

**DETECTING, CLASSIFYING AND LOCATING INFORMAL SETTLEMENTS IN MEGACITIES SUCH
AS CAPE TOWN USING SENTINEL-1 DATA**



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Quote:

"It always seems impossible until it's done." Nelson Rolihlahla Mandela.

DEDICATION

I dedicate this research to all people living under the harsh conditions of informal settlements generally in the whole wide world and more specifically within the city of Cape Town in the areas of Khayelitsha, Mitchell's Plain, in the Cape Flats upon where my research is based.

PLAGIARISM DECLARATION

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ABBREVIATIONS AND ACRONYMS

[1].	ANN:	Artificial Neural Network
[2].	AOI:	Area of Interest
[3].	CA:	Consumer Accuracy
[4].	DEM:	Digital Elevation Model
[5].	DN:	Digital Number
[6].	DT:	Decision Trees
[7].	EM:	Expectation Maximization
[8].	EO:	Earth Observation
[9].	ESA :	European Space Agency
[10].	Etc:	et cetera
[11].	GHz:	Gigahertz
[12].	GIS:	Geographic Information System
[13].	GLCM:	Grey Level Co-occurrence Matrix
[14].	GRD:	Ground Range Detection
[15].	LULC:	Land Use Land Cover
[16].	MLC:	Maximum Likelihood Classification
[17].	ND:	No data
[18].	NGO:	Non-Government Organisation
[19].	Km:	Kilometre
[20].	PA:	Producer Accuracy
[21].	PCA:	Principal Component Analysis
[22].	QGIS:	Quantum Geographic Information System
[23].	ROI:	Region of Interest
[24].	RS:	Remote Sensing
[25].	SAR:	Synthetic Aperture Radar
[26].	SCP:	Semi-automatic Classification Plugins
[27].	SNAP:	Sentinel Application Platform
[28].	SRTM:	Shuttle Radar Topology Mission
[29].	SVM:	Support Vector Machine
[30].	UN:	United Nations
[31].	VH:	Vertical Horizontal
[32].	VV:	Vertical Vertical

ABSTRACT

The use of remote sensing is a method for generating land cover maps. This research utilizes radar remote sensing, specifically the Sentinel-1 sensor. A major advantage of radar remote sensing is its ability to penetrate clouds and vegetation, enabling data collection in all weather conditions. It also provides valuable information on surface roughness and moisture content, improving the accuracy and detail of land cover maps. The sensor was chosen for its ability to acquire data in any weather conditions, as well as during both day and night.

Images were downloaded and processed in SNAP software. The objective of this study was to detect, classify, and map land use and cover, with a focus on informal settlements, using radar remote sensing and GIS techniques. The research had two main objectives: firstly, is to classify land use and land cover using supervised classification, and secondly to conduct an accuracy assessment using QGIS with relevant plugins. The methodology is outlined in Chapter 3, and implementation is detailed in Chapter 4. Results are discussed in Chapter 5, and the conclusion is presented in Chapter 6.

Although there are multiple algorithms for supervised classification, random forest was chosen due to its ability to reduce overfitting in decision trees, improve accuracy, and handle both regression and classification problems. It works well with continuous and categorical values and automates missing data. Classified land cover categories included agricultural land, grassland, bare soil, forested areas, formal settlements, informal settlements, industrial areas and water bodies.

While SNAP lacks built-in functionality for accuracy assessment, it can provide classification accuracy based on the classifier's threshold and replication of classes from training data. The overall classification accuracy was found to be 72.83% with a kappa coefficient of 0.65 when considering no-data pixels. Excluding no-data pixels improves accuracy to 83.24% with a kappa coefficient of 0.78. Informal settlements, the main class of interest, achieved a consumer accuracy of 91.8% and a producer accuracy of 90.7%

Based on the results in Chapter 5, the research met its objectives. The results are valuable for city planners and decision-makers, particularly for rapid response and rescue during natural disasters like floods. It also aids in planning services for informal communities that may not otherwise receive attention due to their exclusion from city or municipal maps.

Key words: Classification, confusion matrix, consumer accuracy, Informal settlements, Khayelitsha, Land cover use, producer accuracy, Quantum Geographic Information Systems, Remote sensing, Sentinel Application Platform, Synthetic Aperture Radar

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1 INTRODUCTION

1.1 BACKGROUND

Informal settlements grow rapidly, frequently covering large urban areas and sometimes forming scattered pockets within formal areas. To address this, classification methods that provide timely and accurate spatial information are needed. Remote sensing is a valuable tool for obtaining data on the location of informal settlements [17].

When urbanization is unplanned and unmanaged, it can lead to increased inequality, the expansion of slums, and severe impacts on climate change (UN-Habitat, 2016). Therefore, monitoring and mapping urban development worldwide is crucial to ensure it occurs in a well-planned, secure and sustainable manner [19].

Satellite images and remote sensing data reveal patterns of urban growth, while Geographic Information Systems (GIS) offer tools for analysis and visualization, transforming data into actionable information for decision-making. Remote sensing provides up-to-date, comprehensive information about the spatial extent and structure of cities [7].

Informal settlements consist of unplanned dwellings constructed without adherence to zoning regulations, land use plans, or service allocations. Often illegal and unplanned, these settlements typically fall off municipal maps due to their undefined boundaries. The lack of accurate information regarding informal settlements hinders decision-making and planning for their improvement [3].

High-resolution satellite imagery can be used to derive land cover and land use information, aiding city managers and planners in making informed decisions regarding future city development. The figures below display sections of Khayelitsha, with one frame showcasing both formal and informal settlements, and the other focusing solely on informal settlements.



Figure 1.1: VIEWS OF KHAYELITSHA FROM DIFFERENT LOCATIONS [18].

1.2 PROBLEM STATEMENT

The rapid urbanization and proliferation of informal settlements in South Africa pose significant challenges to achieving sustainable development goals. As cities like Johannesburg, Durban, and Cape Town experience unprecedented growth, particularly in informal settlements, the ability of local authorities to provide essential services and infrastructure lags behind. Several factors contribute to this phenomenon, including internal migration, influxes of foreign nationals, porous borders, and corruption within governmental institutions.

Informal settlements often emerge without proper oversight from public authorities, leading to substandard living conditions, inadequate sanitation, and high crime rates. The lack of formal urban development exacerbates these issues, creating a pressing need for effective decision-making and urban planning [7].

To address these challenges, it's crucial for municipal officials and city planners to have access to up-to-date information about urban areas. Remote sensing technology offers a powerful tool for detecting and monitoring changes in urban landscapes, providing valuable data for informed decision-making and planning processes [15].

By utilizing remote sensing techniques such as satellite imagery, aerial photography, and geographic information systems (GIS), authorities can gain insights into the spatial distribution and growth patterns of informal settlements. This data can inform urban planning strategies, infrastructure development initiatives, and service provision efforts aimed at improving living conditions in informal settlements and promoting sustainable urban development [15].

Furthermore, remote sensing technology enables the identification of areas at high risk of environmental hazards, such as flooding and landslides, allowing for proactive measures to mitigate these risks and enhance the resilience of informal settlements.

In addition to remote sensing, comprehensive approaches to address the challenges of informal settlements require multi-stakeholder collaboration, community engagement, policy reforms, and investment in social and economic development initiatives. By combining remote sensing technology with holistic urban planning and governance strategies, South Africa can work towards achieving more inclusive, resilient, and sustainable cities for all residents.



FIGURE 1.2: INFORMAL SETTLEMENT POOR LIVING CONDITIONS.

1.3 RESEARCH PURPOSE

The study aims to utilize remote sensing technology to detect, classify, and locate informal settlements and other land cover classes in and around Cape Town, with a specific focus on the Khayelitsha area. Informal settlements have become increasingly fluid, making it challenging for authorities to accurately track their presence and growth. By leveraging remote sensing techniques, the study seeks to provide reliable and up-to-date data on informal settlements, enabling better monitoring and planning for humanitarian purposes.

Traditional data collection methods, such as census statistics, often fail to capture the true extent of informal settlements due to sampling limitations and the transient nature of these settlements.

By employing remote sensing technology, the study aims to overcome these limitations and provide authorities with timely and accurate information about informal settlement dynamics. This data can facilitate proactive planning and intervention strategies to address the challenges associated with informal settlements, including access to basic services, infrastructure development, and social welfare initiatives.

Furthermore, the study emphasizes the need to transform informal settlements into formal settlements and gain greater control over their spatial development. By gaining insights into the spatial distribution and characteristics of informal settlements, authorities can develop targeted policies and interventions aimed at improving living conditions, promoting sustainable urban development, and enhancing social equity [11].

Overall, the study highlights the critical role of remote sensing technology in addressing the complex challenges posed by informal settlements in Cape Town and underscores the importance of data-driven approaches to urban planning and development. By harnessing the

power of remote sensing, authorities can take proactive steps towards achieving more inclusive, resilient and sustainable cities for all residents.

1.4 STUDY OBJECTIVES

To address the research questions and create a model that can reliably distinguish and classify informal settlements from other land cover classes, the following approaches are considered:

1.4.1 Data Availability and Reliability

Explore various data sources, including satellite imagery, aerial photographs and to gather reliable information about the presence and location of informal settlements.

Utilize participatory mapping techniques and community engagement initiatives to involve local residents in data collection processes, ensuring the inclusion of ground-level perspectives and enhancing the accuracy of the data.

Establish partnerships with governmental agencies, non-governmental organizations (NGOs), research institutions, and community-based organizations to access existing data and collaborate on data collection efforts.

1.4.2 Exploiting Sentinel-1 Satellite Data

Sentinel-1 satellite data, with its radar imaging capabilities, can be used to estimate the location and position of informal settlements, especially in areas with cloud cover or during night-time.

Utilize radar backscatter and coherence information from Sentinel-1 data to detect changes in land cover and identify areas with informal settlements.

Implement image processing techniques, such as texture analysis and change detection algorithms, to extract relevant information from Sentinel-1 imagery and identify potential informal settlement areas.

1.4.3 Remote Sensing for Detection of Informal Areas

Leverage spectral and spatial characteristics extracted from high-resolution satellite imagery to detect informal settlement areas within a city. Utilize image classification techniques, such

as supervised or unsupervised classification algorithms, to distinguish between different land cover classes, including formal and informal settlements [21].

Train and validate machine learning models using labelled training data, which includes spectral, spatial, and contextual features of informal settlements and other land cover classes. Assess the accuracy and performance of the machine learning algorithm based on metrics such as overall accuracy, precision, correlation, error rate and Kappa co-efficient, to determine the performance for predicting informal areas.

By addressing these research questions and employing a combination of data collection methods, satellite data analysis, remote sensing techniques, and machine learning algorithms, it is possible to develop a robust model for detecting and classifying informal settlements in urban areas. This model can provide valuable insights for decision-makers and stakeholders, enabling informed interventions and policy decisions to address the challenges associated with informal settlements and promote sustainable urban development.



FIGURE 1.3: REMOTE SENSING SHOWING S-1 MISSION IN SPACE

1.5 STUDY AREA

The description provided highlights the stark contrast between the vibrant yet challenging conditions in Khayelitsha, an informal settlement on the periphery of Cape Town, and the broader context of CT as a major international tourist destination. With a population of 4, 8 million people [Western Cape Government, 2022], CT's allure for tourists and migrants seeking new opportunities is undeniable. However, beneath this facade lies the reality of informal settlements like Khayelitsha, which bear the brunt of poverty, crime, and inadequate infrastructure [18].

Khayelitsha, meaning "New Home" in Xhosa, has a complex history rooted in apartheid-era policies that relegated black South Africans to dormitory areas for migrant workers [18]. Despite its notorious reputation for high crime rates and unemployment, Khayelitsha is also characterized by a resilient community spirit and social development initiatives. It is

emblematic of the broader challenges facing informal settlements in South Africa, where basic necessities such as sanitation, water access, and housing are often lacking.

The dire living conditions in Khayelitsha underscore the severity of the poverty crisis and the glaring gap between the rich and the poor in Cape Town. With an average family income of R20, 000 per year, significantly lower than the city median of R40, 000 [18], Khayelitsha epitomizes the socio-economic disparities prevalent in the city. The prevalence of informal dwellings, with over half of the households residing in such structures, further highlights the urgent need for interventions to address housing and infrastructure deficiencies.

Efforts to improve living conditions in Khayelitsha, including the provision of formal housing and initiatives to stimulate economic growth, are underway [18]. However, the persistence of high unemployment rates and crime underscores the complexity of the challenges facing informal settlements. Addressing these issues requires comprehensive strategies that prioritize community empowerment, economic development, and social inclusion.

As Cape Town continues to grapple with the legacy of apartheid and the socio-economic inequalities it engendered, initiatives aimed at bridging the gap between the rich and the poor and uplifting marginalized communities like Khayelitsha are essential. By addressing the root causes of poverty and investing in inclusive development initiatives, Cape Town can strive towards a more equitable and sustainable future for all its residents.

Khayelitsha is situated on the Cape Flats, a vast area of flat, sandy terrain located between Table Bay and False Bay in the Western Cape province of South Africa. It is geolocated at approximately (-34° 2' 24" latitude, 18° 40' 37.2" longitude) [18]. The area covers approximately 43.51 km², making it one of the largest townships in Cape Town. Khayelitsha has a complex history and is known for its informal settlements, high population density, and socio-economic challenges. Despite these challenges, it is a vibrant community with a rich cultural heritage and a strong sense of resilience



FIGURE 1.4: BAD LIVING CONDITIONS IN KHAYELITSHA [6] [18].

1.6 RESEARCH METHODOLOGY OVERVIEW

The comprehensive methodology outlined demonstrates a meticulous and systematic approach to utilizing synthetic aperture radar (SAR) data from Sentinel-1 for land cover classification, particularly focusing on informal settlements in Khayelitsha, Cape Town. The key steps and methodologies that have been employed are described below.

1.6.1 Data Acquisition and Pre-processing

Utilized Sentinel Application Platform (SNAP) to download and pre-process Sentinel-1 SAR images. Applied various pre-processing techniques, including thermal noise removal, radiometric calibration, image processing, stack creation, speckle filtering, terrain correction, and geometric calibration.

1.6.2 Feature Extraction

Extracted image features such as principal component analysis (PCA) and textures like grey level co-occurrence matrix (GLCM) from Sentinel-1 SAR data to capture relevant information for land cover classification.

1.6.3 Accuracy Assessment

Accuracy assessment to validate the classification results was conducted, where the quantum geographic information system (QGIS) with relevant plugins to perform accuracy assessment was utilised.

Ground truth (reference data) using high-resolution imagery from Google earth was generated and shape files representing different land cover classes were created.

Automated process in QGIS were employed to generate the confusion matrix (contingency matrix) analysis to compare the classification map against the reference data and evaluate measures of effectiveness such as true positives, true negatives, false positives, false negatives, accuracy, precision, correlation, and error rate.

By following these methodological steps, we have ensured a robust and rigorous approach to land cover classification using Sentinel-1 SAR data. The integration of machine learning techniques, remote sensing technology, and geographic information systems (GIS) tools has

enabled the generation of accurate classification maps, facilitating informed decision-making for urban planning and development interventions in informal settlements like Khayelitsha.

1.7 DISSERTATION STRUCTURE

The structure of this research is organized and provides a clear roadmap for readers to understand the scope, methodology, and findings of the study and it briefly summarize each chapter:

1.7.1 Introduction (Chapter One)

Provides an overview of the study, introducing the concept of informal settlements and outlining the problem statement. States the purpose and objectives of the research, emphasizing the need to locate and address the challenges faced by inhabitants of informal settlements.

1.7.2 Literature Review (Chapter Two)

Reviews existing literature and background information on informal settlements, including their causes and characteristics. Explores remote sensing techniques for detecting and mapping informal settlements, discussing the types of satellite sensors used in the study and relevant previous research in the field.

1.7.3 Methodology (Chapter Three)

Describes the research methodology and experimental procedures, including data collection, processing, and analysis. Discusses the datasets and computer tools utilized in the study, as well as the specific methodologies employed for detecting and classifying informal settlements.

1.7.4 Application of SNAP and QGIS Software packages (Chapter Four)

Outlines the use of the SNAP software and the processes implemented for data processing and analysis. Provides a detailed explanation of the functionalities and features of the SNAP software and how they were utilized in the research study.

1.7.5 Results and Discussion (Chapter Five)

Presents the results obtained from the analysis of the data, including classification maps and accuracy assessments. Discusses the findings in relation to the research objectives, explaining the significance of the results and identifying any limitations or gaps in the study.

1.7.6 Conclusion (Chapter Six)

Summarizes the key findings and conclusions drawn from the research. Responds to the research questions posed in the introduction, highlighting the contributions of the study and suggesting areas for future research or intervention.

Overall, this structure effectively gives a guide through the research process, from understanding the problem statement to interpreting the results and drawing conclusions. It provides a framework for addressing the challenges associated with informal settlements using remote sensing technology and geographic information systems (GIS).

2 LITERATURE REVIEW

2.1 INFORMAL SETTLEMENTS

This dissertation provides an overview of informal settlements, highlighting their historical context, definitions, and significance in urbanization processes. There are challenges faced by municipal leaders in managing informal settlements and the importance of reliable spatial information for effective urban planning. Municipal leaders face difficulties in managing informal settlements due to their informal nature, lack of reliable data, and difficulties in spatial documentation [7]. Informal settlements often lack formal infrastructure and services, making it challenging for authorities to provide adequate resources and support to residents. The transformation of informal settlements into formal settlements is crucial for gaining control over spatial development and improving living conditions [2].

2.2 RAPID GROWTH AND URBANIZATION

Informal settlements have experienced rapid growth in recent decades, driven by on-going processes of socioeconomic change and urbanization. Estimates suggest that nearly 25% of the global urban population resides in informal settlements, with this figure expected to rise in the future. (UN Habitat, 2021) In Africa, more than half of urban residents live in informal settlements, and the urban population is projected to triple by 2050, further exacerbating the prevalence of informal settlements [13].

The analysis of urbanization highlights its multifaceted nature and the significant impacts it has on societies worldwide. Urbanization refers to the mass movement of populations from rural to urban areas, leading to physical changes in urban settings [19]. The phenomenon of urbanization is a concrete manifestation of changes in global human settlement patterns, driven by factors such as globalization and migration flows.

Urbanization has far-reaching impacts on various aspects of society, including living conditions, economic opportunities, and public health. Cities serve as hubs for technological development and economic growth but also face challenges such as poverty, inequality, environmental hazards, and communicable diseases [4]. The concentration of rural migrants in urban informal settlements exacerbates issues such as overcrowding, inadequate infrastructure, and vulnerability to health risks [3].

2.3 IMPORTANCE OF SPATIAL INFORMATION

Reliable procedures for detecting and monitoring informal settlements are essential for early intervention and urban planning efforts. Spatial information about informal settlement areas is vital for enhancing urban and regional planning and guiding development interventions [13]. Traditional census surveys have limitations in accurately outlining informal settlement areas and are not frequently updated, highlighting the need for alternative methods [3].

2.4 REMOTE SENSING

Remote sensing involves collecting and interpreting information about the environment and earth's surface from a distance, typically by sensing radiation emitted or reflected by the earth's surface or atmosphere. Examples of remote sensing methods include aerial photography, radar, and satellite imaging [5].

2.4.1 Challenges Addressed by Remote Sensing

Obtaining statistical data on informal settlements can be challenging due to issues such as lack of awareness of their exact locations, extent, and safety concerns associated with manoeuvring through unstructured building patterns. Remote sensing offers a solution to these challenges by providing a means to gather spatial information over large areas with frequent coverage [14].

Overall, this analysis emphasizes the importance of remote sensing technology in addressing the spatial information needs of informal settlements and highlights its potential to support evidence-based decision-making and urban planning efforts. By leveraging remote sensing techniques, authorities can gain valuable insights into the dynamics of informal settlements and develop targeted interventions to improve living conditions and promote sustainable urban development [22].

2.4.2 Role of Remote Sensing in Informal Settlement Analysis

Informal settlements are a significant component of urban housing and economy, yet there is often a lack of comprehensive information about their scale, location, population, and spatial dynamics. Remote sensing can help analyse the spatiotemporal dynamics of informal settlements, such as monitoring densification and expansion processes and assisting in implementing improvement policies [17]. It enables the mapping of informal settlements in hazardous areas and assessing environmental conditions relevant to urban health campaigns.

2.5 DETECTING & MONITORING INFORMAL SETTLEMENTS USING RADAR

Optical sensors, while effective in capturing pictorial 3D views of the environment, have limitations such as reliance on external light sources, making them ineffective at night. Additionally, they struggle to penetrate certain atmospheric conditions like fog, clouds, and rain, limiting their effectiveness during unfavourable weather conditions [19]. SAR overcomes the limitations of optical sensors. It operates independently of external light sources and atmospheric conditions, making it effective both day and night and in various weather conditions. This makes SAR particularly valuable for regions with frequent cloud cover or tropical climates where optical sensors may struggle [10]. While optical sensors have been extensively used for land classification, studies utilizing SAR techniques for the detection of morphologic informal settlements are rare. SAR data's stability and independence from atmospheric conditions make it highly relevant for this purpose, especially in tropical regions where informal settlements are common [20].

2.6 CHALLENGES AND OPPORTUNITIES

While SAR offers advantages, discriminating between different settlement types using SAR data remains challenging. The texture of SAR images plays a crucial role in distinguishing between different settlement types due to the complexity of urban environments. However, SAR's high-resolution capabilities and recent advancements in polarimetric capabilities offer opportunities for more detailed analysis [16].

2.6.1 Complexity of Urban Environments

Urban environments pose significant challenges for remote sensing due to their complexity. SAR, with its ability to convey detailed structural and dielectric properties of urban materials, provides valuable information for analysing urban areas. The ground resolution of SAR for space borne sensors, currently a few meters, allows for detailed analysis of urban features [9].

However, challenges remain in effectively discriminating between different settlement types, highlighting areas for further research and development.

2.7 WHY USE SENTINEL 1 SENSOR

The advent of the Sentinel-1 mission has led to widespread availability of SAR data with almost global coverage and regular time intervals. The Sentinel-1 mission comprises two polar-orbiting satellites equipped with C-band synthetic aperture radar imaging, enabling them to

acquire imagery day and night regardless of weather conditions [1]. The availability of SAR data from satellites like Sentinel-1A and Sentinel-1B provides global coverage and high revisit frequency, making it valuable for various applications, including disaster monitoring and environmental resilience studies. SAR data, especially when used in multi-temporal analysis, can be used for change detection, allowing for the monitoring of natural disasters and environmental changes over time [10]. This makes SAR particularly useful for disaster management and mitigation efforts. SAR can distinguish objects through three distinct methods [6].

- a. *Texture discrimination:*** Analysing the texture of SAR images to differentiate between different features or materials.
- b. *Spectral discrimination:*** Identifying objects based on their spectral characteristics in SAR imagery.
- c. *Change detection:*** Detecting changes in SAR imagery over time to identify areas of interest or significant changes in the landscape.

2.8 STUDIES ON SAR FOR INFORMAL SETTLEMENT CLASSIFICATION

Urban areas around the world exhibit distinct structural characteristics, necessitating a scale-dependent approach in remote sensing analyses. The spatial patterns of formal and informal settlements vary significantly, making the ability to determine the optimal scale for mapping a given area one of the most compelling and challenging research topics in urban remote sensing [8].

The advancements in satellite Synthetic Aperture Radar (SAR) technology, particularly the significant improvement in spatial resolution down to tens of centimetres, are poised to revolutionize the way we analyze and monitor complex urban environments. Low Earth Orbit (LEO) satellite constellations, such as Cosmo-Skymed, and single satellites like TerraSAR-X, are emerging as key players in providing high-resolution SAR data. This data is becoming increasingly attractive for applications that require detailed urban analysis, including infrastructure monitoring, disaster response, and urban planning [12].

Research in radar sensing over urban areas is indeed entering a transformative phase, shifting from optimizing the use of existing SAR data to preparing for the opportunities and challenges that higher-resolution data will bring. With spatial resolutions improving to the point where single structural elements, such as individual buildings or even smaller features, become

visible, new analytical possibilities emerge. However, these advancements introduce complexities that demand novel approaches [8].

One significant challenge is the inadequacy of traditional speckle noise models. In high-resolution SAR data, the limited number of scatterers per resolution cell results in a much narrower statistical base, making conventional statistical models less effective. This calls for the development of advanced noise reduction techniques and statistical frameworks that can better handle the characteristics of high-resolution imagery [22].

Furthermore, the ability to resolve individual structures opens doors for detailed urban analysis but also raises questions about data management, computational requirements, and interpretation methods. For example, the sheer volume and granularity of data will necessitate improvements in processing algorithms, including machine learning techniques, to extract meaningful insights efficiently. [12]

Mapping formal and informal settlements using SAR data will push the boundaries of existing urban mapping methodologies, which have largely been developed for industrialized contexts. These methods may face challenges in adapting to the diverse and often irregular spatial patterns characteristic of informal settlements. Consequently, extensive validation efforts will be essential to ensure the accuracy, reliability, and scalability of SAR-based approaches in these complex environments [23].

Synthetic Aperture Radar (SAR) imagery, being highly sensitive to the geometric properties of a scene, offers unique advantages in addressing this challenge. SAR data provides rich information about spatial structures and their relationships, which is crucial for distinguishing between different urban forms [23].

Technically, a variety of methods have been developed to quantify the spatial relationships among neighbouring pixels in SAR images. Among these, co-occurrence texture analysis has emerged as one of the most widely adopted and effective approaches. This method involves computing co-occurrence texture measures based on the co-occurrence matrix, which captures the frequency of pixel pair occurrences at specific relative positions and intensity levels. These measures—such as contrast, correlation, entropy, and homogeneity—are instrumental in extracting texture-related information from SAR data, enabling a more nuanced analysis of urban structures at varying scales [24].

3 RESEARCH METHODOLOGY

3.1 IMAGES USED FOR THE STUDY

In this research study, Sentinel-1 data ground range detected (GRD) products were used. With these specifications, the Sentinel-1 data provides detailed radar images of the study area on the specified acquisition dates, which are suitable for processing and analysis using the SNAP software. This data is utilized for tasks such as land cover classification in this research study. The specification of the data is summarised in Table 3.1.

TABLE 3.1: SPECIFICATIONS OF THE SENTINEL-1 DATA PRODUCTS

Specification	Description
Acquisition date	13 March 2023 & 28 August 2023
Product	GRD Level 1
Frequency Band	C-Band
Resolution	10 m

Acquisition Date - Two Sentinel-1 images were acquired, with one taken on the 13th of March 2023 and the other on the 28th of August 2023. These images serve as the primary data sources for the study.

Product -The Sentinel-1 data used in the study are Ground Range Detected (GRD) Level 1 products. GRD products undergo processing to correct for geometric distortions caused by the Earth's curvature and sensor motion, resulting in images that represent the ground range projection of the radar signal.

Frequency Band - The Sentinel-1 data belongs to the C-Band frequency, which is a common frequency band used in radar remote sensing applications. C-Band radar offers a balance between spatial resolution and penetration capability.

Resolution- The resolution of the Sentinel-1 data used in the study is specified as 10 meters. This refers to the spatial resolution of the imagery, indicating the smallest discernible feature size in the images.

3.2 OVERVIEW OF THE METHODOLOGY

3.2.1 SNAP application

The Sentinel-1 data was processed using SNAP (Sentinel Application Platform) software which is provided by ESA (European Space Agency). SNAP is open-source software for exploring the EO (earth observation) satellite data. This means it is freely available for users to download and use for exploring and processing EO satellite data. It comprises many processing tools and it can analyse large archives of satellite data by automated image processing techniques using Python scripts. In the SNAP, the Sentinel data is opened and viewed in the display. The subset function will perform both spatial and spectral resampling because the bands in Sentinel data are all various sizes and resolutions. The use of SNAP software for processing Sentinel-1 data offers several advantages, below is a breakdown of the software utilised:

Exploration and Processing Tools. SNAP provides a range of tools for exploring and processing EO satellite data. These tools allow users to visualize, analyze, and manipulate satellite imagery for various applications.

Automated Image Processing with Python Scripts. SNAP supports automated image processing techniques using Python scripts. This capability enables users to streamline and automate repetitive tasks, saving time and effort in data analysis workflows.

Data Viewing and Sub setting. In SNAP, users can open and view Sentinel data directly within the software's interface. Additionally, the subset function allows users to extract specific regions or areas of interest from the original data.

Spatial and Spectral resampling. The subset function in SNAP can perform both spatial and spectral resampling. This is particularly useful when working with satellite data with bands of varying sizes and resolutions. Resampling ensures that all bands have the same size and resolution, facilitating consistent analysis and interpretation of the data.

3.3 DATA COLLECTION & PROCESSING

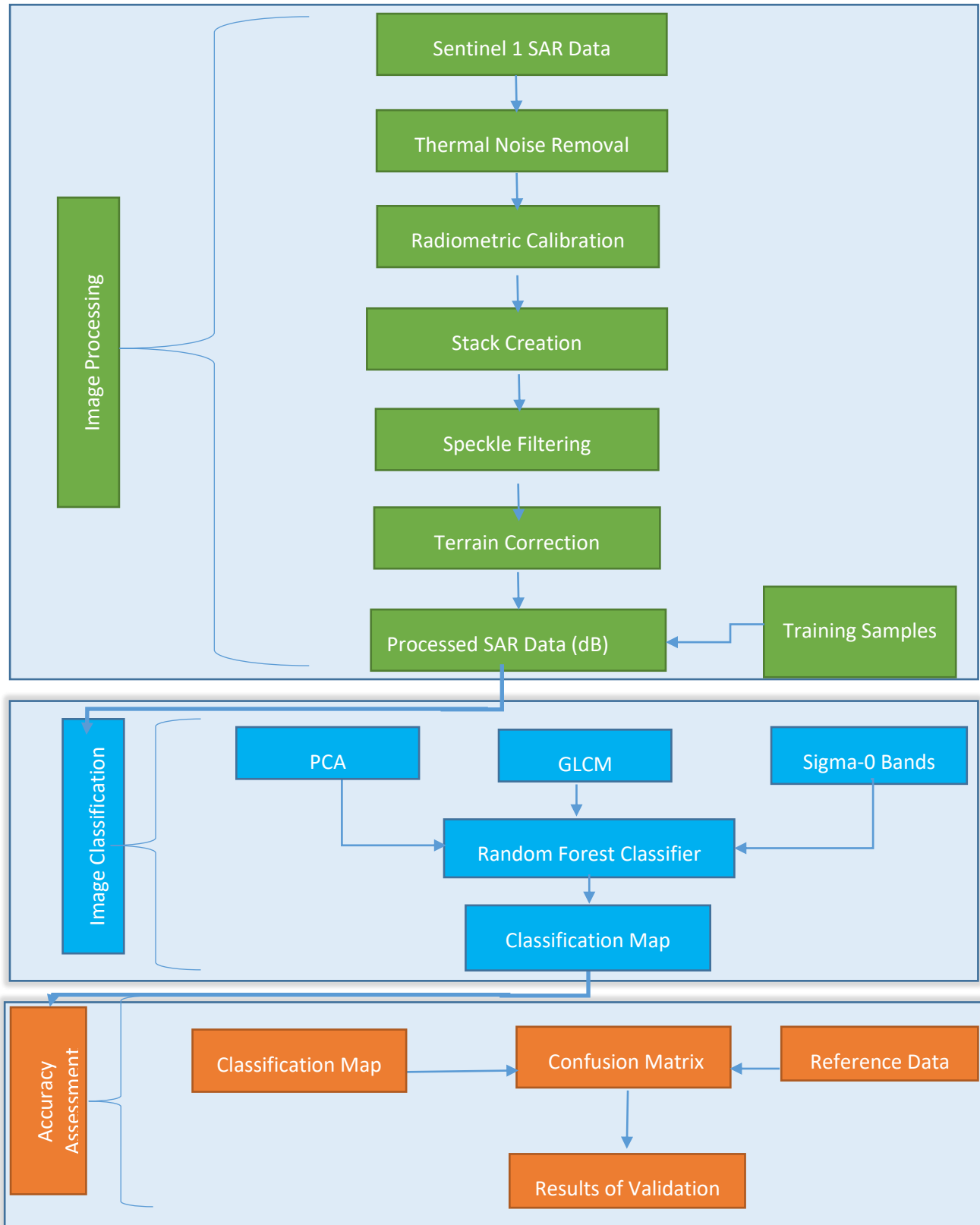


FIGURE 3.1: METHODOLOGY DEPICTED IN THE DIAGRAM

Image Download. Two Sentinel-1 images were downloaded, one on the 13th of March 2023 and the other on the 28th of August 2023.

Subset. A subset of each downloaded image was taken to clip it into a smaller portion, making it more manageable to work with and reducing processing time.

3.3.1 Pre-processing:

The following processes are explained in detail in section 4.2

Thermal Noise Removal. Thermal noise present in the images was removed.

Radiometric Calibration. Radiometric calibration was performed for each of the two images.

Stack Creation. The images were co-registered and stacked together. Speckle, which appears as random noise in radar images, was present in the stack.

Speckle Filtering: The speckle filter was applied to remove the random noise (speckle) in the stack. Speckle filtering is important before performing land use and land cover classification to improve the quality of the classified images.

Geometric Correction. Geometric correction was carried out to remove the impacts of the side-looking geometry of Sentinel images. This was achieved using Range-Doppler terrain correction with the assistance of the SRTM DEM (Shuttle Radar Topography Mission digital elevation model) and bilinear interpolation resampling technique.

Conversion to dB Scale. The processed products were converted from a linear scale to a decibel (dB) scale. This conversion helps increase the reparability threshold between different features in the images.

The preceding processing steps are crucial for ensuring the quality and accuracy of the data before further analysis, such as land use and land cover classification. They will be discussed in detail in Chapter 4 of this research study.

3.4 CREATING IMAGE FEATURES FOR MORE INPUTS

To increase the number of inputs to be used for classification over and above the Sigma-0 bands, PCA features and GLCM textures were created.

In this methodology, two additional techniques are employed to increase the number of inputs for classification: PCA and GLCM. Here's an overview of these techniques.

3.5 PRINCIPAL COMPONENTS ANALYSIS (PCA)

Principal components analysis is created from the stacked products. This technique was performed to identify the redundancies and differences in a stack of bands and transformed them into new uncorrelated bands which have maximized information content. PCA is a statistical technique used to reduce the dimensionality of data while preserving most of its variability. In the context of remote sensing, PCA is applied to multi-spectral or multi-temporal satellite imagery to identify the most important spectral components or features.

By transforming the original stacked bands into a new set of uncorrelated bands (principal components), PCA maximizes the information content of the data while reducing redundancy.

These principal components can then be used as inputs for classification algorithms, potentially improving classification accuracy.

3.6 GREY LEVEL CO-OCCURRENCE MATRIX (GLCM)

Another set of inputs was created using a technique known as grey level co-occurrence matrix, this process was performed to ensure description of the degree of speckle in different parts of the image are consolidated and are therefore also contributing to a better separation of surface types. GLCM is a texture analysis technique used to quantify spatial relationships in an image. It calculates the occurrence of pairs of pixel intensity values at a specified distance and direction within an image. GLCM provides information about the spatial distribution and texture of features in an image, such as the degree of speckle. By consolidating the description of speckle characteristics across different parts of the image, GLCM contributed to better discrimination of surface types during classification.

GLCM is a valuable technique for feature extraction and representation in remote sensing image analysis. By incorporating the derived features from these techniques as inputs for classification, the study aims to enhance the discrimination capability and accuracy of the classification process. These techniques effectively capture and represent important information within the imagery, leading to improved classification results.

3.7 ACCURACY ASSESSMENT

This process is to validate the classification map created however it is performed in the QGIS environment. It takes the results of the classification and compares it with the ground truth (reference data) and generate the comparative results in a form of error matrix or confusion matrix. This process involves validating the classification map created in the SNAP environment by comparing it with ground truth or reference data created in QGIS. An overview of the validation process is outlined below:

Classification Map Creation. In the SNAP a classification map is generated using a classification algorithm such as supervised or unsupervised classification. This map categorizes different land cover or land use classes within the study area based on the input data and classification algorithm.

Ground Truth Data Collection. Ground truth data, also known as reference data, is collected through field surveys, high-resolution imagery, or existing datasets. Ground truth data typically include information about the actual land cover or land use classes present in the study area.

Comparative Analysis. The classification map created in is compared with the ground truth data. This comparison involves assessing the accuracy of the classification map by determining the agreement or disagreement between the classified classes and the ground truth classes.

Confusion Matrix. The results of the comparison are typically summarized in a confusion matrix. These matrices provide a quantitative assessment of the classification accuracy by showing the frequency of correct and incorrect classifications for each land cover or land use class. It tabulates the classification results in rows and columns, with each cell indicating the number of pixels classified correctly or incorrectly for a particular class.

It further summarizes the classification results by comparing the classified classes with the ground truth classes. It provides information about the agreement between the classification map and the ground truth data.

Evaluation Metrics. Various evaluation metrics can be calculated from the confusion matrix to assess the accuracy of the classification map. These metrics may include overall accuracy, producer's accuracy, consumer's accuracy and kappa coefficient.

By comparing the classification map with ground truth data and generating confusion matrix, the accuracy of the classification results can be evaluated and identify areas for improvement

in the classification process. This validation step is essential for ensuring the reliability and validity of the classified land cover or land use information derived from remote sensing data.

4 PROCESS IMPLEMENTATION

4.1 SUBSET IMAGE CREATION

The data that is utilized comes from the Sentinel-1 products downloaded for the area including the heart of Khayelitsha and a part of Mitchell's Plain and covers an area of 43.51 km². Then for the purposes of image processing and to reduce the processing time, a subset of the area is taken using SNAP for further processing to limit the amount of time taken for further data processing. The data was downloaded and then subsetting for further processing using SNAP. Here's an overview of the steps involved:

Data Acquisition. Sentinel-1 data covering the specified area is acquired. This data likely includes radar images captured by the Sentinel-1 satellite constellation.

Subset Selection. To reduce processing time and focus on the specific area of interest, a subset of the downloaded Sentinel-1 data is selected using SNAP. The subset represents a smaller portion of the original data that includes the heart of Khayelitsha and part of Mitchell's Plain.

SNAP Processing. The subsetting data is then processed using SNAP software. This involves various pre-processing steps such as orbit file application, thermal noise removal, radiometric calibration, co-registration, speckle filtering, geometric correction, and conversion to dB scale, as outlined in this earlier description of the methodology.

Further Data Processing. Once the subsetting data has been pre-processed in SNAP, it can be further analysed and processed for specific tasks such as land cover classification, change detection, or feature extraction.

By initially downloading the Sentinel-1 data covering the study area and then subsetting it for further processing using SNAP, it was possible to focus computational resources on the specific area of interest, thereby reducing processing time and improving efficiency in the data analysis workflow.

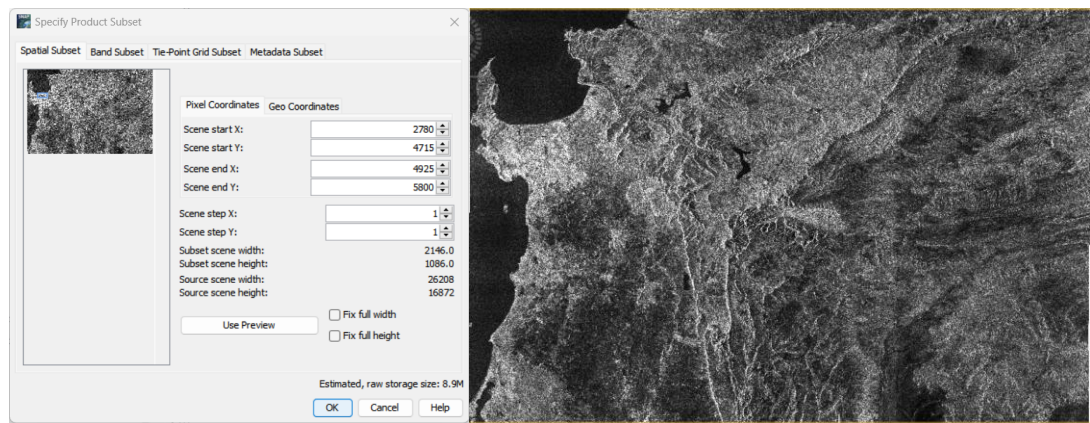


FIGURE 4.1: A SUBSET ON THE LEFT IS CREATED FROM THE IMAGE DOWNLOADED ON THE RIGHT

4.2 PRE-PROCESSING

Sentinel-1 operates at a single wavelength of 5.4 GHz. It operates in a dual polarization mode, whereby vertical waves are emitted from the sensor, and then both vertical and horizontal waves are returned back to the sensor, leading to backscatter intensity and amplitude of VV and VH. For this research study we have downloaded and used two image products. The images were downloaded from exactly the same location, taken on two different dates.

This approach allows for the comparison of radar observations over time, which can be valuable for various applications such as land cover, detecting land use dynamics, or assessing environmental changes. By analysing Sentinel-1 data from multiple acquisition dates, researchers can gain insights into temporal trends and variations in the study area, contributing to a more comprehensive understanding of the dynamics and processes at play.

4.2.1 Thermal Noise removal

Images generated in radar system will inherently contain noise. Thermal noise specifically is most obvious in cross-polarization SAR images, such as VH or HV, and in SAR images with low backscatter. For Sentinel-1, thermal noise can appear as inter-swath discontinuities. This process is mostly effective and intended for data products taken over land and may not be effective over ocean.

Thermal Noise in Cross-Polarization SAR Images. Cross-polarization SAR images, where the transmitted and received signals are in orthogonal polarizations, are particularly susceptible to thermal noise. This noise can manifest as fluctuations in the received signal intensity, leading to distortions and inaccuracies in the imagery.

Effect on Sentinel-1 Images. In the case of Sentinel-1, thermal noise can present as inter-swath discontinuities. Inter-swath discontinuities occur at the boundaries between adjacent radar swaths and can result in inconsistencies or disruptions in the imagery.

Effectiveness Over Land vs. Ocean. The effectiveness of mitigating thermal noise through processing techniques may vary depending on the type of surface being observed. Techniques for noise reduction are generally more effective over land surfaces compared to ocean surfaces. This is because the backscatter characteristics and noise properties of land and ocean surfaces differ significantly.

Overall, understanding and mitigating thermal noise is crucial for ensuring the quality and accuracy of radar imagery, particularly in applications where precise measurements and interpretations are required. Processing techniques aimed at reducing thermal noise can help improve the usability and reliability of radar data for various remote sensing applications.



FIGURE 4.2: THERMAL NOISE REMOVAL APPLIED TO THE IMAGE INTENSITY

4.2.2 Radiometric calibration

This process converts backscatter intensity as received by the sensor to the radar cross section as a calibrated measure, taking into consideration the global incidence angle of the image and other sensor specific characteristics. This was done to remove or reduce the variations in the image that occurred during the data acquisition, this also converts the image pixel values from digital number (DN) to a standard geophysical measurement unit of radar backscatter. This makes radar images of different dates, different sensors or imaging geometries to be compatible. This process was performed for both our images.

Calibration Process. By applying this process, the aim was to remove or reduce variations in the image that occurred during data acquisition. This is essential for ensuring consistency and accuracy in the radar imagery. By converting the image pixel values from DN to standard geophysical measurement units of radar backscatter (such as decibels, dB), the calibrated

images become standardized and comparable across different dates, sensors, or imaging geometries.

Purpose. The primary purpose of calibration is to ensure that the radar imagery accurately represents the physical properties of the observed scene, independent of variations in acquisition conditions or sensor characteristics. Calibrated radar images enable meaningful comparisons and analysis over time, allowing researchers to track changes in land cover, detect environmental phenomena, or monitor land surface dynamics with confidence.

Compatibility. By performing calibration, radar images acquired on different dates, by different sensors, or under different imaging geometries become compatible. This compatibility facilitates seamless integration and analysis of multi-temporal or multi-sensor radar data. Standardizing radar imagery to a common measurement unit facilitates quantitative analysis and interpretation, enhancing the reliability and robustness of remote sensing studies.



FIGURE 4.3: CALIBRATION APPLIED TO THE IMAGE INTENSITY

4.2.3 Co-registration

After both our images were calibrated, the co-registration procedure was done which brings both images into once stack. Even if both images were acquired from the same track, smaller differences in the incidence angle do cause inaccurate pixel positioning in the parts of the image. As such, these differences were identified and compensated by the co-registration operator, which create one product containing both images with the best possible geometric overlay.

The co-registration procedure is an essential step in radar image processing, especially when working with multi-temporal or multi-sensor data. Below paragraph describes an overview of the co-registration process and its significance.

Co-registration involves aligning two or more images spatially so that corresponding pixels in each image represent the same geographic location on the ground.

In the context of this study, the two calibrated Sentinel-1 images were co-registered to ensure accurate pixel alignment and geometric overlay.

Even if the images were acquired from the same track, minor differences in the incidence angle or sensor characteristics can lead to slight inaccuracies in pixel positioning. Co-registration compensates for these differences to achieve the best possible geometric alignment.

Co-registration is crucial for various remote sensing applications, including change detection, feature extraction, and classification. Accurate pixel alignment enables meaningful comparison and analysis of features or changes observed in the images over time.

Co-registration ensures that features in the images are spatially aligned, allowing for reliable interpretation and analysis of spatial relationships and patterns.

The co-registration process involves the use of specialized algorithms or operators within remote sensing software. These operators identify corresponding features or control points in the images and apply geometric transformations to align them accurately.

The goal is to minimize geometric distortions and discrepancies between the images, resulting in a seamless and accurately aligned image stack.

Co-registration is a critical step in radar image processing to ensure accurate spatial alignment and geometric overlay of multi-temporal or multi-sensor data. By aligning the images, co-registration facilitates reliable analysis and interpretation of remote sensing data for various applications in environmental monitoring, land cover mapping.



FIGURE 4.4: STACK CREATED FROM BOTH IMAGES TO FORM ONE PRODUCT (CO-REGISTRATION)

4.2.4 Speckle filtering

This process removes noise, or speckle, in an image. It uses spatial averaging to reduce image speckle noise and converts to ground range, producing an image with a standard pixel size and reduces image resolution. Many types of speckle filters can be applied, and different applications have specific filters that may work best. In this study specifically the Lee adaptive filter with a kernel size of 9x9 was used. This step does not however reduce spatial resolution. Certain parts of the image expected to have a homogenous backscatter intensity are sometimes characterized by the granular patterns. These salt and pepper effects are the speckle which is inherent in any SAR image and caused by different constructive and destructive contribution to backscatter intensity of different scattering mechanisms below the pixel resolution. Adaptive speckle filters are designed to enhance the image quality by suppressing random variations in the image while maintaining sharp edges.

Speckle filtering is essential and it was implemented in this study for improving the quality of synthetic aperture radar (SAR) images by reducing the noise or speckle inherent in the imagery. Here's a detailed explanation of what the speckle filtering process was used for:

Speckle noise, also known as multiplicative noise, is inherent in SAR images and appears as granular patterns or "salt and pepper" effects. Speckle filtering techniques aim to reduce or suppress this noise while preserving the important features and structures in the image.

Speckle filtering often involves spatial averaging, where neighbouring pixel values are combined to produce a smoother representation of the image. By averaging pixel values within a local neighbourhood, speckle noise is attenuated, resulting in a smoother appearance in the filtered image.

The speckle filtering process includes conversion to ground range, which produces an image with a standard pixel size. This step does not reduce spatial resolution but rather ensures that the image is represented in a consistent spatial scale, facilitating accurate interpretation and analysis.

Many types of speckle filters can be applied, each with its own advantages and limitations. Different applications may require specific filters that are most effective for the given imaging conditions and objectives.

Adaptive speckle filters are designed to enhance image quality by suppressing random variations in the image while preserving sharp edges and important features. These filters adjust their parameters based on local image characteristics, allowing for effective noise reduction without sacrificing image details.

Speckle filtering is a crucial step in SAR image processing to improve image quality and enhance the interpretability of the imagery for various applications. By reducing speckle noise while maintaining important image features, speckle filters contribute to more accurate and reliable analysis of SAR data for tasks such as land cover classification and environmental monitoring.



FIGURE 4.5: SPECKLE FILTERING APPLIED

4.2.5 Terrain Correction

SAR geometric distortions such as fore-shortening, layover and shadow are corrected by geocoding the images using a DEM (digital elevation model) and producing a map projected product. It uses a DEM process to remove geometry-dependent radiometric distortions; normalizes measured backscatter with respect to terrain slope. This process converts an image from ground range geometry into a map coordinate system.

This process is also known as SAR geometric correction which involves correcting geometric distortions in synthetic aperture radar (SAR) imagery. A detailed explanation of this process is outlined below:

SAR images can suffer from geometric distortions due to variations in terrain elevation, resulting in effects such as fore-shortening, layover, and shadow.

Fore-shortening occurs when tall objects are tilted toward the sensor, leading to compression in the radar image.

Layover occurs when steep terrain slopes are imaged at an angle greater than 90 degrees, causing the terrain to appear as if it is located beyond its true position.

Shadow occurs when terrain features obstruct the radar signal, resulting in areas of reduced backscatter intensity.

SAR geometric correction involves geo-coding the images using a DEM to account for terrain effects. A DEM provides information about the elevation of the Earth's surface at each pixel location, allowing for the estimation of terrain slopes and angles.

By processing the SAR imagery with the DEM, geometry-dependent radiometric distortions are removed, and the measured backscatter is normalized with respect to terrain slope.

Map Projection. The corrected SAR imagery is then transformed from ground range geometry, where distances are measured along the sensor's line of sight, into a map coordinate system.

Map projection involves projecting the SAR image onto a flat surface, such as a map or grid, using a specific projection method. This process allows for accurate spatial referencing of the SAR imagery in a standard geographic coordinate system, facilitating integration with other geospatial data and analysis.

SAR geometric correction is a critical step in SAR image processing to ensure accurate spatial representation and interpretation of the imagery. By correcting for geometric distortions using a DEM and transforming the imagery into a map coordinate system, SAR data can be effectively utilized for various applications such as terrain mapping and land cover classification.



FIGURE 4.6 : TERRAIN CORRECTION APPLIED

4.2.6 Conversion to DB scale

The terrain corrected product ranges between 0 and 1 in terms of value and statistically speaking this is not ideal. To achieve a more normal distribution of values, the log function is applied to the image to translate the pixel values into a log scale and yield a higher contrast. The values of calibrated dB data roughly range between (-35dB and +10) dB.

The transformation of the terrain corrected SAR product from its original scale (linear scale), ranging between 0 and 1 to a logarithmic scale is a common practice in radar image processing. Here's an explanation of this transformation:

Logarithmic Transformation:

The logarithmic transformation involves applying the logarithm function to the pixel values of the SAR image. This transformation is typically used to enhance the contrast and dynamic range of the image, making it easier to visualize and interpret.

By taking the logarithm of the pixel values, the range of values is compressed, resulting in a more uniform distribution of pixel intensities across the image. The calibrated SAR data typically have values ranging between -35 dB and +10 dB, representing the backscatter intensity measured by the radar sensor.

By applying the logarithmic transformation, these values are converted into a logarithmic scale, which helps to normalize the distribution of values and improve the visual interpretation of the image.

The log transformation effectively spreads out the range of pixel intensities, enhancing the contrast between different features in the image. The logarithmic scale is particularly useful for radar imagery, as it enhances the visibility of subtle features and improves the discrimination of different land cover or land use classes.

It also helps to highlight variations in backscatter intensity across the image, which may correspond to different surface properties or environmental conditions.

Applying a logarithmic transformation to terrain-corrected SAR imagery helps to enhance the visual contrast and interpretability of the image. By converting the pixel values to a logarithmic scale, the range of values is normalized, making it easier to identify and analyse features of interest in the imagery.



FIGURE 4.7: SCALE CHANGED FROM LINEAR TO LOGARITHMIC



FIGURE 4.8: A RESULTANT RGB IMAGE OF THE STACKED PRODUCT

4.2.7 Creating a model

The preceding processes as described above were automated in this work through a function called graph builder in the SNAP environment. This model can be applied and be deployed for the same purpose at any area of interest by simply changing the inputs and the variables to **Error! Reference source not found.** demonstrate the steps that the model follows to generate a processed product. As it can be seen in this case, two images were downloaded and used to create a single processed product.

Automating the preceding processes using a function called Graph Builder in the SNAP environment is a practical approach to streamlining SAR image processing workflows. Below is how this automation works.

Graph Builder Function

The Graph Builder function in SNAP allows users to create processing workflows by connecting different processing modules or operators. Users can define a sequence of processing steps, specifying inputs, parameters, and output products within the Graph Builder interface.

The automated processing workflow, built using the Graph Builder function, includes all the necessary steps described earlier, such as data download, subset selection, calibration, co-registration, speckle filtering, geometric correction, and logarithmic transformation.

Each processing step is represented as a module or operator within the Graph Builder interface, and users can configure parameters and inputs for each module to customize the processing workflow according to their specific requirements.

The automated processing model can be applied and deployed for the same purpose at any area of interest by simply changing the input data and adjusting variables or parameters as needed. Users can input different SAR images, DEM data, and processing parameters to adapt the automated workflow to different study areas or imaging conditions.

Figure 4.9 **Error! Reference source not found.** illustrates the sequence of processing steps followed by the automated model to generate a processed SAR product. Each step in the figure corresponds to a specific processing module or operator within the Graph Builder workflow, showing the flow of data and operations from input to output.

By automating SAR image processing using the Graph Builder function in SNAP, time and effort can be significantly saved, ensure consistency in processing methodologies, and easily replicate the workflow for different study areas or datasets. This approach enhances efficiency and reproducibility in SAR data analysis and facilitates the generation of standardized and reliable processed products for various remote sensing applications.

4.2.8 Pre-processing steps using the Graph Builder

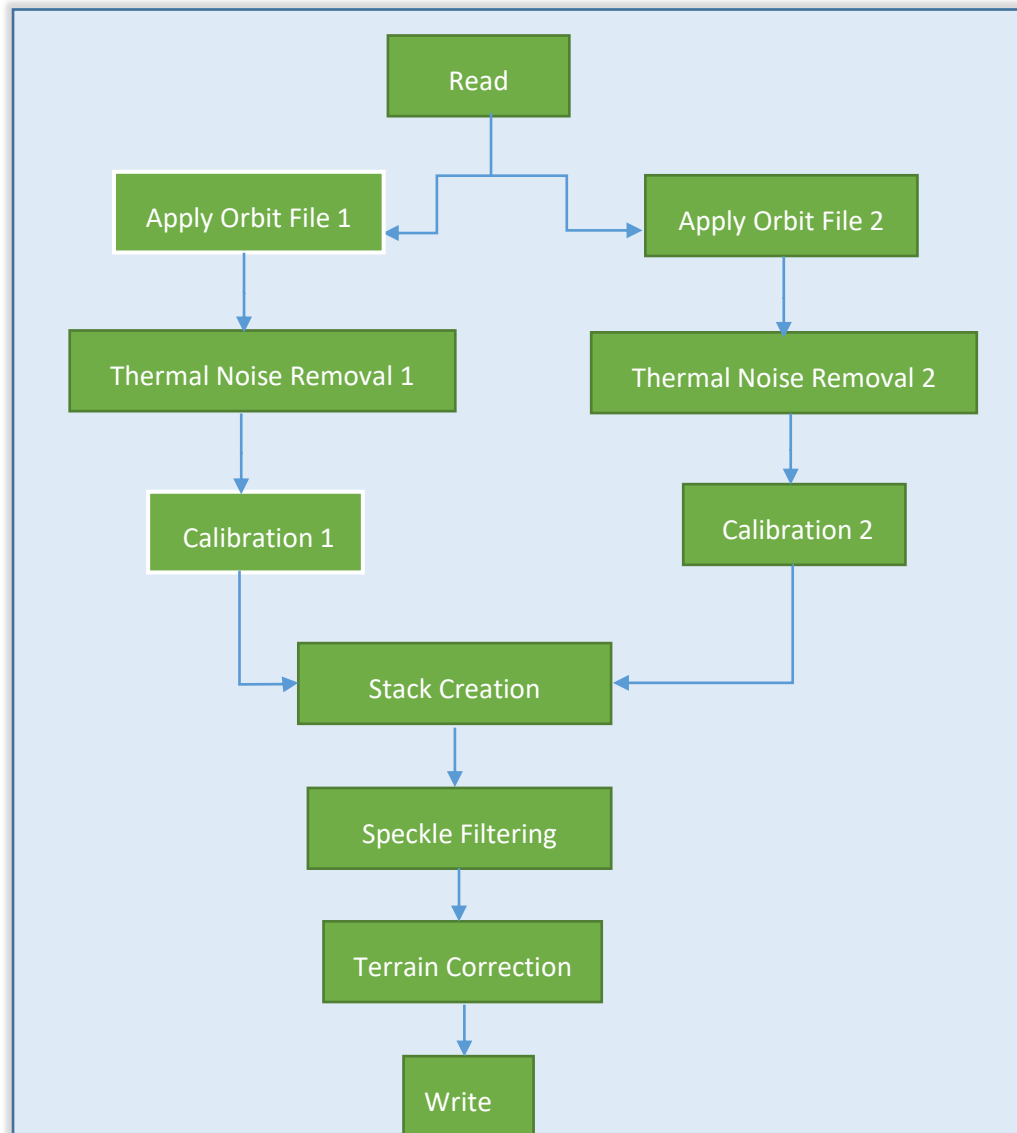


FIGURE 4.9 THE GRAPH BUILDER REPRESENTING THE PRE-PROCESSING STEPS

4.3 IMAGE CLASSIFICATION

4.3.1 PCA

PCA is a powerful tool for reducing the dimensionality of data while preserving its essential information. The goal is to get the best principle components that capture maximum variance. Scale the features to have a mean of 0 and a standard deviation of 1. Suppose there is a dataset with 'w' observations and 'z' features, PCA calculates the covariance matrix of the data. It then finds the eigenvectors and eigenvalues of this covariance matrix. The eigenvectors represent the directions (principal components) of maximum variance in the data, and the corresponding eigenvalues represent the magnitude of this variance along each eigenvector. By sorting the eigenvectors based on their corresponding eigenvalues in descending order, PCA identifies the most significant principal components. Choose some eigenvectors based on their corresponding eigenvalues to form the new feature subspace. Project the original data onto the new feature subspace formed by the selected eigenvectors.

Then Centre the dataset at the origin of the Cartesian plane, if our data is already cantered, which means that the mean is equal to 0, the covariance matrix will be simple as the below equations. Thus, we make our data center-shifted.

$$Cov [X, Y] = E[(X - \mu_x)(Y - \mu_y)] \quad \text{EQUATION 4.1}$$

Since the mean is zero, then $\mu_x = 0 = \mu_y$

$$Cov [X, Y] = E[(X - 0)(Y - 0)] = E[XY] \quad \text{EQUATION 4.2}$$

4.3.2 GLCM

Grey Level Co-occurrence Matrix (GLCM) is a statistical method that measures image texture by considering the spatial relationship between pixels, used in texture analysis and pattern recognition. The complexity of the GLCM algorithm is related to the number of operations required to produce a matrix' Complexity is evaluated for the worst, average or best cases. The GLCM features energy, contrast, homogeneity, entropy and correlation have a complexity notation. Complexity notation refers to the time complexity required to construct the gray-level co-occurrence matrix of an image. For the notation, n represents the number of pixels in the image. Image scanning and calculation of the frequency of pixel pairs with a certain intensity at a certain distance and orientation, generally two loops (nested loops), one for

image rows and one for image columns. Each iteration, the algorithm will calculate the relationship between pixels and their neighbours. So that the image size increases, the time needed to calculate the GLCM matrix will increase quadratically. As an example for a size of 100×100 pixels (10,000 pixels), it is necessary to process more than 100 million (10,000²) operations to calculate the GLCM matrix. We shall consider a few but not all mathematical definitions of some of the features below.

So, the mean gray value is the sum of the values at all pixels divided by the number of pixels.

Suppose a there is a given matrix G with 'i' columns and 'j' rows.

Contrast, also is the sum of square variance. When i and j are the same ie. Square matrix, the cell of interest will be on the diagonal. In this case the values represent pixels entirely similar to the neighbouring pixel, otherwise there will be a contrast.

Contrast

$$\text{Contrast} = \sum_{i,j=0}^{n-1} G(i,j)^2 \quad \text{EQUATION 4.3}$$

Homogeneity

Homogeneity is the inverse Difference Moment

$$\text{Homogeneity} = \sum_{i,j=0}^{n-1} \frac{G_{i,j}}{1+(i-j)^2} \quad \text{EQUATION 4.4}$$

Entropy

Entropy is usually classified as a first degree measure

$$\text{Contrast} = \sum_{i,j=0}^{n-1} G_{i,j} (-\ln G_{i,j}) \quad \text{EQUATION 4.5}$$

Correlation texture measures the linear dependency of grey levels on those of neighbouring pixels. For the symmetrical matrix, the denominator above reduces to the variance (sigma squared). Understanding how to use this equation depends on understanding the Mean equation and Variance equation expressed in terms of the GLCM. What does correlation mean? Correlation between pixels means that there is a predictable and linear relationship between the two neighbouring pixels within the window, expressed by the equation.

Correlation

$$\text{Correlation} = \sum_{i,j=0}^{n-1} \frac{G_{i,j}}{1+(i-j)^2} \quad \text{EQUATION 4.6}$$

Mean

$$\mu_i = \sum_{i=0}^{n-1} i(G_{i,j}) \quad \text{AND} \quad \mu_j = \sum_{j=0}^{n-1} j(G_{i,j}) \quad \text{EQUATION 4.7}$$

4.4 CLASSIFICATION APPROACHES

4.4.1 Machine Learning Techniques

In machine learning, there are two categories that one can use, i.e. supervised and unsupervised machine learning algorithms. ‘Supervised learning’ uses ‘labeled’ data where the desired output is already known, allowing the algorithm to learn the relationship between input and output, while ‘unsupervised learning’ uses ‘unlabeled’ data, where the algorithm must identify patterns and structures within the data without explicit guidance on what to look for. In essence, supervised learning has a ‘supervisor’ providing correct answers, while unsupervised learning must discover patterns on its own.

4.4.1.1 UNSUPERVISED ALGORITHMS

Unsupervised classification, also known as cluster analysis, does not require training and relies solely on clustering algorithms to classify features based on their spectral characteristics. Pixels belonging to the same category in the classification results share similar spectral properties but do not directly indicate the types of ground objects they represent. Instead, spatially distributed samples are grouped into clusters based on similarity, and the actual ground object types corresponding to these clusters must be identified through field investigation or comparison with known reference data. As a result, visual interpretation is necessary to determine feature categories, and categories are often combined during the process. Common clustering algorithms used in unsupervised classification include K-means clustering, hierarchical clustering, and spectral clustering, while dimensionality reduction techniques can aid in improving classification performance.

The K-means method is one of the most popular clustering algorithms in this category. It is an iterative algorithm that continuously adjusts cluster centres to achieve optimal clustering results. The principle behind the algorithm is straightforward: it initially selects random cluster centres and then iteratively refines their positions based on similarity. This process continues

until a predefined number of iterations is reached or the cluster centres stabilize, completing the classification.

4.4.2 Supervised learning algorithms

Supervised learning can be categorized into several types, each with distinct characteristics and applications. Below are some of the most common types of supervised learning algorithms:

Linear Regression: Linear regression is a type of supervised learning regression algorithm that is used to predict a continuous output value. It is one of the simplest and most widely used algorithms in supervised learning.

Logistic Regression: Logistic regression is a type of supervised learning classification algorithm that is used to predict a binary output variable.

Random Forests: Random Forest is made up of multiple decision trees that work together to make predictions. Each tree in the forest is trained on a different subset of the input features and data. The final prediction is made by aggregating the predictions of all the trees in the forest.

Maximum Likelihood Classification. Maximum likelihood classification (MLC) is one of the most widely used supervised classification methods. It assumes that various distribution functions are normal distribution, selects training areas, calculates the attribution probability of each sample area to be classified, and performs classification (an image classification method). Its discriminant rule is based on probability.

Support Vector Machine Classification. Support vector machines. SVM is a class of generalized linear classifiers that perform binary classification on data in a supervised learning manner, and its decision boundary is the maximum margin hyperplane that solves the learning samples. It takes the minimization of the confidence interval value as the optimization objective and the training error as the constraint condition of the optimization problem; that is, SVM is a statistical method based on the structural risk minimization criterion.

Decision Tree Classification. Decision tree is a tree-like structure that is used to model decisions and their possible consequences. Each internal node in the tree represents a decision, while each leaf node represents a possible outcome. It is a very common method in data mining. Its

purpose is to predict the value of the target variable from the value of the input variable. A decision tree can express the decision-making process explicitly.

4.4.3 Selection of the technique

Evaluation of various machine learning techniques, such as support vector machines (SVM), random forests, and convolutional neural networks (CNN) has been done by other researchers. We do not explore all these machine learning techniques in this study. We have selected one technique and discuss why that one in particular was chosen.

Supervised classification over unsupervised classification was chosen due to prior knowledge of the number of land cover classes within the area of interest and the benefit of the availability of high-resolution images from Google earth. A machine learning approach using the Random Forest algorithm for classification, leveraging the object-based approach was implemented.

This is a supervised machine learning algorithm used for classification tasks. Random Forest classification is a powerful and widely used approach for land use classification in remote sensing studies due to its stability, performance, and flexibility. It works by constructing a multitude of decision trees during training and outputs the mode of the classes or mean prediction of the individual trees. Each decision tree in the Random Forest is trained on a random subset of the training data, and during classification, the final prediction is determined by aggregating the predictions of all individual trees. By leveraging the strengths of Random Forest, this study aims to accurately classify land use types from SAR imagery, contributing to a better understanding of the study area's land cover dynamics.

4.4.4 Model Parameters.

Parameters such as the number of trees in the forest, maximum depth of the trees, and minimum number of samples required to split a node can impact the performance of the Random Forest classifier and should be carefully tuned.

4.4.4.1 TRAINING SAMPLES.

Training Data. The accuracy of the classification results depends on the quality and representativeness of the training data used to train the Random Forest model. Digitizing training samples for supervised classification is a crucial step in preparing data for land cover classification. FIGURE 4.10 illustrates the collected training samples for different land cover

classes, showcasing the variety and distribution of samples across the study area. Visualizing the training samples helps ensure that they are representative of the different land cover types and provide a visual reference for the classification process.

By manually digitizing training samples and collecting diverse examples of each land cover class, the foundation for training a supervised classification algorithm is laid. These samples will be used to train the classifier to accurately classify land cover types across the study area, contributing to the success of the land cover classification efforts.

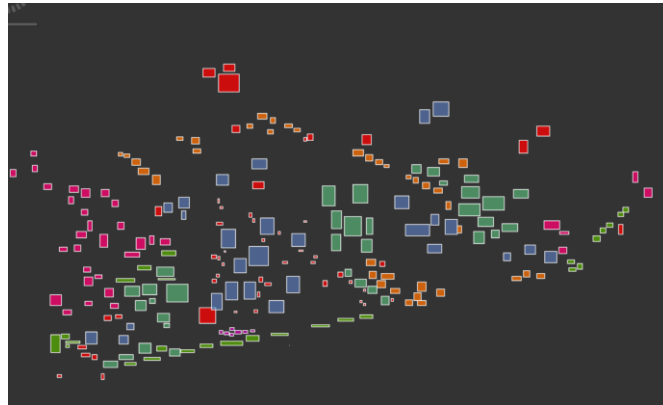


FIGURE 4.10: TRAINING SAMPLES FOR RANDOM FOREST CLASSIFIER

4.5 ACCURACY ASSESSMENT USING QGIS

This process is to validate the classification map created however it is performed in the QGIS environment. It takes the results of the classification and compares it with the ground truth (reference data) and generate the comparative results in a form of error matrix or confusion matrix. This process involves validating the classification map created in the SNAP environment by comparing it with ground truth or reference data created in QGIS. An overview of the validation process is outlined below:

Classification Map Creation. In the SNAP a classification map is generated using a classification algorithm such as supervised or unsupervised classification. This map categorizes different land cover or land use classes within the study area based on the input data and classification algorithm.

Ground Truth Data Collection. Ground truth data, also known as reference data, is collected through field surveys, high-resolution imagery, or existing datasets. Ground truth data typically include information about the actual land cover or land use classes present in the study area.

Comparative Analysis. The classification map created in is compared with the ground truth data. This comparison involves assessing the accuracy of the classification map by determining the agreement or disagreement between the classified classes and the ground truth classes.

Confusion Matrix. The results of the comparison are typically summarized in an error matrix or confusion matrix. These matrices provide a quantitative assessment of the classification accuracy by showing the frequency of correct and incorrect classifications for each land cover or land use class. It tabulates the classification results in rows and columns, with each cell indicating the number of pixels classified correctly or incorrectly for a particular class.

It further summarizes the classification results by comparing the classified classes with the ground truth classes. It provides information about the agreement between the classification map and the ground truth data.

Evaluation Metrics. Various evaluation metrics can be calculated from the confusion matrix to assess the accuracy of the classification map. These metrics may include overall accuracy, producer's accuracy, consumer's accuracy and kappa coefficient.

By comparing the classification map with ground truth data and generating confusion matrix, the accuracy of the classification results can be evaluated and identify areas for improvement in the classification process. This validation step is essential for ensuring the reliability and validity of the classified land cover or land use information derived from remote sensing data.

5 RESULTS AND DISCUSSION

5.1 LAND COVER CLASSIFICATION

5.1.1 Input Products:

Three different sets of input products were used for classification, those are shown in Table

TABLE 5.1: TYPES OF INPUTS USED FOR CLASSIFICATION

No	Input
1.	Sigma-0 bands
2.	PCA features
3.	GLCM textures

Sigma-0 bands generated two sets for each polarization, ie. Sigma-0 VV for March and Sigma-0 VV for August as well as Sigma-0 VH for March and Sigma-0 VH for August images. Only the Sigma-0_VV product from the March image and the Sigma0_VH product from the August image were considered for classification, this is done to avoid errors related to multiple input products.

Based on this information, training samples were collected from the processed SNAP raster image using eight vector data containers for each of the classes. Ten samples were collected for each of the eight classes for the classifier, which amounts to a total of eighty training sample diagonals. The number of trees chosen was 100 for the 5000 randomly selected pixels for iterated process in SNAP. The evaluate classifier box was checked during the classification process so that the process outputs the evaluation results.

Each set of input products provides different information about the spectral and textural characteristics of the land cover classes, enhancing the classifier's ability to differentiate between them.

5.1.2 Creation of Classified Product

After the classification process was completed, a new product was generated containing a band called 'Labeled_Classes' This band represents the results of the classification, with each pixel assigned to one of the training classes based on the classification decision made by the Random Forest algorithm.

FIGURE 5.1 illustrates the product of classification, showing the pixels assigned to different

land cover classes with default colour assignment. Visualizing the classified product helps to assess the accuracy and effectiveness of the classification results and provides insights into the spatial distribution of different land cover types across the study area.

By applying Random Forest classification to the selected input products, we have generated a classified product that delineates different land cover classes in the study area. This output will serve as a valuable resource for further analysis and interpretation of land cover dynamics and changes over time.

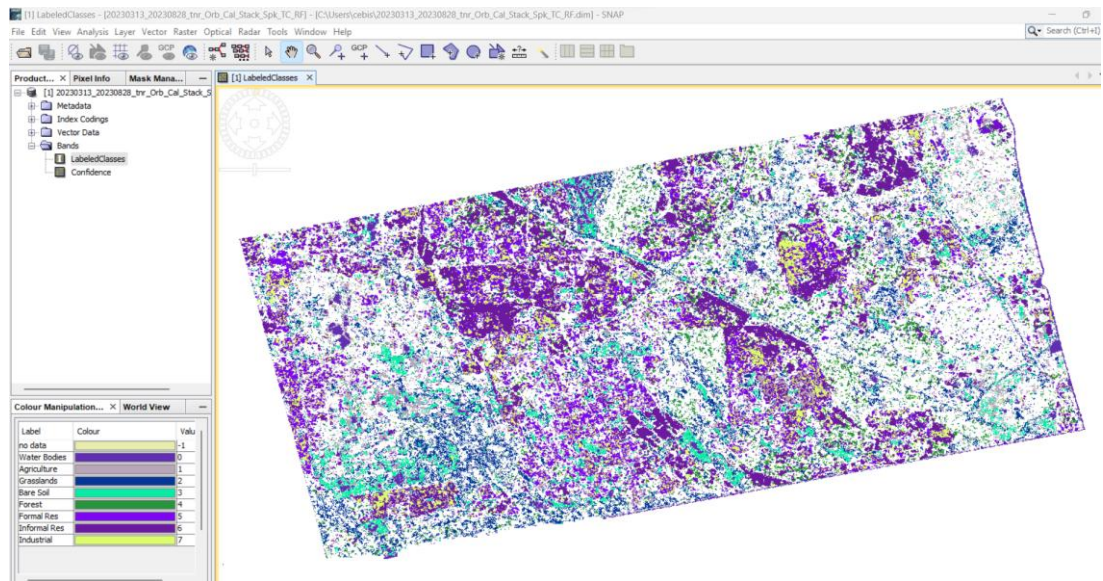


FIGURE 5.1: SNAP MAP AFTER RANDOM FOREST CLASSIFIER WITH DEFAULT COLOUR CODES

5.2 IMAGE CLASSIFICATION

Based on assistance from Google satellite imagery, the land was categorized into eight different classes as listed in **Error! Reference source not found..**

TABLE 5.2: DIFFERENT LAND COVER CLASSES WITHIN THE AREA OF INTEREST

No	Abbr.	Land cover class
1	AL	Agricultural lands
2	GL	Grass lands
3	BS	Bare soil
4	Fo	Forests
5	FS	Formal settlements
6	IS	Informal settlements
7	IA	Industrial Areas
8	WB	Water Bodies

By following these steps and configuring the classification parameters appropriately, a robust and systematic approach to land cover classification is ensured. The inclusion of evaluation metrics will provide valuable insights into the accuracy and reliability of the classification results, enabling one to assess the effectiveness of the classification process and make any necessary adjustments if needed. The colour manipulation of the map was applied to get the colours that make sense to each of the land cover classes such as in figure 5.2



FIGURE 5.2: CLASSIFICATION MAP WITH COLOUR MANIPULATION APPLIED IN SNAP

5.3 VALIDATING THE TRAINING ACCURACY WITHIN THE SNAP ENVIRONMENT

Random Forest is known for its robustness, scalability, and ability to handle high-dimensional data with complex relationships between features. It also provides measures of variable importance, which can be useful for understanding the most influential features for classification.

By selecting the 'evaluate classifier' option, we obtained information on the performance of the Random Forest classifier in classifying the training data. This analysis aids in understanding the effectiveness of the classifier in accurately categorizing the training samples according to their respective land cover classes.

It's worth emphasizing that while this process offers valuable insights into the accuracy of the training data classification, it does not validate the accuracy of the entire prediction. This distinction is crucial for interpreting the results accurately and understanding the limitations of the validation process.

Error! Reference source not found. is auto-generated in SNAP by selecting the “evaluate classifier” option giving the different measures of effectiveness which are given in percentages for all land cover classes.

TABLE 5.3: VALIDATION OF THE TRAINING ACCURACY

Metrics	AL	BS	For	FS	GL	IA	IS	WB	# of Pixels
Accuracy	94.4 %	98.1%	96.5%	93.1%	95.3%	94.1%	95.27%	99.3%	
Precision	80.4%	90.9%	89.2%	70.1%	77.6%	80.6%	89.11%	98.4%	
Correlation	76.5%	92.2%	85.2%	74.3%	81.7%	75.2%	79.1%	94.5%	
Error Rate	5.6%	1.87%	3.46%	6.92%	4.75 %	5.86 %	4.73 %	0.72 %	
True positives	477	597	526	523	564	460	458	308	3913
False positives	116	60	64	224	163	111	56	5	799
True negatives	3971	4027	4023	3863	3924	3976	4031	4370	32185
False negatives	148	28	99	102	61	165	167	29	799

A mask manager field within the SNAP environment is utilized to identify which pixels satisfy which specific conditions, facilitating the calculation of accuracy metrics necessary for evaluating the classifier's performance.

Although there are eight different classes in this land cover map, our focus is on the column highlighted in green in **Error! Reference source not found.**, representing informal settlement cover. **Error! Reference source not found.** reveals that the Random Forest classification training model predicted informal settlements with an accuracy rate of 95.27%, with a precision of 89.11%, a correlation of 79.4%, and an error rate of 4.73%.

Specifically, the model correctly classified 458 pixels as informal settlements and accurately identified 4031 pixels as not informal settlements. However, it misclassified 56 pixels as informal settlements when they belonged to a different class, and 167 pixels were erroneously labelled as a different land cover despite being assigned as informal settlements by the model.

The discrepancy in pixel assignment arises from certain areas having mixed categories during classification. This issue becomes evident as tiles with mixed categories of land cover are classified, leading to confusion in pixel assignment and ultimately reducing accuracy.

5.4 TRAINING AND TESTING DATA

Training data serves as the reference dataset used to teach the classification algorithm how to differentiate between different land cover classes. These samples provide examples of each land cover class to the classifier, enabling it to learn the characteristics and spectral signatures associated with each class.

To capture the variability within each land cover class, samples in different forms or subtypes of the same class were collected. For example, a forested area may include samples of shrubs, dense forest, and areas with different tree types, ensuring that the classifier can accurately distinguish between these variations, employ manual digitization of training samples.

Manual digitization involves visually identifying and delineating polygons or areas on the imagery that represent distinct land cover classes. For this study, training samples were collected by manually digitizing vectors for each of the eight land cover classes across the entire area of interest. It's important to ensure that training samples are representative of the variability within each class and are collected from diverse locations within the study area, employ visualization of training samples.

5.5 APPLICATION OF QGIS FOR ACCURACY ASSESSMENT

While obtaining the results of the classification model is important, the crucial question remains: How reliable are the maps generated by the model, and can they be used with confidence for decision-making? Before releasing maps for usability, it's essential to validate the accuracy of the classifier's results.

To assess classification accuracy, several metrics are required, including the total number of pixels, true positives & negatives, false positives& negatives. These metrics provide insight into the performance of the model. To validate the classification results, the accuracy assessment method in QGIS software was employed. Initially, the ground reference data was generated within the region of interest by delineating vector polygons corresponding to each of the eight land cover classes discussed earlier. Utilizing the Google hybrid function, five samples for each land cover class were created as a minimum within my ROI. With the ground reference data established, the classification map generated in SNAP software was imported into the QGIS environment. Subsequently, we utilized the Semi-Automatic Classification Plugin (SCP) in QGIS to compare the classification SNAP raster map with the ground reference data. This process allowed for a comprehensive evaluation of the classification accuracy, ensuring alignment between the classified map and the ground truth data established through delineation.

5.5.1 Outcome of the accuracy assessment

5.5.1.1 CONFUSION MATRIX

The classification accuracy assessment utilized shape-files created for each of the classes using independent high-resolution images from Google maps as reference data. Considering a total number of pixels within the map, overall accuracy and kappa coefficient were calculated using formula in $k_{hat} = Obs - exp1 - exp$ Equation 5.1. During classification, certain pixels were not assigned to any class by the model due to the fact that the pixel has statistical value which does not match any of the training data. As a result, these pixels are regarded as 'no data' pixels and they amount to 7480 pixels. **Error! Reference source not found.** and **Error! Reference source not found.** give the similar results, except that the former includes the "no data" pixels in the calculation while the latter excludes the no data pixels in the calculation hence the slight difference in pixel numbers between the two tables.

5.5.1.2 CLASSIFICATION ACCURACY ASSESSMENT

Tables for Accuracy Assessment

Reference Data

Shape-files were created for each land cover class using high-resolution images from Google Maps as reference data. This independent reference data is used to validate the classified map generated by the Random Forest classifier.

Accuracy Metrics

Overall Accuracy: Measures the proportion of correctly classified pixels to the total number of pixels. Kappa Coefficient: A statistical measure that compares the observed accuracy with the expected accuracy, taking into account the possibility of agreement occurring by chance.

Calculation Formula

The formula used for calculating overall accuracy and kappa coefficient is based on standard methods for accuracy assessment in remote sensing.

TABLE 5.4: CONFUSION MATRIX (WITH “NO-DATA” PIXELS TAKEN INTO ACCOUNT)

				Ground-Truth								TOTAL	CA (%)
			(-1)	0	1	2	3	4	5	6	7		
	ND	WB	AL	GL	BS	FO	FS	IS	IA				
Classification	-1	ND	0	0	2032	1360	756	819	762	1512	239	7480	0
	0	WB	0	0	427	1	28	0	0	0	3	459	0
	1	AL	0	0	3475	34	78	8	370	194	581	4740	73.31
	2	GL	0	0	46	2060	101	54	0	37	3	2301	89.52
	3	BS	0	0	210	59	3135	0	0	0	0	3404	92.09
	4	FO	0	0	23	25	0	1627	21	380	9	2085	78.03
	5	FS	0	0	19	0	8	1	5823	439	1315	7605	76.56
	6	IS	0	0	34	2	13	18	289	22546	1639	24541	91.87
	7	IA	0	0	1	3	0	26	1003	1272	4923	7228	68.11
TOTAL			0	0	6267	3544	4119	2553	8268	26380	8712	43589	
PA (%)			0	55.44	58.12	76.11	63.72	70.42	85.46	56.50			
Total # Pixels												59843	
Overall Accuracy													72.83%

TABLE 5.5: CONFUSION MATRIX (WITH THE 'NO-DATA' PIXELS NOT TAKEN INTO ACCOUNT)

		Ground-Truth										
		0	1	2	3	4	5	6	7	TOTAL	CA (%)	
		WB	AL	GL	BS	FO	FS	IS	IA			
Classification	0	WB	0	427	1	28	0	0	0	3	459	0
	1	AL	0	3475	34	78	8	370	194	581	4740	73.31
	2	GL	0	46	2060	101	54	0	37	3	2301	89.52
	3	BS	0	210	59	3135	0	0	0	0	3404	92.09
	4	FO	0	23	25	0	1627	21	380	9	2085	78.03
	5	FS	0	19	0	8	1	5823	439	1315	7605	76.56
	6	IS	0	34	2	13	18	289	22546	1639	24541	91.87
	7	IA	0	1	3	0	26	1003	1272	4923	7228	68.11
TOTAL			0	4235	2184	3363	1734	7506	24868	8473	43589	
PA (%)			0	82.0	94.32	93.22	93.8	77.57	90.66	58.10		
Total # Pixels											52363	
Overall Accuracy												83.24%

5.5.2 Discussion of the error matrix

As summarized in **TABLE**, the overall performance of the classification and accuracy assessment is presented. Notably, confusion arose between the covers of formal settlements and industrial areas, as well as between informal settlements and industrial areas. Additionally, some grass patches within formal and informal areas were misclassified as grasslands, contributing to confusion in the results.

Furthermore, agricultural plantations located within formal areas were erroneously assigned to agricultural land instead of formal areas, leading to further confusion in classification.

The confusion matrix yields several effectiveness measures, including producer's accuracy, consumer's accuracy, and overall accuracy.

Producer's accuracy serves as a quality measure of omission error, which occurs when a pixel is not classified as belonging to its actual class. This metric indicates how accurately the classification represents the perspective of the map producer. It is calculated by dividing the diagonal value (number of correctly classified pixels) by the column total.

On the other hand, consumer's accuracy serves as a quality measure of commission error, which occurs when a pixel is classified as belonging to a class it actually does not belong to. This metric reflects the accuracy of identifying pixels from the perspective of the map user. It is calculated by dividing the number of correctly identified pixels by the total number of pixels claimed to be in that class from the classification.

Additionally, the kappa coefficient serves as another important variable in determining confidence in the classified map. It measures the agreement between two maps, considering all elements of the error matrix. Derived from the error matrix, the kappa coefficient provides a comprehensive assessment of classification accuracy, accounting for both commission and omission errors. It is defined in terms of the confusion matrix as given by the **Error! Reference source not found.** below.

$$k_{hat} = \frac{Obs-exp}{1-exp} \quad \text{EQUATION 5.1}$$

Where 'obs' represents the results that are observed correctly, it represents accuracy reported in the confusion matrix (overall accuracy).

Next is 'exp' which represents the results that are expected to be correct, it represents the correct classification.

5.6 CALCULATION OF EQUATION 1 VARIABLES (USE TABLE 5.4)

5.6.1 Calculation of variable 'obs'

GT is short for the grand total, it is the sum of rows and column = 52363

TC is short for the total correct, it is the sum of the diagonal cells = 43589

$$obs = \frac{GT_1}{TC_1} = \frac{43589}{52363} = 0.8324 . \quad \text{EQUATION 5.2}$$

5.6.2 Calculation of Expected correct (Use Table 5.6)

To calculate the variable "exp" as found in **Error! Reference source not found.**, a matrix similar to **Error! Reference source not found.** and **Error! Reference source not found.** needs to be generated. The confusion matrix does help in understanding the performance of the classification model by comparing the predicted classes with the actual classes from the reference data. The confusion matrix of Table 5.6 includes all combinations of actual and predicted classes, with each cell containing the product of the corresponding row and column totals from **Error! Reference source not found.** to work out the entries of this matrix, we take the entries of **Error! Reference source not found.** and calculate the products of rows and columns for each entry in the matrix. For an example the value for first entry in the matrix is equal to the product of column 1 total multiplied by row 1 total (6267x7480 = 46877160), second entry is equal to the product of column 1 total multiplied by row 2 total (6267 x 459 = 2876553), and so we proceed with the rest of the matrix entries using **Error! Reference source not found.**

By generating and analysing this confusion matrix, we can better understand the model's

strengths and weaknesses, allowing for more accurate land cover classification and identification of potential areas for improvement.

Similar to $obs = GT_1 \div TC_1 = 4358952363 = 0.8324$. Equation 5.2

$$GT_2 = 3133559009$$

$$TC_2 = 830444461$$

$$exp = \frac{TC_2}{GT_2} = \frac{830444461}{3133559009} = 0.265 \quad \text{EQUATION 5.3}$$

TABLE 5.6: ERROR MATRIX FOR PRODUCTS OF ROWS AND COLUMNS

				Ground-Truth							
				0	1	2	3	4	5	6	7
			ND	WB	AL	GL	BS	FO	FS	IS	IA
		ND	ND	ND	46877160	26509120	30810120	19096440	61844640	197322400	65165760
Classification	0	WB	ND	140	2876553	1626696	1890621	1171827	3795012	12108420	3998808
	1	AL	ND	ND	29705560	16798560	19524060	12101220	39190320	125041200	41294880
	2	GL	ND	ND	14420367	8154724	9477819	5874453	19024668	60700380	20046312
	3	BS	ND	ND	21332868	12063776	14021056	8690412	28144272	89797520	29655648
	4	FO	ND	ND	13066695	7389240	8588115	5322985	17238780	55002300	18164520
	5	FS	ND	ND	47660535	26952120	31324995	19415565	62878120	200619900	66254760
	6	IS	ND	ND	153798447	86973304	101084379	62653173	202904988	647391560	213801192
	7	IA	ND	ND	45297876	25616032	29772132	18453084	59761104	190674640	62970316

5.6.3 Kappa co-efficient calculation

The results demonstrate that the accuracy of classified images achieved an overall accuracy of 72.83% as shown in **Error! Reference source not found.**, with a kappa coefficient of 0.63. These values were obtained when samples with no data were considered in the calculation.

$$k_{hat1} = \frac{obs-exp}{1-exp} = \frac{0.7284-0.265}{1-0.265} = 0.63 \quad \text{EQUATION 5.4}$$

However, upon excluding pixels with no data from the calculation of effectiveness measures, there was a notable improvement in overall accuracy, which increased to 83.24%, accompanied by a kappa coefficient of 0.77, as seen in **Error! Reference source not found.**

These results indicate that the classification output achieved quite good results, which can be utilized with a high level of confidence. The outcomes of accuracy metrics underscore the reliability and usability of the classified map for decision-making purposes whether or not we include the “no data” pixels in the calculations.

5.7 CREATION OF LAND COVER MAPS

After all the processes have been performed, a classification map of the area of interest was generated. This map in FIGURE 5.3 shows the position and location of each land cover class and provides the colour legend. It also indicates where the true north is, as indicated by the arrow in the map. The map further gives the indication of the size of the area as the scale is also provided.

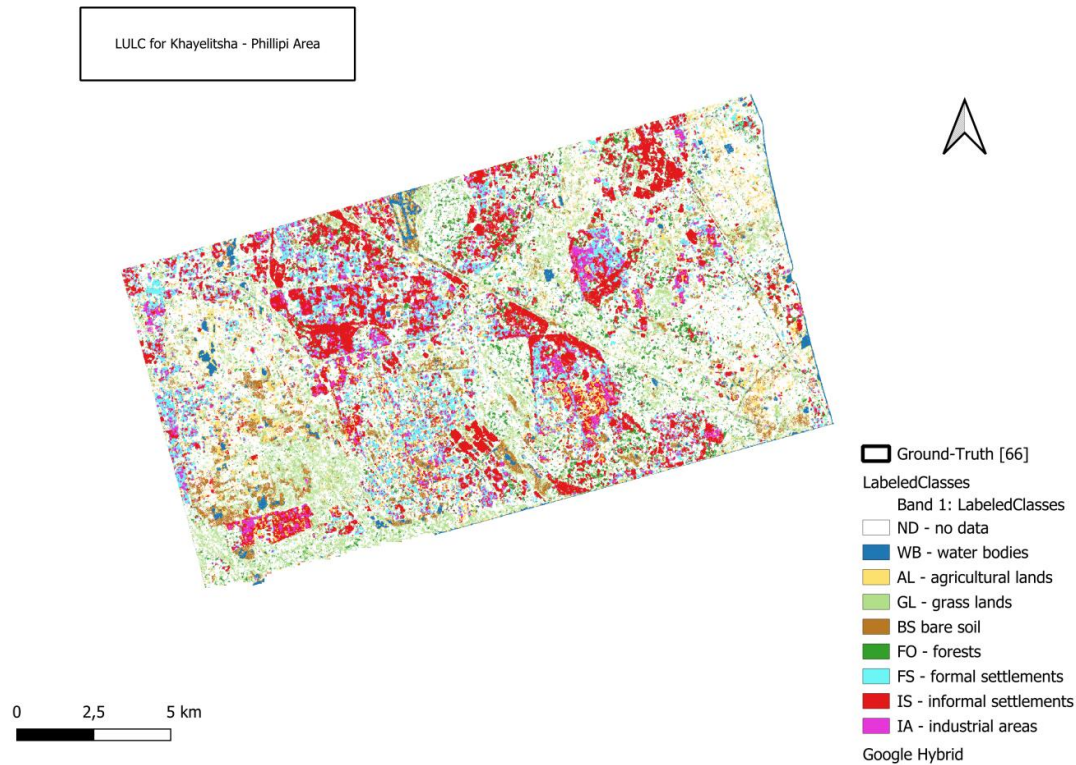


FIGURE 5.3: CLASSIFICATION MAP FOR AREA OF INTEREST CREATED IN QGIS

6 CONCLUSION

This study aims to detect, classify, and locate informal settlements in a megacity using remote sensing technology. The research focuses on the Cape Flats, specifically the Khayelitsha-Mitchell's Plain region within the City of Cape Town, Western Cape Province, South Africa. It utilizes radar data and high-resolution images sourced from Google Earth to develop a detailed land use/land cover (LULC) map for the area.

Acknowledging the permanence of informal settlements, this dissertation emphasizes the need to integrate them into society and improve living conditions. Rather than turning a blind eye to their existence, officials and stakeholders must find ways to address the challenges faced by inhabitants and work towards inclusive and equitable urban development.

The study employs the Random Forest classification algorithm as the primary machine learning technique for data analysis and classification. Image downloading and processing are conducted using the Sentinel Application Platform (SNAP) software, enabling effective integration and manipulation of remote sensing data.

The findings of this study demonstrate that its objectives were successfully achieved. The study effectively detected, classified, and located informal settlements in the Khayelitsha region. The resulting data provides valuable insights into the presence and precise locations of informal settlements, which can support informed decision-making processes.

Additionally, radar remote sensing was successfully utilized, leveraging the spectral and spatial characteristics of the data to achieve accurate results. This highlights the potential of remote sensing technology as a powerful tool for urban planning and management in complex and rapidly changing environments.

By exploring the themes discussed within the study, this dissertation provides valuable insights into the complex dynamics of informal settlements and underscores the importance of addressing their challenges in the context of urbanization and sustainable development. It calls for proactive measures to integrate informal settlements into broader urban planning frameworks and improve the quality of life for their inhabitants.

The accuracy assessment process evaluates the performance of a classification algorithm by comparing the classified map to reference data. During the classification process, some pixels may not be assigned to any land class by the classifier; these are referred to as no-data pixels. By analysing the accuracy both with and without these no-data pixels in separate tables, one

can assess how these unclassified pixels impact the overall accuracy and the kappa coefficient. This dual analysis offers a deeper understanding of the classification performance and underscores the significance of addressing no-data pixels in remote sensing analysis.

Random Forest was selected for its superior stability in accurately allocating pixels to the appropriate land use class compared to other classification methods. This algorithm has consistently demonstrated strong performance across various remote sensing applications, particularly in land cover classification. Its ability to handle both categorical and continuous input variables makes it highly adaptable to diverse datasets. Additionally, Random Forest is less prone to overfitting than many other classification algorithms, making it well-suited for managing noisy or complex data effectively.

The area of interest contains a total of 59,843 pixels, of which 37,696 pixels were used for the training dataset, as shown in Table 4. The remaining 22,147 pixels were reserved for testing the classifier. In this study, a 'per-pixel' basis calculation was employed, despite its limitations. This approach may not be the most accurate due to potential issues with the precise location of individual pixels.

Overall accuracy, calculated by dividing the sum of correctly classified pixels (the diagonal of the confusion matrix) by the total number of pixels, provides a general measure of classification performance. However, it represents only an average value across all classes and does not indicate whether classification errors are evenly distributed or concentrated within specific classes.

In this study, the consumer accuracy and producer accuracy for informal settlements were observed to be 91.87% and 85.47%, respectively, demonstrating satisfactory results for this class of interest. These metrics provide valuable insights into the classification performance for individual classes, which is essential for assessing the reliability and usability of the classified map.

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