332	alt333
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				21.00	48.0	9.00	24.00	290.00
132.00	47.0	16.00	102.00	733.00	176.00	60.00	136.0	12.00
				alt334	alt335	alt336	alt337	alt338
alt339	alt340	alt341	alt342	alt343	alt344	alt345	alt346	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				41.00	98.00	296.00	96.00	860.00
143.00	103.00	272.00	50.00	65.00	546.00	243.00	70.00	

[ reached getopt("max.print") -- omitted 2 rows ]

WARNING: Availability not provided to 'apollo\_mnl' (or some elements are NA).  
Full availability assumed.



b_landuse9	0.0014	0.0014	0.0014
0.0014	0.0014	0.0014	0.0014
b_landuse10	0.0014	0.0014	0.0014
0.0014	0.0014	0.0014	0.0014
b_displacement_cbd_shift	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000
b_density_cbd_shift	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000
		b_landuse9	b_landuse10
b_displacement_cbd_shift	b_density_cbd_shift		
b_cbd		0.0001	0.0000
0		-3e-04	
b_displacement		0.0000	0.0000
0		0e+00	
b_density		0.0000	0.0000
0		0e+00	
b_landuse1		0.0014	0.0014
0		0e+00	
b_landuse3		0.0014	0.0014
0		0e+00	
b_landuse4		0.0014	0.0014
0		0e+00	
b_landuse5		0.0014	0.0014
0		0e+00	
b_landuse6		0.0014	0.0014
0		0e+00	
b_landuse7		0.0014	0.0014
0		0e+00	
b_landuse8		0.0014	0.0014
0		0e+00	
b_landuse9		0.0016	0.0014
0		0e+00	
b_landuse10		0.0014	0.0015
0		0e+00	
b_displacement_cbd_shift		0.0000	0.0000
0		0e+00	
b_density_cbd_shift		0.0000	0.0000
0		0e+00	

Robust covariance matrix:

	b_density	b_cbd	b_displacement	
b_cbd		b_landuse1	b_landuse3	
		0.0036		0
	0	0.0000	0.0001	0
b_displacement		0.0000		0
	0	0.0000	0.0000	0
b_density		0.0000		0
	0	0.0000	0.0000	0
b_landuse1		0.0000		0
	0	0.0015	0.0013	0
b_landuse3		0.0001		0
	0	0.0013	0.0026	0
b_landuse4		0.0003		0
	0	0.0013	0.0013	0

b_landuse5		0.0002		0
	0	0.0014	0.0014	
b_landuse6		0.0002		0
	0	0.0013	0.0014	
b_landuse7		0.0003		0
	0	0.0013	0.0014	
b_landuse8		0.0002		0
	0	0.0013	0.0014	
b_landuse9		0.0002		0
	0	0.0013	0.0014	
b_landuse10		-0.0001		0
	0	0.0014	0.0014	
b_displacement_cbd_shift		0.0000		0
	0	0.0000	0.0000	
b_density_cbd_shift		-0.0001		0
	0	0.0000	0.0000	
		b_landuse4	b_landuse5	
	b_landuse6	b_landuse7	b_landuse8	
b_cbd		0.0003	0.0002	
	0.0002	0.0003	0.0002	
b_displacement		0.0000	0.0000	
	0.0000	0.0000	0.0000	
b_density		0.0000	0.0000	
	0.0000	0.0000	0.0000	
b_landuse1		0.0013	0.0014	
	0.0013	0.0013	0.0013	
b_landuse3		0.0013	0.0014	
	0.0014	0.0014	0.0014	
b_landuse4		0.0019	0.0014	
	0.0014	0.0014	0.0014	
b_landuse5		0.0014	0.0017	
	0.0014	0.0014	0.0014	
b_landuse6		0.0014	0.0014	
	0.0018	0.0014	0.0015	
b_landuse7		0.0014	0.0014	
	0.0014	0.0015	0.0014	
b_landuse8		0.0014	0.0014	
	0.0015	0.0014	0.0018	
b_landuse9		0.0014	0.0014	
	0.0014	0.0014	0.0014	
b_landuse10		0.0014	0.0014	
	0.0014	0.0014	0.0014	
b_displacement_cbd_shift		0.0000	0.0000	
	0.0000	0.0000	0.0000	
b_density_cbd_shift		0.0000	0.0000	
	0.0000	0.0000	0.0000	
		b_landuse9	b_landuse10	
b_displacement_cbd_shift		b_density_cbd_shift		
b_cbd		0.0002	-0.0001	
	0	-1e-04		
b_displacement		0.0000	0.0000	
	0	0e+00		
b_density		0.0000	0.0000	
	0	0e+00		

b_landuse1		0.0013	0.0014
	0	0e+00	
b_landuse3		0.0014	0.0014
	0	0e+00	
b_landuse4		0.0014	0.0014
	0	0e+00	
b_landuse5		0.0014	0.0014
	0	0e+00	
b_landuse6		0.0014	0.0014
	0	0e+00	
b_landuse7		0.0014	0.0014
	0	0e+00	
b_landuse8		0.0014	0.0014
	0	0e+00	
b_landuse9		0.0016	0.0014
	0	0e+00	
b_landuse10		0.0014	0.0015
	0	0e+00	
b_displacement_cbd_shift		0.0000	0.0000
	0	0e+00	
b_density_cbd_shift		0.0000	0.0000
	0	0e+00	

Classical correlation matrix:

	b_density	b_cbd	b_displacement b_landuse3
b_cbd		1.0000	0.0473
	0.1838	-0.1443	0.0244
b_displacement		0.0473	1.0000
	0.0891	-0.0262	-0.0210
b_density		0.1838	0.0891
	1.0000	0.0663	0.0742
b_landuse1		-0.1443	-0.0262
	0.0663	1.0000	0.6570
b_landuse3		0.0244	-0.0210
	0.0742	0.6570	1.0000
b_landuse4		0.0927	-0.0365
	0.0396	0.7886	0.6199
b_landuse5		0.0699	-0.0376
	0.1604	0.8168	0.6466
b_landuse6		0.0517	-0.0248
	0.1987	0.7944	0.6394
b_landuse7		0.1037	-0.0420
	0.1262	0.8755	0.6958
b_landuse8		0.0637	-0.0548
	0.2473	0.8093	0.6501
b_landuse9		0.0414	-0.0410
	0.0851	0.8623	0.6867
b_landuse10		-0.0097	-0.0427
	0.1215	0.8871	0.6953
b_displacement_cbd_shift		-0.2104	-0.3999
	-0.0649	-0.0342	-0.0228
b_density_cbd_shift		-0.9702	-0.0092
	-0.3002	0.1176	-0.0291

	b_landuse6	b_landuse4	b_landuse5
b_cbd		b_landuse7	b_landuse8
	0.0517	0.0927	0.0699
b_displacement	-0.0248	0.1037	0.0637
		-0.0365	-0.0376
b_density	0.1987	-0.0420	-0.0548
		0.0396	0.1604
b_landuse1	0.7944	0.1262	0.2473
		0.7886	0.8168
b_landuse3	0.6394	0.8755	0.8093
		0.6199	0.6466
b_landuse4	0.7483	0.6958	0.6501
		1.0000	0.7792
b_landuse5	0.7929	0.8455	0.7642
		0.7792	1.0000
b_landuse6	1.0000	0.8736	0.8154
		0.7483	0.7929
b_landuse7	0.8489	0.8489	0.8065
		0.8455	0.8736
b_landuse8	0.8065	1.0000	0.8704
		0.7642	0.8154
b_landuse9	0.8331	0.8704	1.0000
		0.8195	0.8481
b_landuse10	0.8473	0.9174	0.8517
		0.8281	0.8627
b_displacement_cbd_shift	-0.0369	0.9290	0.8676
		-0.0552	-0.0344
b_density_cbd_shift	-0.0696	-0.0569	-0.0302
		-0.1073	-0.0967
		-0.1216	-0.0878
		b_landuse9	b_landuse10
b_displacement_cbd_shift		b_density_cbd_shift	
b_cbd	-0.2104	0.0414	-0.0097
		-0.9702	
b_displacement	-0.3999	-0.0410	-0.0427
		-0.0092	
b_density	-0.0649	0.0851	0.1215
		-0.3002	
b_landuse1	-0.0342	0.8623	0.8871
		0.1176	
b_landuse3	-0.0228	0.6867	0.6953
		-0.0291	
b_landuse4	-0.0552	0.8195	0.8281
		-0.1073	
b_landuse5	-0.0344	0.8481	0.8627
		-0.0967	
b_landuse6	-0.0369	0.8331	0.8473
		-0.0696	
b_landuse7	-0.0569	0.9174	0.9290
		-0.1216	
b_landuse8	-0.0302	0.8517	0.8676
		-0.0878	
b_landuse9	-0.0588	1.0000	0.9159
		-0.0406	

b_landuse10	0.9159	1.0000
-0.0592	-0.0006	
b_displacement_cbd_shift	-0.0588	-0.0592
1.0000	0.0712	
b_density_cbd_shift	-0.0406	-0.0006
0.0712	1.0000	

Robust correlation matrix:

	b_cbd	b_displacement b_landuse3
b_density	0.2076	0.1117
b_landuse1	0.0117	0.0339
b_displacement	0.1117	1.0000
0.1212	-0.0504	-0.0775
b_density	0.2076	0.1212
1.0000	0.0943	0.1265
b_landuse1	0.0117	-0.0504
0.0943	1.0000	0.6806
b_landuse3	0.0339	-0.0775
0.1265	0.6806	1.0000
b_landuse4	0.1240	-0.0796
0.0783	0.8061	0.6136
b_landuse5	0.0842	-0.0760
0.1781	0.8439	0.6479
b_landuse6	0.0869	-0.0844
0.2543	0.8164	0.6400
b_landuse7	0.1384	-0.1095
0.1534	0.8974	0.6965
b_landuse8	0.0774	-0.0687
0.3099	0.8300	0.6531
b_landuse9	0.0859	-0.0904
0.1890	0.8820	0.6839
b_landuse10	-0.0491	-0.1162
0.1856	0.9068	0.6991
b_displacement_cbd_shift	-0.1286	-0.4239
-0.1632	0.0021	-0.0196
b_density_cbd_shift	-0.9559	-0.0634
-0.3411	-0.0403	-0.0504
	b_landuse4	b_landuse5
b_cbd	b_landuse7	b_landuse8
0.0869	0.1240	0.0842
b_displacement	0.1384	0.0774
-0.0844	-0.0796	-0.0760
b_density	-0.1095	-0.0687
0.2543	0.0783	0.1781
b_landuse1	0.1534	0.3099
0.8164	0.8061	0.8439
b_landuse3	0.8974	0.8300
0.6400	0.6136	0.6479
b_landuse4	0.6965	0.6531
0.7427	1.0000	0.7800
b_landuse5	0.8436	0.7548
0.7950	0.7800	1.0000
	0.8711	0.8072

b_landuse6	0.7427	0.7950
1.0000	0.8475	0.8138
b_landuse7	0.8436	0.8711
0.8475	1.0000	0.8684
b_landuse8	0.7548	0.8072
0.8138	0.8684	1.0000
b_landuse9	0.8112	0.8479
0.8403	0.9238	0.8582
b_landuse10	0.8194	0.8602
0.8457	0.9262	0.8687
b_displacement_cbd_shift	-0.0884	-0.0534
-0.0721	-0.0960	-0.0503
b_density_cbd_shift	-0.1520	-0.1212
-0.1120	-0.1514	-0.1176
	b_landuse9	b_landuse10
b_displacement_cbd_shift	b_density_cbd_shift	
b_cbd	0.0859	-0.0491
-0.1286	-0.9559	
b_displacement	-0.0904	-0.1162
-0.4239	-0.0634	
b_density	0.1890	0.1856
-0.1632	-0.3411	
b_landuse1	0.8820	0.9068
0.0021	-0.0403	
b_landuse3	0.6839	0.6991
-0.0196	-0.0504	
b_landuse4	0.8112	0.8194
-0.0884	-0.1520	
b_landuse5	0.8479	0.8602
-0.0534	-0.1212	
b_landuse6	0.8403	0.8457
-0.0721	-0.1120	
b_landuse7	0.9238	0.9262
-0.0960	-0.1514	
b_landuse8	0.8582	0.8687
-0.0503	-0.1176	
b_landuse9	1.0000	0.9133
-0.1111	-0.0915	
b_landuse10	0.9133	1.0000
-0.0960	0.0211	
b_displacement_cbd_shift	-0.1111	-0.0960
1.0000	-0.0289	
b_density_cbd_shift	-0.0915	0.0211
-0.0289	1.0000	

20 worst outliers in terms of lowest average per choice prediction:

ID	Avg prob per choice
6803533354303611904	0.0001587093
13853233355017904128	0.0001722338
11480148089940199424	0.0001763258
1809392133632938496	0.0001772273
1.8288945217247e+19	0.0001787013
4926675220532828160	0.0001794105
12267183877589512192	0.0001803652

1428742674930758144	0.0001821432
2726713354250044416	0.0001821432
3141016703902427648	0.0001821432
3171972514679971328	0.0001821432
3369660437955168768	0.0001821432
4802580418056599552	0.0001821432
4873251256534693888	0.0001821432
5948743482505696256	0.0001821432
6076174213617401856	0.0001821432
6.740326964775e+18	0.0001821432
7272184300913737728	0.0001821432
7306366009760183296	0.0001821432
9786248872423342080	0.0001821432

Changes in parameter estimates from starting values:

	Initial	Estimate	Difference
b_cbd	0	5.6246	5.6246
b_displacement	0	-0.0781	-0.0781
b_density	0	-0.0145	-0.0145
b_landuse1	0	1.0769	1.0769
b_landuse2	0	0.0000	0.0000
b_landuse3	0	-0.3346	-0.3346
b_landuse4	0	-0.2196	-0.2196
b_landuse5	0	0.4879	0.4879
b_landuse6	0	-0.2251	-0.2251
b_landuse7	0	0.6067	0.6067
b_landuse8	0	-0.4329	-0.4329
b_landuse9	0	-0.5144	-0.5144
b_landuse10	0	-0.3070	-0.3070
b_displacement_cbd_shift	0	0.0325	0.0325
b_density_cbd_shift	0	-0.1799	-0.1799

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX I**

Full estimation output of Model 5

Model run using Apollo for R, version 0.1.0  
 www.ApolloChoiceModelling.com

Model name : MNL\_MyCiTi\_Model5  
 Model description : MNL Model of MyCiTi IRT System on RP data  
 Model run at : 2021-01-28 22:01:30  
 Estimation method : bfgs  
 Model diagnosis : successful convergence  
 Number of individuals : 31681  
 Number of observations : 45970

Number of cores used : 1  
 Model without mixing

LL(start) : -268760.8  
 LL(0) : -268760.8  
 LL(final) : -244572.8  
 Rho-square (0) : 0.09  
 Adj.Rho-square (0) : 0.0899  
 AIC : 489175.5  
 BIC : 489306.5  
 Estimated parameters : 15  
 Time taken (hh:mm:ss) : 01:33:16.1  
 Iterations : 26  
 Min abs eigenvalue of hessian : 75.42534

Estimates:

	Estimate	Std.err.	t.ratio(0)	Rob.std.err.
Rob.t.ratio(0)				
b_cbd	6.9499	0.1075	64.64	0.0934
74.41				
b_displacement	-0.0780	0.0006	-133.37	0.0007
-108.21				
b_density	-0.0153	0.0008	-18.21	0.0009
-16.66				
b_landuse1	1.1072	0.0407	27.20	0.0383
28.88				
b_landuse2	0.0000	NA	NA	NA
NA				
b_landuse3	-0.3394	0.0503	-6.74	0.0507
-6.70				
b_landuse4	-0.0425	0.0439	-0.97	0.0436
-0.98				
b_landuse5	0.5836	0.0422	13.83	0.0417
13.98				
b_landuse6	-0.2351	0.0423	-5.56	0.0423
-5.55				
b_landuse7	0.5348	0.0393	13.60	0.0390
13.71				
b_landuse8	-0.4444	0.0423	-10.51	0.0421
-10.55				
b_landuse9	-0.5198	0.0394	-13.20	0.0396
-13.13				
b_landuse10	-0.3176	0.0390	-8.14	0.0390

-8.14  
b\_displacement\_cbd\_shift 0.0322 0.0012 26.67 0.0011  
29.41  
b\_density\_cbd\_shift -0.2401 0.0043 -55.27 0.0040  
-59.45  
b\_landuse7\_cbd\_shift 0.7978 0.0389 20.52 0.0429  
18.58

Overview of choices for model component "MNL"

	alt1	alt2	alt3	alt4	alt5
alt6	alt7	alt8	alt9	alt10	alt11
alt12	alt13	alt14			
Times available	45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen	2191.00	2	64.00	102.00	273.00
81.00	59.00	18.00	40.00	343.00	6.00
	alt15	alt16	alt17	alt18	alt19
alt20	alt21	alt22	alt23	alt24	alt25
alt26	alt27	alt28			
Times available	45970.00	45970.00	45970.00	45970.00	45970.00
45970.0	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen	1921.00	72.00	79.00	25.00	23.00
90.0	20.00	108.00	5.00	68.00	208.00
	alt29	alt30	alt31	alt32	alt33
alt34	alt35	alt36	alt37	alt38	alt39
alt40	alt41	alt42			
Times available	45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.0	45970.00	45970.00	45970.0	45970.00
Times chosen	27.00	23.00	8.00	35.00	74.00
35.00	139.0	15.00	14.00	230.0	10.00
	alt43	alt44	alt45	alt46	alt47
alt48	alt49	alt50	alt51	alt52	alt53
alt54	alt55	alt56			
Times available	45970.0	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen	186.0	86.00	26.00	204.00	429.00
72.00	104.00	42.00	255.00	5.00	120.00
	alt57	alt58	alt59	alt60	alt61
alt62	alt63	alt64	alt65	alt66	alt67
alt68	alt69	alt70			
Times available	45970.00	45970.00	45970.00	45970.00	45970.0
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen	7.00	34.00	289.00	6.00	274.0
3479.00	216.00	81.00	66.00	55.00	22.00
	alt71	alt72	alt73	alt74	alt75
alt76	alt77	alt78	alt79	alt80	alt81
alt82	alt83	alt84			
Times available	45970.0	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen	45.0	87.00	83.00	49.00	20.00
42.00	220.00	38.00	9.00	317.00	23.00
	alt85	alt86	alt87	alt88	alt89
alt90	alt91	alt92	alt93	alt94	alt95
alt96	alt97	alt98			
Times available	45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen	84.00	202.00	51.00	37.00	252.00
113.00	26.00	9.00	1047.00	46.0	154.00
	alt99	alt100	alt101	alt102	alt103
alt104	alt105	alt106	alt107	alt108	alt109
alt110	alt111	alt112			
Times available	45970.00	45970.00	45970.00	45970.00	45970.00

45970.00	45970	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				21.00	89.00	16.00	235.00	26.00
28.00	1	82.00	180.00	4.00	3.00	310.00	159.00	39.00
				alt113	alt114	alt115	alt116	alt117
alt118	alt119	alt120	alt121	alt122	alt123	alt124	alt125	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				77.00	145.00	69.00	21.00	103.00
38.00	33.00	28.00	22.00	105.00	95.00	430.00	165.00	
				alt126	alt127	alt128	alt129	alt130
alt131	alt132	alt133	alt134	alt135	alt136	alt137	alt138	alt139
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970
Times chosen				58.00	137.0	109.00	59.00	70.00
53.00	57.00	23.00	18.00	151.00	13.00	29.00	29.00	2
				alt140	alt141	alt142	alt143	alt144
alt145	alt146	alt147	alt148	alt149	alt150	alt151	alt152	alt153
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.0	45970.00	45970.00	45970.0	45970.00	45970.00	45970.0	45970	45970.00
Times chosen				14.00	43.00	13.00	33.00	363.00
44.0	28.00	87.00	186.0	5.00	28.00	92.0	1	396.00
				alt154	alt155	alt156	alt157	alt158
alt159	alt160	alt161	alt162	alt163	alt164	alt165	alt166	alt167
Times available				45970.00	45970.00	45970.00	45970.0	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	63.00	80.00	230.0	38.00
12.00	159.00	180.00	4.00	66.00	4.00	148.00	71.00	14.00
				alt168	alt169	alt170	alt171	alt172
alt173	alt174	alt175	alt176	alt177	alt178	alt179	alt180	alt181
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				219.00	18.00	119.00	61.00	28.00
28.00	113.00	60.00	139.0	72.00	34.00	40.00	55.00	167.00
				alt182	alt183	alt184	alt185	alt186
alt187	alt188	alt189	alt190	alt191	alt192	alt193	alt194	alt195
Times available				45970.00	45970.00	45970.00	45970.00	45970
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				11.00	221.00	7.00	12.00	2
25.00	62.00	66.00	108.00	6.00	5.00	55.00	15.00	67.00
				alt196	alt197	alt198	alt199	alt200
alt201	alt202	alt203	alt204	alt205	alt206	alt207	alt208	alt209
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				394.00	45.0	118.00	953.00	36.00
185.0	20.00	14.00	54.00	171.00	204.00	17.00	147.00	60.00
				alt210	alt211	alt212	alt213	alt214
alt215	alt216	alt217	alt218	alt219	alt220	alt221	alt222	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				110.00	37.00	27.00	30.00	60.00
43.00	11.00	8.00	39.00	95.00	141.00	86.00	53.00	
				alt223	alt224	alt225	alt226	alt227
alt228	alt229	alt230	alt231	alt232	alt233	alt234	alt235	alt236
Times available				45970.00	45970.00	45970.00	45970	45970.00

45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970	45970.00	45970.00
Times chosen				35.00	11.00	143.00	1	63.00
63.00	481.00	48.0	8.00	86.00	272.00	2	59.00	212.00
				alt237	alt238	alt239	alt240	alt241
alt242	alt243	alt244	alt245	alt246	alt247	alt248	alt249	alt250
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00
Times chosen				52.00	146.00	13.00	60.00	9.00
244.00	128.00	14.00	38.00	65.00	46.0	222.00	180.00	5.00
				alt251	alt252	alt253	alt254	alt255
alt256	alt257	alt258	alt259	alt260	alt261	alt262	alt263	alt264
Times available				45970.00	45970.00	45970.0	45970.00	45970.00
45970.00	45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00
Times chosen				22.00	41.00	92.0	318.00	59.00
29.00	11.00	48.0	34.00	89.00	180.00	61.00	332.00	59.00
				alt265	alt266	alt267	alt268	alt269
alt270	alt271	alt272	alt273	alt274	alt275	alt276	alt277	alt278
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				33.00	117.00	30.00	96.00	8.00
131.00	164.00	34.00	16.00	118.00	667.00	80.00	230.0	17.00
				alt279	alt280	alt281	alt282	alt283
alt284	alt285	alt286	alt287	alt288	alt289	alt290	alt291	alt292
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0
Times chosen				235.00	178.00	39.00	32.00	218.00
114.00	69.00	86.00	65.00	32.00	71.00	15.00	465.00	94.0
				alt293	alt294	alt295	alt296	alt297
alt298	alt299	alt300	alt301	alt302	alt303	alt304	alt305	alt306
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00	45970.00	45970.00
Times chosen				178.00	217.00	100.00	25.00	115.00
253.00	17.00	19.00	2184.00	35.00	690.0	21.00	84.00	258.00
				alt307	alt308	alt309	alt310	alt311
alt312	alt313	alt314	alt315	alt316	alt317	alt318	alt319	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				68.00	34.00	124.00	25.00	43.00
119.00	10.00	66.00	35.00	259.00	59.00	64.00	405.00	
				alt320	alt321	alt322	alt323	alt324
alt325	alt326	alt327	alt328	alt329	alt330	alt331	alt332	alt333
Times available				45970.00	45970.0	45970.00	45970.00	45970.00
45970.00	45970.0	45970.00	45970.00	45970.00	45970.00	45970.00	45970.0	45970.00
Times chosen				21.00	48.0	9.00	24.00	290.00
132.00	47.0	16.00	102.00	733.00	176.00	60.00	136.0	12.00
				alt334	alt335	alt336	alt337	alt338
alt339	alt340	alt341	alt342	alt343	alt344	alt345	alt346	
Times available				45970.00	45970.00	45970.00	45970.00	45970.00
45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	45970.00	
Times chosen				41.00	98.00	296.00	96.00	860.00
143.00	103.00	272.00	50.00	65.00	546.00	243.00	70.00	

[ reached getopt("max.print") -- omitted 2 rows ]

WARNING: Availability not provided to 'apollo\_mnl' (or some elements are NA).

Full availability assumed.

Classical covariance matrix:

	b_density	b_landuse1	b_cbd	b_displacement	b_landuse3
b_cbd	0	-0.0003	0.0116	0.0001	0
b_displacement	0	0.0000	0.0000	0.0000	0
b_density	0	0.0000	0.0000	0.0000	0
b_landuse1	0	0.0000	-0.0003	0.0000	0
b_landuse3	0	0.0017	0.0001	0.0013	0
b_landuse4	0	0.0013	0.0008	0.0025	0
b_landuse5	0	0.0014	0.0005	0.0014	0
b_landuse6	0	0.0014	0.0002	0.0014	0
b_landuse7	0	0.0014	0.0001	0.0014	0
b_landuse8	0	0.0014	0.0002	0.0014	0
b_landuse9	0	0.0014	0.0001	0.0014	0
b_landuse10	0	0.0014	-0.0001	0.0014	0
b_displacement_cbd_shift	0	0.0000	0.0000	0.0000	0
b_density_cbd_shift	0	0.0000	-0.0005	0.0000	0
b_landuse7_cbd_shift	0	0.0000	0.0026	0.0000	0
		b_landuse4	b_landuse5	b_landuse6	b_landuse7
b_cbd	0.0002	0.0001	0.0008	0.0002	0.0005
b_displacement	0.0000	0.0000	0.0000	0.0000	0.0000
b_density	0.0000	0.0000	0.0000	0.0000	0.0000
b_landuse1	0.0014	0.0014	0.0014	0.0014	0.0014
b_landuse3	0.0014	0.0014	0.0014	0.0014	0.0014
b_landuse4	0.0014	0.0014	0.0019	0.0014	0.0014
b_landuse5	0.0014	0.0014	0.0014	0.0014	0.0018
b_landuse6	0.0018	0.0014	0.0014	0.0014	0.0014

b_landuse7	0.0014	0.0014	0.0014
b_landuse8	0.0014	0.0014	0.0014
b_landuse9	0.0014	0.0014	0.0014
b_landuse10	0.0014	0.0014	0.0014
b_displacement_cbd_shift	0.0000	0.0000	0.0000
b_density_cbd_shift	0.0000	0.0000	0.0000
b_landuse7_cbd_shift	0.0000	0.0003	0.0002
		-0.0001	0.0000
		b_landuse9	b_landuse10
b_displacement_cbd_shift	b_density_cbd_shift	b_landuse7_cbd_shift	
b_cbd	0.0001	-0.0001	
	0	-5e-04	0.0026
b_displacement	0.0000	0.0000	0.0000
	0	0e+00	0.0000
b_density	0.0000	0.0000	0.0000
	0	0e+00	0.0000
b_landuse1	0.0014	0.0014	0.0014
	0	0e+00	0.0001
b_landuse3	0.0014	0.0014	0.0014
	0	0e+00	0.0000
b_landuse4	0.0014	0.0014	0.0014
	0	0e+00	0.0003
b_landuse5	0.0014	0.0014	0.0014
	0	0e+00	0.0002
b_landuse6	0.0014	0.0014	0.0014
	0	0e+00	0.0000
b_landuse7	0.0014	0.0014	0.0014
	0	0e+00	-0.0001
b_landuse8	0.0014	0.0014	0.0014
	0	0e+00	0.0000
b_landuse9	0.0015	0.0015	0.0014
	0	0e+00	0.0000
b_landuse10	0.0014	0.0014	0.0015
	0	0e+00	0.0000
b_displacement_cbd_shift	0.0000	0.0000	0.0000
	0	0e+00	0.0000
b_density_cbd_shift	0.0000	0.0000	0.0000
	0	0e+00	-0.0001
b_landuse7_cbd_shift	0.0000	0.0000	0.0000
	0	-1e-04	0.0015

Robust covariance matrix:

	b_density	b_cbd	b_displacement	
b_cbd		b_landuse1	b_landuse3	
	0	0.0087	0	
b_displacement		0.0001	0.0001	0
	0	0.0000	0.0000	

b_density		0.0000		0
	0	0.0000	0.0000	
b_landuse1		0.0001		0
	0	0.0015	0.0013	
b_landuse3		0.0001		0
	0	0.0013	0.0026	
b_landuse4		0.0008		0
	0	0.0013	0.0013	
b_landuse5		0.0004		0
	0	0.0013	0.0014	
b_landuse6		0.0002		0
	0	0.0013	0.0014	
b_landuse7		0.0001		0
	0	0.0013	0.0014	
b_landuse8		0.0002		0
	0	0.0013	0.0014	
b_landuse9		0.0002		0
	0	0.0013	0.0014	
b_landuse10		-0.0002		0
	0	0.0014	0.0014	
b_displacement_cbd_shift		0.0000		0
	0	0.0000	0.0000	
b_density_cbd_shift		-0.0004		0
	0	0.0000	0.0000	
b_landuse7_cbd_shift		0.0031		0
	0	0.0000	0.0000	
		b_landuse4	b_landuse5	
	b_landuse6	b_landuse7	b_landuse8	
b_cbd		0.0008	0.0004	
	0.0002	0.0001	0.0002	
b_displacement		0.0000	0.0000	
	0.0000	0.0000	0.0000	
b_density		0.0000	0.0000	
	0.0000	0.0000	0.0000	
b_landuse1		0.0013	0.0013	
	0.0013	0.0013	0.0013	
b_landuse3		0.0013	0.0014	
	0.0014	0.0014	0.0014	
b_landuse4		0.0019	0.0014	
	0.0013	0.0014	0.0014	
b_landuse5		0.0014	0.0017	
	0.0014	0.0014	0.0014	
b_landuse6		0.0013	0.0014	
	0.0018	0.0014	0.0015	
b_landuse7		0.0014	0.0014	
	0.0014	0.0015	0.0014	
b_landuse8		0.0014	0.0014	
	0.0015	0.0014	0.0018	
b_landuse9		0.0014	0.0014	
	0.0014	0.0014	0.0014	
b_landuse10		0.0014	0.0014	
	0.0014	0.0014	0.0014	
b_displacement_cbd_shift		0.0000	0.0000	
	0.0000	0.0000	0.0000	

b_density_cbd_shift	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000
b_landuse7_cbd_shift	0.0004	0.0002	0.0002
0.0000	-0.0001	0.0000	0.0000
	b_landuse9	b_landuse10	
b_displacement_cbd_shift	b_density_cbd_shift	b_landuse7_cbd_shift	
b_cbd	0.0002	-0.0002	
0	-4e-04	0.0031	
b_displacement	0.0000	0.0000	
0	0e+00	0.0000	
b_density	0.0000	0.0000	
0	0e+00	0.0000	
b_landuse1	0.0013	0.0014	
0	0e+00	0.0000	
b_landuse3	0.0014	0.0014	
0	0e+00	0.0000	
b_landuse4	0.0014	0.0014	
0	0e+00	0.0004	
b_landuse5	0.0014	0.0014	
0	0e+00	0.0002	
b_landuse6	0.0014	0.0014	
0	0e+00	0.0000	
b_landuse7	0.0014	0.0014	
0	0e+00	-0.0001	
b_landuse8	0.0014	0.0014	
0	0e+00	0.0000	
b_landuse9	0.0016	0.0014	
0	0e+00	0.0000	
b_landuse10	0.0014	0.0015	
0	0e+00	0.0000	
b_displacement_cbd_shift	0.0000	0.0000	
0	0e+00	0.0000	
b_density_cbd_shift	0.0000	0.0000	
0	0e+00	-0.0001	
b_landuse7_cbd_shift	0.0000	0.0000	
0	-1e-04	0.0018	

Classical correlation matrix:

	b_density	b_cbd	b_displacement
b_cbd	0.1167	1.0000	0.0403
b_displacement	0.0891	-0.0792	1.0000
b_density	1.0000	0.0403	-0.0206
b_landuse1	0.0626	-0.0250	0.0891
b_landuse3	0.0737	0.1167	0.0737
b_landuse4	0.0184	0.0626	-0.0250
b_landuse5	0.1602	-0.0792	0.6580
		1.0000	-0.0206
		0.0165	1.0000
		0.6580	-0.0344
		0.1621	0.6126
		0.7878	-0.0368
		0.1106	0.6444
		0.8167	

b_landuse6	0.0339	-0.0239
0.1980	0.7952	0.6393
b_landuse7	0.0332	-0.0403
0.1281	0.8691	0.6919
b_landuse8	0.0421	-0.0542
0.2460	0.8100	0.6501
b_landuse9	0.0288	-0.0397
0.0842	0.8636	0.6867
b_landuse10	-0.0191	-0.0413
0.1207	0.8876	0.6951
b_displacement_cbd_shift	-0.1794	-0.3999
-0.0635	-0.0347	-0.0228
b_density_cbd_shift	-0.9768	-0.0090
-0.1847	0.0479	-0.0177
b_landuse7_cbd_shift	0.6158	0.0024
-0.0497	0.0416	-0.0048
	b_landuse4	b_landuse5
b_landuse6	b_landuse7	b_landuse8
b_cbd	0.1621	0.1106
0.0339	0.0332	0.0421
b_displacement	-0.0344	-0.0368
-0.0239	-0.0403	-0.0542
b_density	0.0184	0.1602
0.1980	0.1281	0.2460
b_landuse1	0.7878	0.8167
0.7952	0.8691	0.8100
b_landuse3	0.6126	0.6444
0.6393	0.6919	0.6501
b_landuse4	1.0000	0.7771
0.7372	0.8136	0.7522
b_landuse5	0.7771	1.0000
0.7901	0.8556	0.8128
b_landuse6	0.7372	0.7901
1.0000	0.8446	0.8064
b_landuse7	0.8136	0.8556
0.8446	1.0000	0.8660
b_landuse8	0.7522	0.8128
0.8064	0.8660	1.0000
b_landuse9	0.8103	0.8448
0.8331	0.9123	0.8517
b_landuse10	0.8164	0.8579
0.8470	0.9239	0.8674
b_displacement_cbd_shift	-0.0576	-0.0346
-0.0368	-0.0557	-0.0300
b_density_cbd_shift	-0.1763	-0.1309
-0.0423	-0.0328	-0.0540
b_landuse7_cbd_shift	0.1724	0.0959
-0.0119	-0.0888	-0.0139
	b_landuse9	b_landuse10
b_displacement_cbd_shift	b_density_cbd_shift	b_landuse7_cbd_shift
b_cbd	0.0288	-0.0191
-0.1794	-0.9768	0.6158
b_displacement	-0.0397	-0.0413
-0.3999	-0.0090	0.0024

b_density	0.0842	0.1207
-0.0635	-0.1847	-0.0497
b_landuse1	0.8636	0.8876
-0.0347	0.0479	0.0416
b_landuse3	0.6867	0.6951
-0.0228	-0.0177	-0.0048
b_landuse4	0.8103	0.8164
-0.0576	-0.1763	0.1724
b_landuse5	0.8448	0.8579
-0.0346	-0.1309	0.0959
b_landuse6	0.8331	0.8470
-0.0368	-0.0423	-0.0119
b_landuse7	0.9123	0.9239
-0.0557	-0.0328	-0.0888
b_landuse8	0.8517	0.8674
-0.0300	-0.0540	-0.0139
b_landuse9	1.0000	0.9156
-0.0588	-0.0247	-0.0068
b_landuse10	0.9156	1.0000
-0.0595	0.0119	-0.0145
b_displacement_cbd_shift	-0.0588	-0.0595
1.0000	0.0629	-0.0126
b_density_cbd_shift	-0.0247	0.0119
0.0629	1.0000	-0.6966
b_landuse7_cbd_shift	-0.0068	-0.0145
-0.0126	-0.6966	1.0000

Robust correlation matrix:

	b_density	b_cbd	b_displacement
b_cbd	0.1086	1.0000	0.0802
b_displacement	0.1230	0.0284	1.0000
b_density	1.0000	0.0802	-0.0764
b_landuse1	0.0913	0.1086	0.1230
b_landuse3	0.0913	0.0913	0.1255
b_landuse4	0.0515	0.0284	-0.0479
b_landuse5	0.1881	1.0000	0.6816
b_landuse6	0.2526	0.0145	-0.0764
b_landuse7	0.1483	0.6816	1.0000
b_landuse8	0.3070	0.2020	-0.0759
b_landuse9	0.1871	0.7998	0.6057
b_landuse10	0.1840	0.1151	-0.0747
b_cbd	0.1086	0.8404	0.6469
b_displacement	0.1230	0.0447	-0.0824
b_density	1.0000	0.8176	0.6399
b_landuse1	0.0913	0.0347	-0.1077
b_landuse3	0.0913	0.8930	0.6916
b_landuse4	0.0515	0.0399	-0.0671
b_landuse5	0.1881	0.8317	0.6531
b_landuse6	0.2526	0.0443	-0.0875
b_landuse7	0.1483	0.8834	0.6838
b_landuse8	0.3070	-0.0514	-0.1138
b_landuse9	0.1871	0.9064	0.6985
b_landuse10	0.1840		

b_displacement_cbd_shift	-0.1296	-0.4226
-0.1567	0.0004	-0.0193
b_density_cbd_shift	-0.9811	-0.0452
-0.1744	-0.0424	-0.0218
b_landuse7_cbd_shift	0.7743	0.0118
-0.0284	0.0175	-0.0086
	b_landuse4	b_landuse5
b_landuse6	b_landuse7	b_landuse8
b_cbd	0.2020	0.1151
0.0447	0.0347	0.0399
b_displacement	-0.0759	-0.0747
-0.0824	-0.1077	-0.0671
b_density	0.0515	0.1881
0.2526	0.1483	0.3070
b_landuse1	0.7998	0.8404
0.8176	0.8930	0.8317
b_landuse3	0.6057	0.6469
0.6399	0.6916	0.6531
b_landuse4	1.0000	0.7732
0.7302	0.8083	0.7423
b_landuse5	0.7732	1.0000
0.7950	0.8535	0.8088
b_landuse6	0.7302	0.7950
1.0000	0.8412	0.8136
b_landuse7	0.8083	0.8535
0.8412	1.0000	0.8618
b_landuse8	0.7423	0.8088
0.8136	0.8618	1.0000
b_landuse9	0.8011	0.8460
0.8402	0.9178	0.8582
b_landuse10	0.8065	0.8563
0.8449	0.9192	0.8681
b_displacement_cbd_shift	-0.1033	-0.0588
-0.0713	-0.0903	-0.0488
b_density_cbd_shift	-0.2137	-0.1327
-0.0539	-0.0321	-0.0588
b_landuse7_cbd_shift	0.1995	0.0913
-0.0129	-0.0840	-0.0111
	b_landuse9	b_landuse10
b_displacement_cbd_shift	b_density_cbd_shift	b_landuse7_cbd_shift
b_cbd	0.0443	-0.0514
-0.1296	-0.9811	0.7743
b_displacement	-0.0875	-0.1138
-0.4226	-0.0452	0.0118
b_density	0.1871	0.1840
-0.1567	-0.1744	-0.0284
b_landuse1	0.8834	0.9064
0.0004	-0.0424	0.0175
b_landuse3	0.6838	0.6985
-0.0193	-0.0218	-0.0086
b_landuse4	0.8011	0.8065
-0.1033	-0.2137	0.1995
b_landuse5	0.8460	0.8563
-0.0588	-0.1327	0.0913

b_landuse6	0.8402	0.8449
-0.0713	-0.0539	-0.0129
b_landuse7	0.9178	0.9192
-0.0903	-0.0321	-0.0840
b_landuse8	0.8582	0.8681
-0.0488	-0.0588	-0.0111
b_landuse9	1.0000	0.9126
-0.1110	-0.0421	-0.0140
b_landuse10	0.9126	1.0000
-0.0966	0.0326	-0.0201
b_displacement_cbd_shift	-0.1110	-0.0966
1.0000	0.0315	-0.0528
b_density_cbd_shift	-0.0421	0.0326
0.0315	1.0000	-0.8175
b_landuse7_cbd_shift	-0.0140	-0.0201
-0.0528	-0.8175	1.0000

20 worst outliers in terms of lowest average per choice prediction:

ID	Avg prob per choice
6803533354303611904	0.0001575750
13853233355017904128	0.0001708027
11480148089940199424	0.0001762058
4926675220532828160	0.0001766789
1809392133632938496	0.0001770929
1.8288945217247e+19	0.0001772759
12267183877589512192	0.0001789114
1428742674930758144	0.0001807091
2726713354250044416	0.0001807091
3141016703902427648	0.0001807091
3171972514679971328	0.0001807091
3369660437955168768	0.0001807091
4802580418056599552	0.0001807091
4873251256534693888	0.0001807091
5948743482505696256	0.0001807091
6076174213617401856	0.0001807091
6.740326964775e+18	0.0001807091
7272184300913737728	0.0001807091
7306366009760183296	0.0001807091
9786248872423342080	0.0001807091

Changes in parameter estimates from starting values:

	Initial	Estimate	Difference
b_cbd	0	6.9499	6.9499
b_displacement	0	-0.0780	-0.0780
b_density	0	-0.0153	-0.0153
b_landuse1	0	1.1072	1.1072
b_landuse2	0	0.0000	0.0000
b_landuse3	0	-0.3394	-0.3394
b_landuse4	0	-0.0425	-0.0425
b_landuse5	0	0.5836	0.5836
b_landuse6	0	-0.2351	-0.2351
b_landuse7	0	0.5348	0.5348
b_landuse8	0	-0.4444	-0.4444
b_landuse9	0	-0.5198	-0.5198

b_landuse10	0	-0.3176	-0.3176
b_displacement_cbd_shift	0	0.0322	0.0322
b_density_cbd_shift	0	-0.2401	-0.2401
b_landuse7_cbd_shift	0	0.7978	0.7978

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX J**

Code developed for Model 5 estimation

```

# ##### #
####      MODELLING INTEGRATED RAPID TRANSIT CHOICE      ####
# ##### #

####      A STUDY DONE ON THE MYCITI IRT SYSTEM IN CAPE TOWN      ####

# ##### #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS      ####
# ##### #

### Clear memory
rm(list = ls())

#install.packages("plyr", dependencies=T)
require("plyr")

#install.packages("dplyr")
library(dplyr)

### Load Apollo library
library(apollo)

### Load Plyr library
library(plyr)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="MNL_MyCiTi_Model5",
  modelDescr ="MNL Model of MyCiTi IRT System on RP data",
  indivID    ="CARD_NUM",
  workInLogs = TRUE,
  panelData  = TRUE
)

# ##### #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS      ####

```

```

# ##### #

### Load AFC data for November 2015 accrued from The City of Cape Town
database = read.csv("Nov2015.csv",header=TRUE) #one month data, November 2015
database_Monday01 = subset(database,database$REPORTING_DATE=='20151130')
database_Sunday = subset(database,database$REPORTING_DATE=='20151129')
database_Saturday = subset(database,database$REPORTING_DATE=='20151128')
database_Friday = subset(database,database$REPORTING_DATE=='20151127')
database_Thursday = subset(database,database$REPORTING_DATE=='20151126')
database_Wednesday = subset(database,database$REPORTING_DATE=='20151125')
database_Tuesday = subset(database,database$REPORTING_DATE=='20151124')
database_Monday02 = subset(database,database$REPORTING_DATE=='20151123')

#AFC data for 25/11/2015
database = database_Wednesday
#the Wednesday selected to represent daily commuter travel choices.

#Minimizing the data memory
database_Monday01 = list(NULL)
database_Tuesday = list(NULL)
database_Wednesday = list(NULL)
database_Thursday = list(NULL)
database_Friday = list(NULL)
database_Saturday = list(NULL)
database_Sunday = list(NULL)
database_Monday02 = list(NULL)

#Remove non relevant data columns from dataset, to minimize file size
database[,c("DEVICE_ID","ROUTE_ID","ROUTE_NAME","UPLOAD_DATE","TOTAL_TAPS",
            "STOP_ID")] = list(NULL)

#Filter origin transactions
database1 = subset(database,database$TRANSACTION_TYPE=='1st boarding')
#isolate all 1st boarding transactions
database1 <- database1 %>% rename(STOP_NAME.x = STOP_NAME, TOTAL_AMOUNT.x =
TOTAL_AMOUNT, HOURS.x = HOURS, MINUTES.x = MINUTES, TRANSACTION_TYPE.x = TRANSACTION_TYPE )
#database1=database1[!duplicated(database1[,c('CARD_NUM', 'REPORTING_DATE')]),]
#Note: Only to be used in extreme cases where only the first origin transaction per user is allowed.

```

```

#Filter destination transactions
database2 = subset(database,database$TRANSACTION_TYPE=='Alighting')
#isolate all alighting transactions, there cannot be more alighting transactions than 1st boarding - also, this
shows us the errors in the data -> more 1st boarding transactions than alighting transactions.
database2 <- database2 %>% rename(STOP_NAME.y = STOP_NAME, TOTAL_AMOUNT.y =
TOTAL_AMOUNT, HOURS.y = HOURS, MINUTES.y = MINUTES, TRANSACTION_TYPE.y = TRANSACTION_TYPE )
#database2=database2[!duplicated(database2[,c('CARD_NUM', 'REPORTING_DATE')]),]
#Note: Only to be used in extreme cases where only the first origin transaction per user is allowed.

#It is noted that no transaction fee is charged on "Connection" transactions.
Excluding these transactions therefore does not influence trip cost or origin-destination pairing.

#Origin-destination pairing by Card Number and Reporting Date
database3 = join(database1,database2,by=c("CARD_NUM","REPORTING_DATE"),
type ="left", match="all")
#we need to merge the data per upload date, as this is the sorting element when we use a dataset larger than 1 day.
database=database3

#MyCiTi IRT stop numeric identification
source("Stopnames.R")
source("Stopcodes.R")

stopcodes_app = mapply(function(stopnames,stopcodes){stopcodes},stopnames,
stopcodes,SIMPLIFY = FALSE,USE.NAMES = TRUE)

database$STOP_X = as.character(database$STOP_NAME.x)
database$STOP_X = stopcodes_app[database$STOP_X]
database$STOP_X = as.character(database$STOP_X)
database = subset(database, database$STOP_X != 'NULL')
database$STOP_X = as.numeric(database$STOP_X)
database = subset(database,database$STOP_X<367)

database$STOP_Y = as.character(database$STOP_NAME.y)
database$STOP_Y = stopcodes_app[database$STOP_Y]
database$STOP_Y = as.character(database$STOP_Y)
database = subset(database, database$STOP_Y != 'NULL')
database$STOP_Y = as.numeric(database$STOP_Y)
database = subset(database,database$STOP_Y<367)

```

```

#Calculation of paired origin-destination travel time and cost
database$TotTime = database$HOURS.y*60 + database$MINUTES.y - database$HOURS.x*60 -
database$MINUTES.x #Travel time expressed in minutes
database$TotCost = database$TOTAL_AMOUNT.x + database$TOTAL_AMOUNT.y
#Total travel cost expressed in Rand

#Filtering accurate origin-destination pairing
database = subset(database,database$TotCost>0)
database = subset(database,database$TotTime>0)
database = subset(database,database$TotTime<1200)
#2.5 hours max as per MyCiTi fare guide
database = subset(database, subset = database$TotCost %in% c(11.5,7.8,8.2,5.5,13.3,
9.8,9.4,6.9,17.8,12.5,12.6,8.8,19.8,14.8,13.9,10.4,21.0,16.5,14.8,11.6,24.6,19.4,17.4,
13.7,27.7,22.0,19.5,15.5,30.2,24.1,21.3,17.0,61.4,61.4,50.0,44.2))

database$CheckTimeCost= ifelse(database$TotTime<61 & database$TotCost==11.50, "Y",
ifelse(database$TotTime<61 & database$TotCost==7.8 , "Y", ifelse(database$TotTime<61 &
database$TotCost==8.2 , "Y",ifelse(database$TotTime<61 & database$TotCost==5.5 , "Y",
ifelse(database$TotTime<121 & database$TotCost==13.3, "Y",ifelse(database$TotTime<121 &
database$TotCost==9.8, "Y",ifelse(database$TotTime<121 & database$TotCost==9.4, "Y",
ifelse(database$TotTime<121 & database$TotCost==6.90, "Y",
ifelse(database$TotTime<241 & database$TotCost==17.8, "Y",ifelse(database$TotTime<241 &
database$TotCost==12.5, "Y",ifelse(database$TotTime<241 & database$TotCost==12.6, "Y",
ifelse(database$TotTime<241 & database$TotCost==8.8, "Y",
ifelse(database$TotTime<361 & database$TotCost==19.8 , "Y",ifelse(database$TotTime<361 &
database$TotCost==14.8, "Y",ifelse(database$TotTime<361 & database$TotCost==13.9 , "Y",
ifelse(database$TotTime<361 & database$TotCost==10.4 , "Y",
ifelse(database$TotTime<481 & database$TotCost==21.0, "Y",ifelse(database$TotTime<481 &
database$TotCost==16.5, "Y",ifelse(database$TotTime<481 & database$TotCost==14.8, "Y",
ifelse(database$TotTime<481 & database$TotCost==11.6, "Y",
ifelse(database$TotTime<601 & database$TotCost==24.6, "Y",ifelse(database$TotTime<601 &
database$TotCost==19.4, "Y",ifelse(database$TotTime<601 & database$TotCost==17.4, "Y",
ifelse(database$TotTime<601 & database$TotCost==13.7, "Y",
ifelse(database$TotTime<721 & database$TotCost==27.7, "Y",ifelse(database$TotTime<721 &
database$TotCost==22.0, "Y",ifelse(database$TotTime<721 & database$TotCost==19.5, "Y",
ifelse(database$TotTime<721 & database$TotCost==15.5, "Y",
ifelse(database$TotTime<1200 & database$TotCost==30.2, "Y",ifelse(database$TotTime<1200 &
database$TotCost==24.1,"Y", ifelse(database$TotTime<1200 & database$TotCost==21.3, "Y",
ifelse(database$TotTime<1200 & database$TotCost==17.0, "Y", ifelse(database$TotCost==61.4,

```

```

"Y",ifelse(database$TotCost==50.0, "Y",ifelse(database$TotCost==44.2, "Y","N")))))))
))))))))))))))))))))))))))))))))))))))))))

databaseTimeCost = database
#To review the outcome of the time & cost sensitivity analysis in an external dataset
database = subset(databaseTimeCost,databaseTimeCost$CheckTimeCost=="Y")
#Only allow data that complies with the time and cost sensitivities
database=database[!duplicated(database[,c('CARD_NUM', 'STOP_X', 'HOURS.x', 'MINUTES.x')]),]
database[,c("CheckTimeCost")] = list(NULL)

#Origin and destination not allowed to be the same stop
database = subset(database, database$STOP_X != database$STOP_Y)

#Calculation of travel time mean
database_mean = mean(database$TotTime)

#Expansion of the dataset

#Add peak and off-peak determinator to the dataset based on the MyCiTi
operational guidelines, peak times stated 06:45 - 08:00 and 16:15 - 17:30
database$Peak = ifelse(((database$HOURS.x*60)+(database$MINUTES.x)) > 404 &
((database$HOURS.x*60)+(database$MINUTES.x)<481, "1",
ifelse(((database$HOURS.x*60)+(database$MINUTES.x)) > 974 & ((database$HOURS.x*60)+
(database$MINUTES.x)<1051, "1", "0"))
database$Peak = as.numeric(database$Peak)

#Geographical displacement between IRT stops in km
displacement = read.csv("IRT_Displacement_StopNo.csv",header=TRUE)

#IRT density
voldensity = read.csv("IRT_Density_StopNo.csv",header=TRUE)

#Land use classification
landuse = read.csv("IRT_Landuse_StopNo.csv",header=TRUE)

#CBD classification
cbd = read.csv("IRT_CBD_StopNo.csv",header=TRUE)

#Minimizing memory

```

```

database1 = list(NULL)
database2 = list(NULL)
database3 = list(NULL)
databaseTimeCost = list(NULL)

gc()

#Merging the data expansion
database = merge(database,displacement,by=c("STOP_X"))
database = merge(database,voldensity,by=c("STOP_X"))
database = merge(database,landuse,by=c("STOP_X"))
database = merge(database,cbd,by=c("STOP_X"))
database[,c("STOP_NAME.x","STOP_NAME.y","TRANSACTION_TYPE.x","TRANSACTION_TYPE.y",
"TOTAL_AMOUNT.x","TOTAL_AMOUNT.y", "HOURS.x", "MINUTES.x", "HOURS.y", "MINUTES.y")] = list(NULL)

# ##### #
#### DEFINE MODEL PARAMETERS #####
# ##### #

### Vector of parameters, including any that are kept fixed in estimation

apollo_beta=c(b_cbd          = 0,
              b_displacement = 0,
              b_density      = 0,
              b_landuse1     = 0,
              b_landuse2     = 0,
              b_landuse3     = 0,
              b_landuse4     = 0,
              b_landuse5     = 0,
              b_landuse6     = 0,
              b_landuse7     = 0,
              b_landuse8     = 0,
              b_landuse9     = 0,
              b_landuse10    = 0,
              b_displacement_cbd_shift = 0,
              b_density_cbd_shift = 0,
              b_landuse7_cbd_shift = 0)

### Vector with names (in quotes) of parameters to be kept fixed at their starting

```

```

value in apollo_beta, use apollo_beta_fixed = c() if none
apollo_fixed = c("b_landuse2")

### No starting values imported from existing model output file

# ##### #
#### GROUP AND VALIDATE INPUTS #####
# ##### #

apollo_inputs = apollo_validateInputs()

# ##### #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION #####
# ##### #

#stopnames = gsub('[:,punct:] ',' ', stopnames)

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings,
  order is irrelevant

  J = 346
  V = list()

  for(j in 1:J) V[[paste0("alt",j)]] = b_cbd*get(paste0("CBD_",j)) +
(b_displacement + b_displacement_cbd_shift*get(paste0("CBD_",j)))*get(paste0("Dist_",j)) +
(b_density + b_density_cbd_shift*get(paste0("CBD_",j)))*get(paste0("VOL_",j)) +
b_landuse1*(get(paste0("Land_",j))==1) + b_landuse2*(get(paste0("Land_",j))==2) +
b_landuse3*(get(paste0("Land_",j))==3) + b_landuse4*(get(paste0("Land_",j))==4) +
b_landuse5*(get(paste0("Land_",j))==5) + b_landuse6*(get(paste0("Land_",j))==6) +
(b_landuse7 + b_landuse7_cbd_shift*get(paste0("CBD_",j)))*get(paste0("Land_",j))==7) +

```

```

b_landuse8*(get(paste0("Land_",j))==8) + b_landuse9*(get(paste0("Land_",j))==9) +
  b_landuse10*(get(paste0("Land_",j))==10)

### Define settings for MNL model component
mnl_settings = list(
  alternatives = setNames(1:J, names(V)),
  avail       = 1 ,
  choiceVar   = STOP_Y,
  V           = V )

### Compute probabilities using MNL model
P[['model']] = apollo_mnl(mnl_settings, functionality)

### Take product across observation for same individual
P = apollo_panelProd(P, apollo_inputs, functionality)

### Prepare and return outputs of function
P = apollo_prepareProb(P, apollo_inputs, functionality)
return(P)
}

# ##### #
#### MODEL ESTIMATION #####
# ##### #

model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

# ##### #
#### MODEL OUTPUTS #####
# ##### #

# ----- #
#---- FORMATTED OUTPUT (TO SCREEN) ---- #
# ----- #

apollo_modelOutput(model) #modelOutput_settings

# ----- #
#---- FORMATTED OUTPUT (TO FILE, using model name) ---- #

```

```
# ----- #
```

```
apollo_saveOutput(model) #saveOutput_settings
```

```
# ##### #  
##### POST-PROCESSING #####  
# ##### #
```

A GEOSPATIAL INVESTIGATION OF DESTINATION CHOICE MODELLING  
THE CASE OF THE MYCITI INTEGRATED RAPID TRANSIT BUS SYSTEM, CAPE TOWN,  
SOUTH AFRICA

**APPENDIX K**

Ethics Clearance

## ETHICS APPLICATION FORM


**Please Note:**


Any person planning to undertake research in the Faculty of Engineering and the Built Environment (EBE) at the University of Cape Town is required to complete this form **before** collecting or analysing data. The objective of submitting this application *prior* to embarking on research is to ensure that the highest ethical standards in research, conducted under the auspices of the EBE Faculty, are met. Please ensure that you have read, and understood the **EBE Ethics in Research Handbook** (available from the UCT EBE, Research Ethics website) prior to completing this application form: <http://www.ebe.uct.ac.za/ebe/research/ethics1>

APPLICANT'S DETAILS		
Name of principal researcher, student or external applicant	Joanet Smith	
Department	Civil Engineering	
Preferred email address of applicant:	STYJOA002@MYUCT.AC.ZA	
If Student	Your Degree: e.g., MSc, PhD, etc.	MSc (Civil Engineering)
	Credit Value of Research: e.g., 60/120/180/360 etc.	180
	Name of Supervisor (if supervised):	Prof Mark Zuidgeest
If this is a research contract, indicate the source of funding/sponsorship	N/A	
Project Title	<b>A Geospatial Investigation of Destination Choice Modelling</b>	

**I hereby undertake to carry out my research in such a way that:**

- there is no apparent legal objection to the nature or the method of research; and
- the research will not compromise staff or students or the other responsibilities of the University;
- the stated objective will be achieved, and the findings will have a high degree of validity;
- limitations and alternative interpretations will be considered;
- the findings could be subject to peer review and publicly available; and
- I will comply with the conventions of copyright and avoid any practice that would constitute plagiarism.

APPLICATION BY	Full name	Signature	Date
<b>Principal Researcher/ Student/External applicant</b>	Joanet Smith	Signed by candidate	24/09/2020
SUPPORTED BY	Full name	Signature	Date
<b>Supervisor (where applicable)</b>	MHP Zuidgeest		28/09/2020

APPROVED BY	Full name	Signature	Date
<b>HOD (or delegated nominee)</b> Final authority for all applicants who have answered NO to all questions in Section 1; and for all Undergraduate research (Including Honours).	Dyllon Randall		5 Oct 2020
<b>Chair: Faculty EIR Committee</b> For applicants other than undergraduate students who have answered YES to any of the questions in Section 1.			

## ETHICS APPLICATION FORM


**Please Note:**


Any person planning to undertake research in the Faculty of Engineering and the Built Environment (EBE) at the University of Cape Town is required to complete this form **before** collecting or analysing data. The objective of submitting this application *prior* to embarking on research is to ensure that the highest ethical standards in research, conducted under the auspices of the EBE Faculty, are met. Please ensure that you have read, and understood the **EBE Ethics in Research Handbook** (available from the UCT EBE, Research Ethics website) prior to completing this application form: <http://www.ebe.uct.ac.za/ebe/research/ethics1>

APPLICANT'S DETAILS		
Name of principal researcher, student or external applicant	Joanet Smith	
Department	Civil Engineering	
Preferred email address of applicant:	STYJOA002@MYUCT.AC.ZA	
If Student	Your Degree: e.g., MSc, PhD, etc.	MSc (Civil Engineering)
	Credit Value of Research: e.g., 60/120/180/360 etc.	180
	Name of Supervisor (if supervised):	Prof Mark Zuidgeest
If this is a research contract, indicate the source of funding/sponsorship	N/A	
Project Title	<b>A Geospatial Investigation of Destination Choice Modelling</b>	

**I hereby undertake to carry out my research in such a way that:**

- there is no apparent legal objection to the nature or the method of research; and
- the research will not compromise staff or students or the other responsibilities of the University;
- the stated objective will be achieved, and the findings will have a high degree of validity;
- limitations and alternative interpretations will be considered;
- the findings could be subject to peer review and publicly available; and
- I will comply with the conventions of copyright and avoid any practice that would constitute plagiarism.

APPLICATION BY	Full name	Signature	Date
<b>Principal Researcher/ Student/External applicant</b>	Joanet Smith	<div style="border: 1px solid black; padding: 2px; display: inline-block;">Signed by candidate</div>	24/09/2020
SUPPORTED BY	Full name	Signature	Date
<b>Supervisor (where applicable)</b>	MHP Zuidgeest		28/09/2020

APPROVED BY	Full name	Signature	Date
<b>HOD (or delegated nominee)</b> Final authority for all applicants who have answered NO to all questions in Section 1; and for all Undergraduate research (Including Honours).			
<b>Chair: Faculty EIR Committee</b> For applicants other than undergraduate students who have answered YES to any of the questions in Section 1.	R Behrens		12 Oct 2020