

Masters Program in **Geospatial Technologies**



Advanced Techniques in Mapping Urban Poverty: Analysis of Slums utilizing Remote Sensing

M.Sc. Geospatial Technologies

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Advanced Techniques in Mapping Urban Poverty: Analysis of Slums utilizing Remote Sensing

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Abstract

This thesis aims to explore advanced geospatial techniques for slum identification and mapping, focusing on two case studies: Between **Nairobi** and **Rio de Janeiro**. Employing high resolution satellite imagery and **Geographical Information System (GIS)** technologies, the study adopts the Modified generic slum ontology scale to measure off urban poverty. Thus, **six parameters** were used to compare slum areas with the formal settlements, including the slope of the territory, the distance from industrial facilities, fractal dimension, roof density, the area of buildings, and the irregularity of roads' networks. The method used in the paper combines the use of **Remote Sensing, Generic Slum Ontology Framework** and **Object-Oriented Image Analysis (OOA)** to give an appreciation of the form of slums. Comparing Nairobi slum and Rio slum, research shows that there exist striking variations on topography, city expansion, and structure congestion. Slope measurements also suggested that slums in both cities are most likely sited on steep and risky slopes, which makes development of infrastructures even more challenging. Ideas such as the fractal dimension and road irregularity indicated the clustered nature of slum formation. The study concludes with a step forward in this field and substantive discussion to assist the urban planners to use these spatial findings while implementing the slum upgrading interventions towards the realization of the **sustainable development goal 11. 1.**

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KEYWORDS

Remote sensing

GIS

Fractal Dimension

Digital image processing

Generic Slum Ontology

Urban Planning

Free, open-source software

Nairobi

Rio De Janeiro

ACRONYMS

CRS – Coordinate Reference System

CSV – Comma Separated Values

DEM – Digital Elevation Model

GSO – Generic Slum Ontology

GIS – Geographic Information System

NDVI – Normalized Difference Vegetation Index

OSM – OpenStreetMap

RS – Remote Sensing

SRTM – Shuttle Radar Topography Mission

VHR – Very High Resolution (Imagery)

OOA – Object-Oriented Image Analysis

SVM – Support Vector Machine

SRS – Spatial Reference System

UN-Habitat – United Nations Human Settlements Programme

SDG – Sustainable Development Goal

1. Introduction

1.1. Motivation

Over Urbanization is one of the most significant trends of the twenty-first century. Currently, 55% of the world's population is living in urban areas and the projection for the year 2050 is 68 percent (UN 2018). This paper aims at discussing the effect of urbanization as a social process that is regarded as the driving force of economic development resulting in the enhancement of living standards, yet bearing social shifts, mostly in the developing world. One of the challenges which are evident is the problem of increase in slum areas which are real signs of poverty in the urban areas. According to the United Nations, slums lack fundamental amenities in the house and the surrounding environment including potable water and sanitation, as well as security of tenure (UN-Habitat, 2020). These settlements are usually highly populated with dwellers struggling to adequate living spaces thereby raising their risk points on different socio-economic as well as health parameters.

The factors that foster the growth of slums are among the following the high rate of migration from rural areas to urban areas in the hope of looking for better-paying jobs. But this has led to a problem for these growing cities where their infrastructures cannot expand to accommodate these people or provide the necessary services which leads to squatter areas. Thus, this scenario poses a major challenge to the attainment of SDG 11 that focuses on fostering sustainable urban development which is inclusive and safe (UN, 2015). Specifically, SDG 11. The first one seeks to ensure access to adequate, safe and affordable housing, as well as slum upgrading by the year 2030. To meet this goal, therefore, there is need for timely, precise, usable and efficient means of identifying and tracking slum areas.

Previous methods of mapping the slum areas that involve census data, maps that have been drawn in collaboration with inhabitants of the slum areas, and the use of advanced satellite image interpretation have been deemed insufficient. These methods do not have the precision

and admittance needed to respond to the diverse and dynamic character of slum settings (Kohli et al. , 2012). However, they are often flexible by nature and may be hampered by the costs and time required to perform them, and thus are not always feasible in many such instances, especially in the developing world. Therefore, there is an urgent call for new solutions that would help to get over these shortcomings and offer proper information to the legislators and urban designers.

The emerging technologies such as Geographic Information Systems (GIS), and remote sensing these days provides very viable solutions to these issues. Also, it combines Object Based Image Analysis (OBIA) with the pixel based methods which help in capturing both the spatial and spectral properties of slums to have a better perception about such urban environments (Hofmann et al ., 2008).

This research is as a result catalyzed by the necessity of using these advancements in technology to come up with a solution that is sound, expandable, and universal in addressing the issue of poverty through mapping of slums. This study therefore seeks to contribute to the ongoing efforts of enhancing living standards in the slum regions through harnessing the interdisciplinary potential of the three approaches of using GIS and remote sensing data towards meeting global urban development goals. The findings of this research may be useful to stakeholders concerned with urban planning, policy making and development; thus, assisting in the development of urban environments that are more equitable and sustainable.

1.2. Study Area

The study area encompasses two major urban centers: Brazil's Rio de Janeiro and Kenya's Nairobi are some of the cities which host an international film festival. Both the cities represent the phenomenon of Urbanization and the consequent generation of urban poor or the slums as they are called. In Rio de Janeiro GPS, favelas are mostly sited in the northern and western parts of the city occupying slopes and other inconvenient terrains which are not feasible for construction of proper structures. These areas present minimal orderly human settlement patterns, weak infrastructural developments, and subject to Strenuous Socio-economic hurdles.

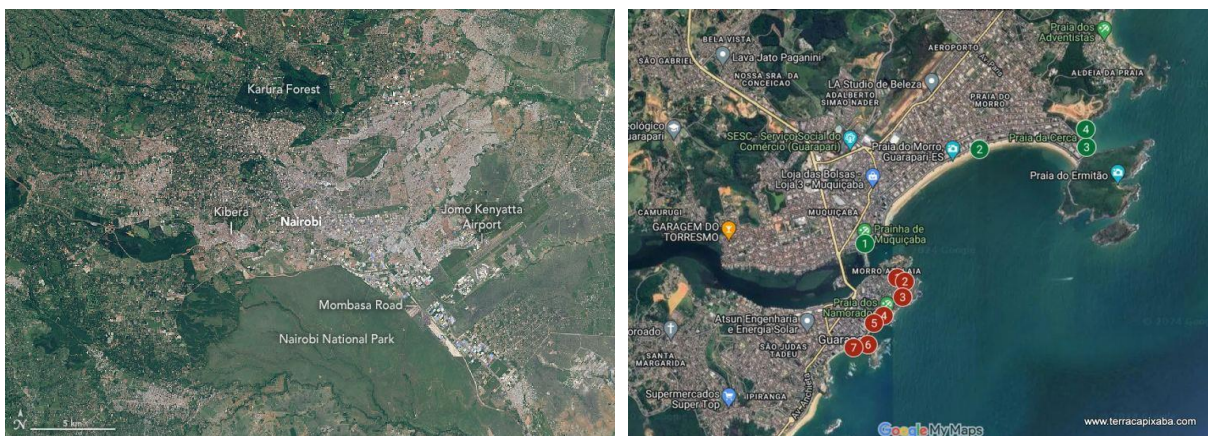


Figure 1: Aerial View Satellite images of Nairobi & Rio

However, the situation in the capital city of Kenya, Nairobi, has been different as it has since experienced growth of slums especially in the eastern and southern regions of the city. They are areas with high population density and grossly lacking in essential infrastructure like water and sanitation and electricity and they have a very high poverty rate for their inhabitants. The differences in physical and socio-economic nature and structure of slums in Rio de Janeiro and Nairobi, make them useful cases for understanding the nature of urban poverty through advanced remote sensing technologies. The choice of these cities enables the comparative analysis on how the findings of this study may apply globally and how remote sensing can perform in varied urban settings (UN-Habitat, 2020).

1.3. Data

These sources of data to be utilized in this study comprise diverse spatial datasets required for mapping and analyzing poverty in urban areas of the selected study areas. For Rio de Janeiro as well as Nairobi, Satellite data with the sensor Sentinel-2 were selected with a spatial resolution of 10m. These images were Level-2A (Bottom of Atmosphere) reflectance in order to be useful for the spatial analysis. In addition to the satellite images, SRTM DEM with 30 meters resolution was used to derive topographical information such as slopes which are vital for the identification of slum settlement. Further, the base vector datasets like the building footprint, the road network, and land use data were imported from OpenStreetMap and carefully preprocessed with an aim at fixing geometrical issues. These datasets were used to compute the GSO indicators when coming up with the physical structure of the slum in both cities. Each and all data set used was then transformed to its respective coordinate system that have each place in Nairobi being brought under WGS 84/UTM Zone 37S, while Rio de Janeiro was brought under WGS 84/UTM Zone 23S (OpenStreetMap, 2023).

2. Scope and Objective

This thesis examines the application of remote sensing and GIS technologies in mapping urban poverty and more specifically analysis of slums. It explores the integration of the Generic Slum Ontology (GSO) with free and easily accessible earth observation data improving the precision and expandability of slum identification. The study calls for the use of both pixel level and object level analysis so as to capture the varying attributes of slums at different spatial scales. As a result of these analysis, the current study will propose a strong research approach that can be utilized across the globe to assist in meeting SDG 11. 1, aimed at approaching cities to be more than merely effective places that are safe, resilient and sustainable. This work encompasses the identification and categorization of various parameters that define slums from the planned communities with an emphasis on a comparative assessment of slum regions in Rio de Janeiro, Brazil and Nairobi, Kenya.

2.1. Objectives

- Develop an advanced methodology to map urban poverty using earth observation data.
- Integrate the Generic Slum Ontology (GSO) with remote sensing and GIS technologies.
- Analyze and validate key indicators that differentiate slums from planned settlements.
- Conduct a comparative analysis of slum characteristics in Rio de Janeiro and Nairobi.
- Assess the scalability and global applicability of the developed methodology.

2.2. Research Questions

1. How accurately can GSO indicators measurable with freely available data differentiate between slums and planned settlements?
2. How do these indicators vary between slum areas in different countries, specifically comparing cities in South America and Africa?
3. Can the identified GSO indicators establish a two-way relationship between their presence and the identification of slum areas, contributing to global efforts in urban poverty mapping?

3. Related work (Literature Review)

3.1. Ontology

In this case, Ontology, borrowed from Aristotle in the domain of philosophy is a concept that relates to the study of being or existence. Ontology in the context of slum mapping is crucial for developing a structured understanding of slum characteristics. Originally a philosophical concept, ontology in information science refers to a formalized system of knowledge for specific domains (Gruber, 1993). In remote sensing, it plays a pivotal role in systematically interpreting high-resolution satellite imagery to identify slums.

Structured Knowledge: Ontology organizes domain-specific data for precise slum identification.

Three-Level Categorization: Environs, Settlement, Object – each level aids in slum detection.

Advanced Detection: Combines VHR imagery with expert knowledge for accurate slum mapping.

Improved Scalability: GSO adapts to different regions, enhancing slum identification across scales

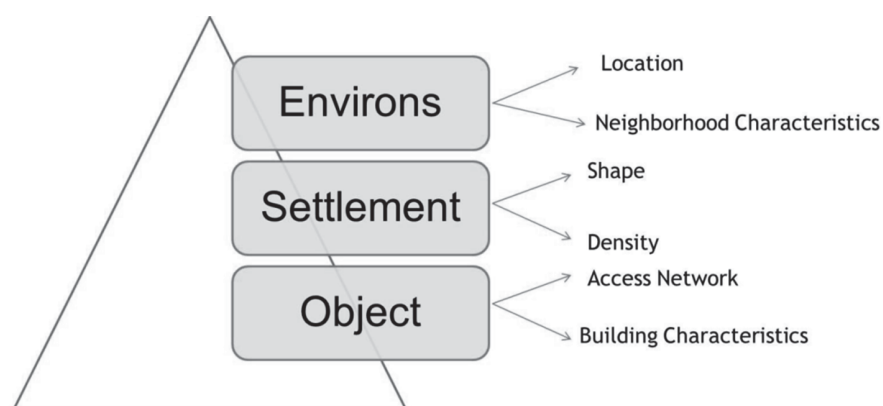


Figure 2 The six general indicators categorized to form a hierarchy to represent concepts at three spatial levels.

Generic Slum Ontology (GSO) is grounded in UN-Habitat's "durable housing"

indicator and categorizes slums into three spatial levels: environs, settlement, and object, aiding in precise slum detection (Hofmann et al., 2008). VHR imagery combined with expert knowledge enhances the GSO's accuracy, enabling slum identification across different regions.

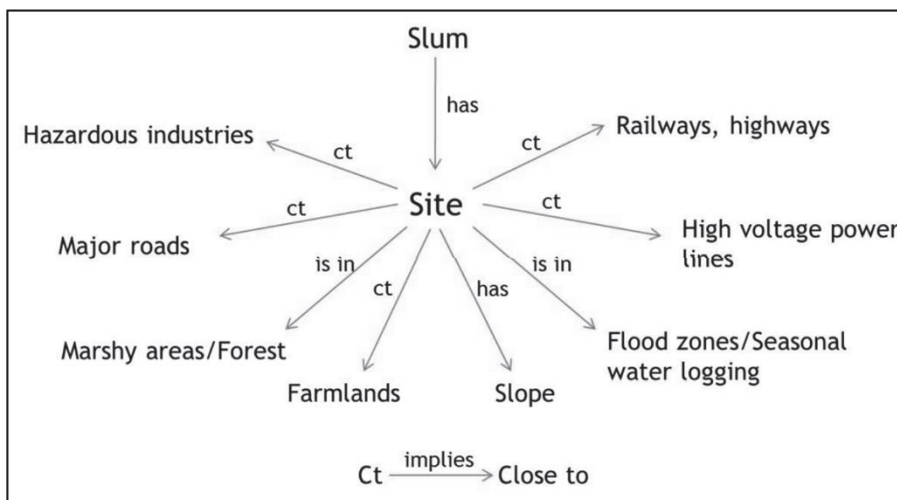


Figure 3 Diagram showing possible site conditions of a slum derived from expert survey.

The GSO framework supports scalable, regionally adaptable approaches, improving urban policymaking and interventions by providing a formal method to analyze slum morphology (Ebert et al., 2009). This structured approach is instrumental in meeting global urban development goals.

3.2. Previous Work on Slum Identification and Mapping

The identification and mapping of slums are one of the key areas for several methodologies in recent past. These methodologies can broadly be categorized into three approaches: Census based participatory and by remote sensing method.

Census-Based Approach

In census-based approach the data used is derived from national census surveys which provide information about the social civil, economic and infrastructural floor space of households. Census-based methodologies leverage national surveys to provide socio-economic and infrastructural data, spatially disaggregated to various levels (Baud et al., 2008). These datasets are useful for mapping poverty and slum areas, particularly in the developed world where spatial information on informal

settlements may not be readily available (Baud et al., 2009). However, limitations include outdated data due to infrequent surveys and challenges with data aggregation across wards of different sizes.

Participatory Approach

The participatory approach mainly entails the use of representatives from the slum itself whereby the people take an active role in mapping. Participatory mapping generally uses questionnaires, focus group discussions and other methods with the aim of getting both spatial and non-spatial information on slum regions. This method engages local communities to map informal settlements by utilizing local knowledge, often through questionnaires and focus groups. This generates highly specific data for urban planning (Hasan, 2006; Karanja, 2010). The participatory approach is, however, time-consuming and expensive, making it difficult to scale in larger urban areas.

Remote Sensing-Based Approach

The task of slum identification and mapping has been found to benefit from the use of the remote sensing (RS)-based approach. Remote sensing is a multidisciplinary scientific method of acquiring spatial data on environment / urban areas from satellite and aerial photographs. Remote sensing offers advantages in capturing large areas quickly, allowing frequent updates. Techniques have evolved from visual interpretation to Object-Oriented Image Analysis (OOA), which is more efficient in detecting slum morphology using high-resolution imagery (Mason & Fraser, 1998; Hofmann et al., 2008). OOA provides more precise slum mapping by analyzing objects (e.g., buildings) and their spatial relationships, although challenges remain with image quality and heterogeneity of slum geography.

Object-Oriented Image Analysis Methods for Slum Identification

Object-Oriented Image Analysis (OOA) enhances traditional pixel-based methods

by focusing on collections of pixels, or objects, like buildings and streets. This approach enables more accurate slum identification by analyzing objects' spectral, spatial, and textural characteristics. OOA also considers the interaction between neighboring objects, providing a contextual analysis that improves precision in urban environments. Hofmann et al. (2008) and Kuffer et al. (2014) demonstrated OOA's success in slum delineation using VHR satellite imagery. Despite its effectiveness, OOA faces challenges such as fine-tuning segmentation parameters and designing classification rules. To address these issues, advanced machine learning techniques like support vector machines (SVM) and random forests have been integrated into OOA frameworks, improving accuracy. When applied correctly, OOA offers a rich, context-aware understanding of urban spaces, facilitating more effective slum identification and urban planning.

Uncertainty Analysis for Image Interpretations of Urban Slums

Uncertainty analysis is critical in remote sensing, especially when interpreting high-resolution imagery of urban slums. Factors such as human perception, diverse slum characteristics, and architectural density contribute to ambiguities in identifying slum areas. Errors can arise in the interpretation of densely populated regions, like Kibera slums, due to variations in imagery quality and urban complexity. This analysis uses quantitative measurements and probabilities to address potential errors in slum identification, ensuring accurate urban planning decisions. Understanding these uncertainties is essential for developing reliable methodologies that minimize misclassification and improve the accuracy of slum detection in policy and urban development frameworks.

Sources of Uncertainty

Several factors contribute to uncertainty in image interpretation for slum identification:

1. **Image Resolution and Quality:** The coverage and the resolution of satellite pictures assume critical importance as regards the identification of slums. However, higher resolution photos provide finer detail about the images and this brings problems of volume of data and processing. However, high resolution pictures could produce over-simplified images of the urban area, and this leads to the wrong classification of slum areas. Further, factors such as temporal fluctuations, noise from the sensors, and other atmospheric helps also blur the images and introduce noise to the analysis.
2. **Variability in Slum Characteristics:** Slums are not homogeneous in general, and there are drastic variations with regard to infrastructural facilities, population densities, types of materials used, and spatial organization in slum areas within or between different zones of vulnerability. Such variations cause some troubles in defining which places can be considered as slumps and creating unified protocols, which further raises the rates of misunderstandings. It becomes very hard to exercise uniformity of classification approach; for instance, one may have highly populated slum in a given city while another in another city may have different spectral and morphological characteristics despite high population density.
3. **Subjectivity in Interpretation:** Human Interpretation of imagery information is a process that is subjective in nature that depends on the analyst's experience, knowledge and preconceptions. This opens up the method to subjectivity that results in inconsistencies in the identification and classification of slum areas especially when different analysts are engaged to undertake the assessment. This subjectivity, however, can still be minimized through the use of automated classification methods using OOA as only these procedures are still dependent on human input in the form of initial classification set and validation set.
4. **Temporal Changes:** Slums in urban areas are fluid and respond to different forces majoring on growth in population density, migration, and different political actions.

The temporal aspect poses a problem when using imagery from a different period as the conditions that can be observed in imagery may not be relevant for the state of the slum areas in the present days. This is especially the case with old images or when otherwise there is delay in capturing the image and analyzing it.

3.3. Approaches to Managing Uncertainty

Addressing uncertainty in slum identification involves combination of methodological approaches and validation strategies:

1. **Multi-Temporal Analysis:** For this purpose, it is possible to use multi-temporal analysis in order to explain temporal changes and reduce certain levels of uncertainty. Community monitoring – this involves the use of several images taken at different time intervals in order to review the changes of the slum areas. The analysis based on trends allows eliminating some uncertainty by revealing whether slum areas are growing or shrinking or are under some other type of change.
2. **Ensemble Classification Techniques:** Another approach is the ensemble method, herein integration of various classification algorithms, which, if applied to slum identification, reduces the impact of volatile output of a particular algorithm. If we use many classifiers, it is possible to combine their results using such approaches as majority voting, weighted averaging, or stacking to enhance the accuracy of slum area identification.
3. **Validation with Ground Truth Data:** Image based identification of slums requires ground truth data which involves either field survey or participatory mapping in the process. The errors are quantified and enumerated with results that are yielded by the satellite-derived classifications compared with the actual ground observations. This validation process assists greatly in the fine-tuning of the classification models so as to enhance sufficient accuracy levels.
4. **Uncertainty Quantification Techniques:** Three different statistical techniques

which can be used to estimate the level of variability in slum identification are Review of Literature and GIS. For example, confidence intervals, error matrices, all kinds of probability structures can be employed in order to estimate the probability of classification and in order to find out where the model fails. These techniques give the useful information regarding the reliability of the classification results for supporting decision making in the urban planning and policy. An example of sensitivity analysis includes the periodic

Sensitivity Analysis: Sensitivity analysis involves systematically varying the input parameters of the classification models to assess their impact on the results. An example of sensitivity analysis includes the periodic adjustment of the input parameters of the classification models in order to evaluate the effects of such changes on the outcome. These allow in determining which causes contribute much to uncertainty and the consequent fine-tuning of the model parameters to reduce these impacts. Sensitivity analysis is very effective in object-oriented image analysis for the segmentation parameters that can affect the identification of slum areas to a large extent.

3.4. Case Studies of Uncertainty Analysis in Slum Mapping

Regarding the measurement of slums, the methods used have also assessed the uncertainty analysis in studies several research. For example, Kuffer et al. ,(2016), made an uncertainty assessment of slum mapping in Nairobi Kenya with VHR imagery available. To reduce uncertainty in the study, the research used multi-temporal analysis and more so ensemble classification techniques. Kohli et al. (2012) performed research on slum mapping using uncertainty quantification approach wherein, the credibility of slum mapping for different benchmarks of India was estimated and it revealed the need for ground truthing for minimizing classification variability.

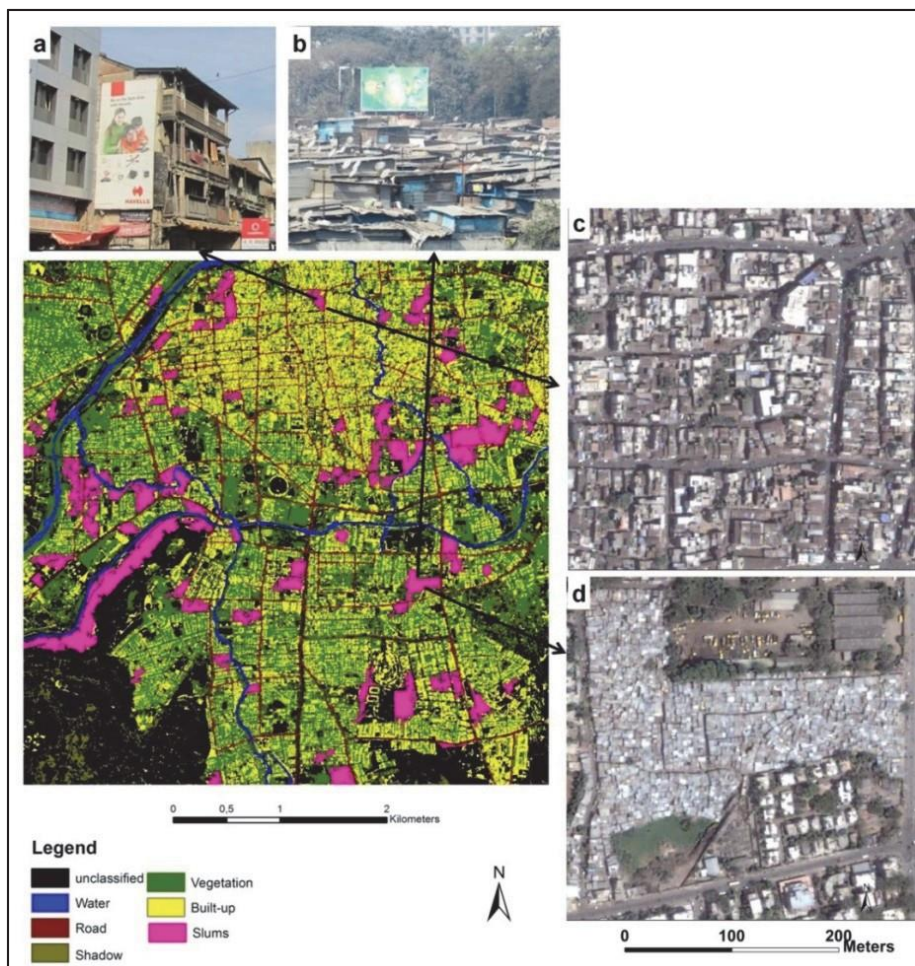


Figure 4 Final classified map of the study area with slums, ground pictures and corresponding zoomed views of image:

(a) Ground photograph of buildings in Old City. (b) Ground photograph of a typical slum settlement; (c) Magnified view of a part of Oldcity misclassified as slum on final map; (d) A typical slum settlement.

It includes identification of the different sources of uncertainty, powering techniques for uncertainty control and reduction, and checking of such results with ground truth information. Geographical systematically dealing with uncertainty, geographical researchers improve the reliability of the slum mapping studies and, consequently, increase the chance of making better decisions in these areas of urban growth and poverty reduction.

4. Methodology

The methodology section outlines the systematic approach undertaken in this research to identify and analyze the physical characteristics of slum areas in two cities, Rio de Janeiro (Brazil) and Nairobi (Kenya). This research relies on advanced satellite image data and other GIS data to analyze the relative merits of Generic Slum Ontology (GSO) indicators. The workflow is divided into three main objectives: identification of the types of data required, data collection and data cleaning process, computation of the GSO indicators and lastly comparison of the characteristics of the slum across the cities.

Methodology Overview

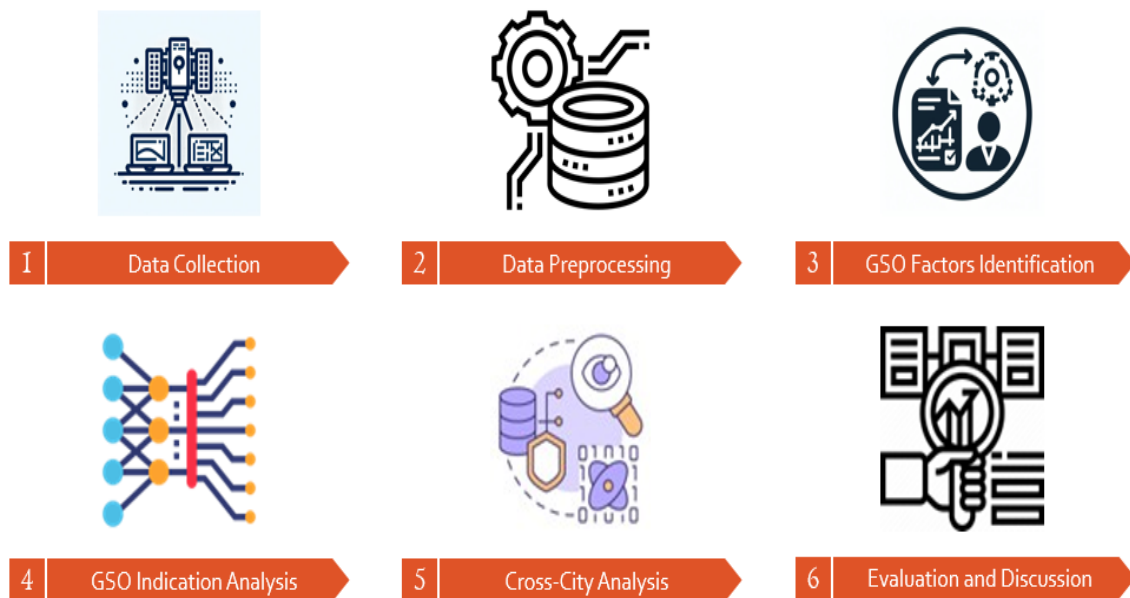


Figure 5 Pictorial Form of Methodology Overview

Methodology Workflow

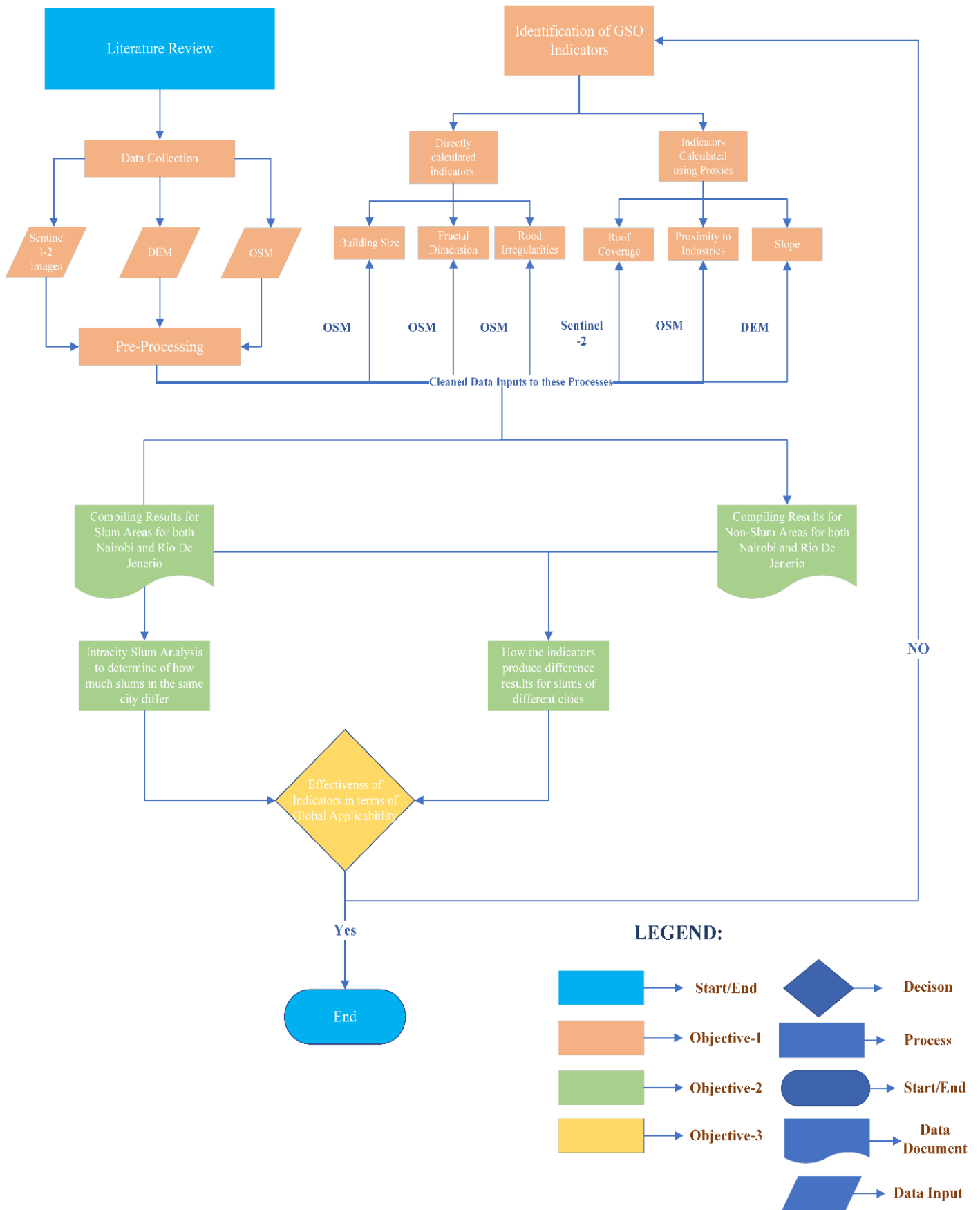


Figure 6 Flow Chart view of Methodology

4.1. Workflow Overview

The research methodology is structured into three primary phases:

1. **Data Collection and Pre-Processing:** In this phase, the required satellite imagery, DEMs will be procured and OSM observational data will also be collected. The data is then preprocessed so as to ensure that it is in the right format and resolution for further assessment.
2. **Identification and Calculation of GSO Indicators:** In this phase, specific indices which characterize a slum are defined and computed. These indicators are drawn established by direct measurement based on vector data and by indirect measurement by means of remote sensing data surrogates.
3. **Comparative Analysis:** The last stage includes the comparison of calculated indices in the framework of particular cities and the comparison of the two compared cities. The rationale for this step is to analyze the differences in the slum characteristics at different spatial scales and assess the generality of the identified indicators.

The details of each of the steps incorporated in the methodology are discussed below.

4.2. Data Collection and Pre-Processing

Study Area Selection

The study focuses on two cities with significant slum populations: Brazil and Kenya; two cities, Rio de Janeiro (rectangle coordinates (lng,lat): -43.273,-22.947 x -43.134,-22.866) and Nairobi (GPS rectangle coordinates (lng,lat): 36.744,-1.331 x 36.913,-1.225) respectively. These cities were chosen because of their different geographical, social and economic environments in order to compare properties of slums in different urban settings.

Satellite Imagery Acquisition

The primary data in this study embraced Sentinel-2 satellite imagery in a 10 m spatial resolution collected in the year 2017 in accordance with literature. This is the reason why Sentinel-2 was selected with a high spatial resolution that can help in the identification of fine features within urban areas. The images were obtained from Level 2A archive which contains images containing BOA reflectance.

Digital Elevation Model (DEM) Acquisition

Among the data sets that have been employed in this study is the Shuttle Radar Topography Mission (SRTM) DEM which yields elevation data at a thirty-meter raster resolution. The DEM was relevant for determining the other topographical attributes of the slum zones including slopes which are key aspects of slum formation and spread.

OpenStreetMap (OSM) Data

Recent geographic data was also acquired from OSM for the two study areas comprising of vector data comprising of roads, buildings, land use and other places of interest. But this data contained geometrical errors hence needed so much cleaning and correction to yield the results displayed above. Consequently, all the layers that were prepared for Nairobi were reprojected with WGS 84/UTM Zone 37S while those for Rio de Janeiro were reprojected with the same WGS 84/UTM Zone 23S.

4.3. Data Pre-Processing

Data preprocessing involved several critical steps:

1. **DEM Gap-Filling and Reprojection:** However, problems such as sinks or gaps in the SRTM DEM were also evident, particularly where there was dense vegetation or water cover. Ablations of gaps were performed using interpolation techniques in order to obtain a smooth surface in analysis of slope. The DEM was also transformed to the right spatial reference system (SRS) of the cities in question.

2. **OSM Data Cleaning:** The OSM data was checked for topological inconsistencies and entities like Place, Addr: addr and Railway were simply checked for topological errors like overlapping of features, alignments and merged features were separated. This step was important to minimize the errors in vector-based calculations for the GSO indicators.
3. **Reprojection and Resampling:** Each of these datasets was then reprojected into a common CRS and resampled to concur with the spatial resolution of the Sentinel-2 imagery acquired during the analysis. This step makes it possible to ensure all datasets have the same spatial references to allow for accurate overlay and analysis.

4.4. Identification and Calculation of GSO Indicators

The methodology's second stage is devoted to determining and computing certain indicators from the GSO framework. The physical characteristics of slums are described by these markers at different geographical dimensions, from single structures to entire neighborhoods.

GSO Indicators Selection

The Generic Slum Ontology framework categorizes slum characteristics into three spatial scales: environs, settlement, and object level. This study focuses on six primary indicators: three that can be directly calculated from **vector data (shape, building size, and access network)** and three that require the use of **physical proxies** derived from remote sensing imagery (**slope, proximity to industries, and green roof coverage**). These indicators were selected based on their relevance to slum morphology and the availability of data for their calculation.

Level	Indicator	Physical Characteristics/Matrix
Environs	Location	Slope
	Neighbourhood Characteristics	Proximities to Industries and CBD
Settlement level	Shape	Fractal Dimension
	Density	Roof Coverage
Object level	Access Network	Roads Irregularity
	Building Characteristics	Building size

Table 1 GSO Characteristics with relevant Spatial Levels

4.5. Physical Characteristics and Proxies

The selected indicators and their corresponding physical characteristics or proxies are outlined below:

1. **Slope (Environs Level):** Slope is a critical factor in slum formation, as slums are often located on steep terrains that are unsuitable for formal development. The slope was calculated from the SRTM DEM using the Zonal Statistics tool in QGIS, providing the minimum, mean, and maximum slope values for each slum area.
2. **Proximity to Industries and Socio-Economic Activities (Neighborhood Level):** Slums are typically located near areas of high socio-economic activity, such as industries or central business districts (CBDs), where employment opportunities are more abundant. Proximities were calculated by creating a 500-meter buffer around slum areas and analyzing the land-use composition within this buffer using OSM data.
3. **Shape (Settlement Level):** The shape of slum areas often reflects the constraints imposed by surrounding linear features, such as roads, railways, or rivers. Fractal Dimension was used as a measure of shape complexity, calculated by rasterizing slum polygons at varying cell sizes and applying the box-counting method. This method assesses the relationship between the box size and the count needed to cover the slum area, with higher fractal dimensions indicating more complex shapes.
4. **Roof Coverage (Settlement Level):** Roof coverage serves as a proxy for population

density and the degree of open space within slum areas. Roof coverage was calculated as the ratio of the area of green roof slum footprints to the total area of pixels within the slum boundaries with NDVI as base layer. Sentinel-2 imagery was classified using NDVI threshold to differentiate between built-up and non-built-up areas, facilitating the calculation of roof coverage.

5. **Building Size (Object Level):** Slum areas are characterized by small, densely packed buildings. The area of building footprints was calculated using OSM data, providing an estimate of building size. This indicator helps differentiate between slum and non-slum areas based on the typical size of buildings.
6. **Road Network Irregularity (Object Level):** The irregularity of road networks within slum areas was quantified by calculating the number of nodes per kilometer of roads within the slum boundaries. This indicator was derived from OSM road network data and reflects the often chaotic and unplanned nature of slum infrastructure.

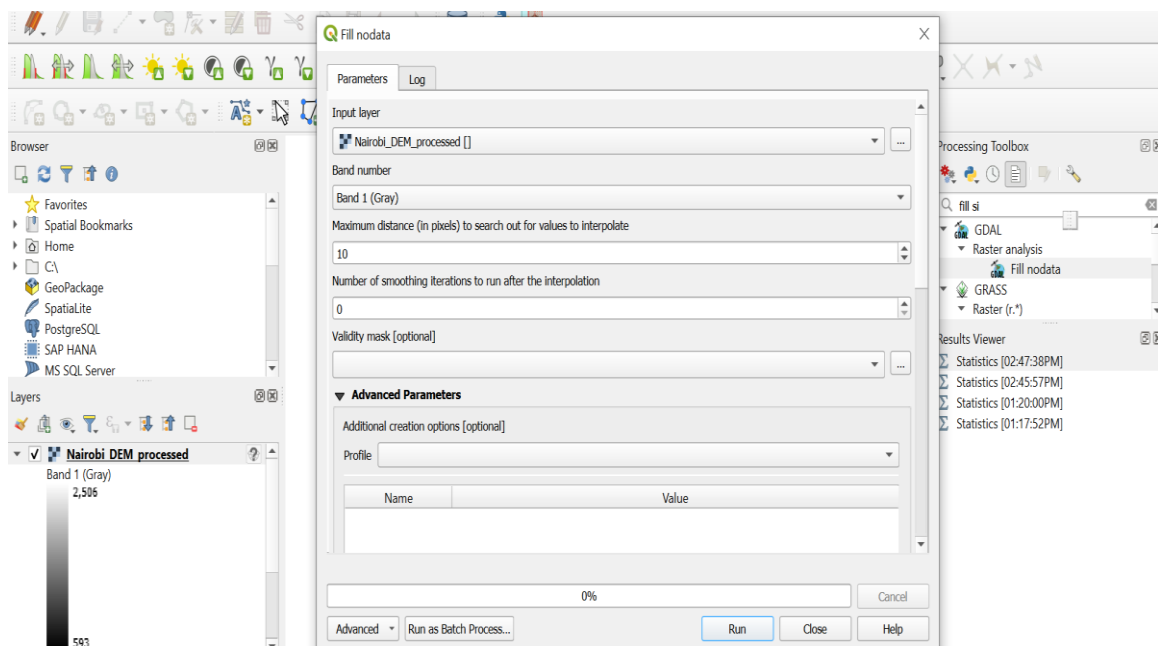
4.6. Geospatial Processes for Indicator Calculation

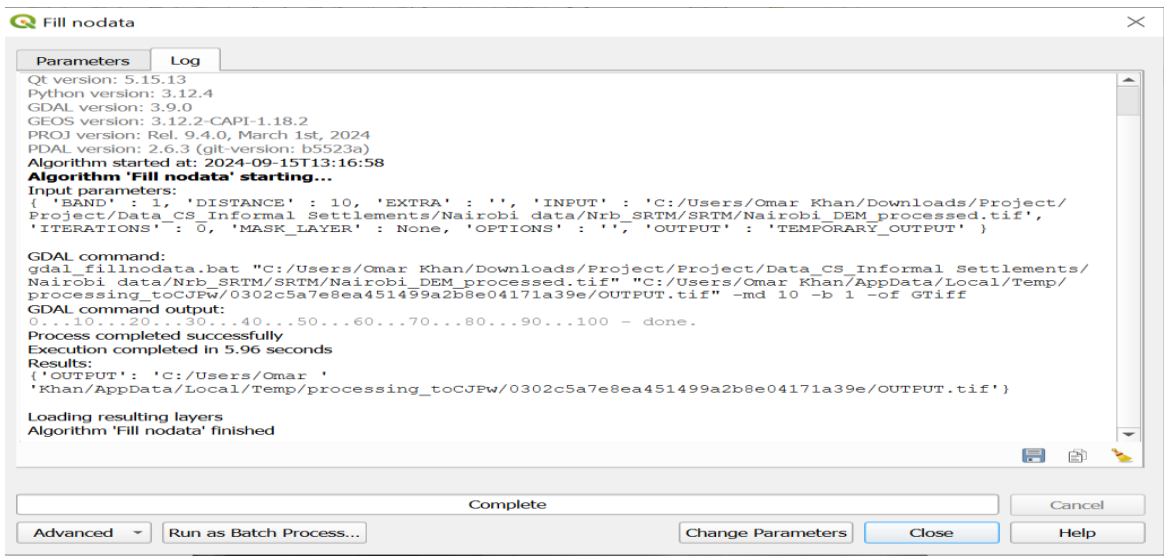
The following geospatial processes were applied with detailed screenshots (hence no mention of figure numbers on these) from the QGIS software interface have been added to highlight the detailed steps undertaken to calculate the above indicators:

- **Slope Calculation:** The calculation of the slope is pivotal in establishing the spatial dynamics of the spread of slum, more so in regions with differentiated topography, for instance Nairobi and Rio de Janeiro. This is so because slope is very influential in the general growth and development of the urban areas; areas with high slopes are considered undesirable for planned settlements hence are characterized by the informal structure. In this study, SRTM DEM data was imported into Q-GIS for both the cities and for data analysis, two main variables were incorporated into this study which include the following: The DEM derived from the raster data having a resolution of 30 meters was used to compute slope. For this purpose, the QGIS contains the built-in tool

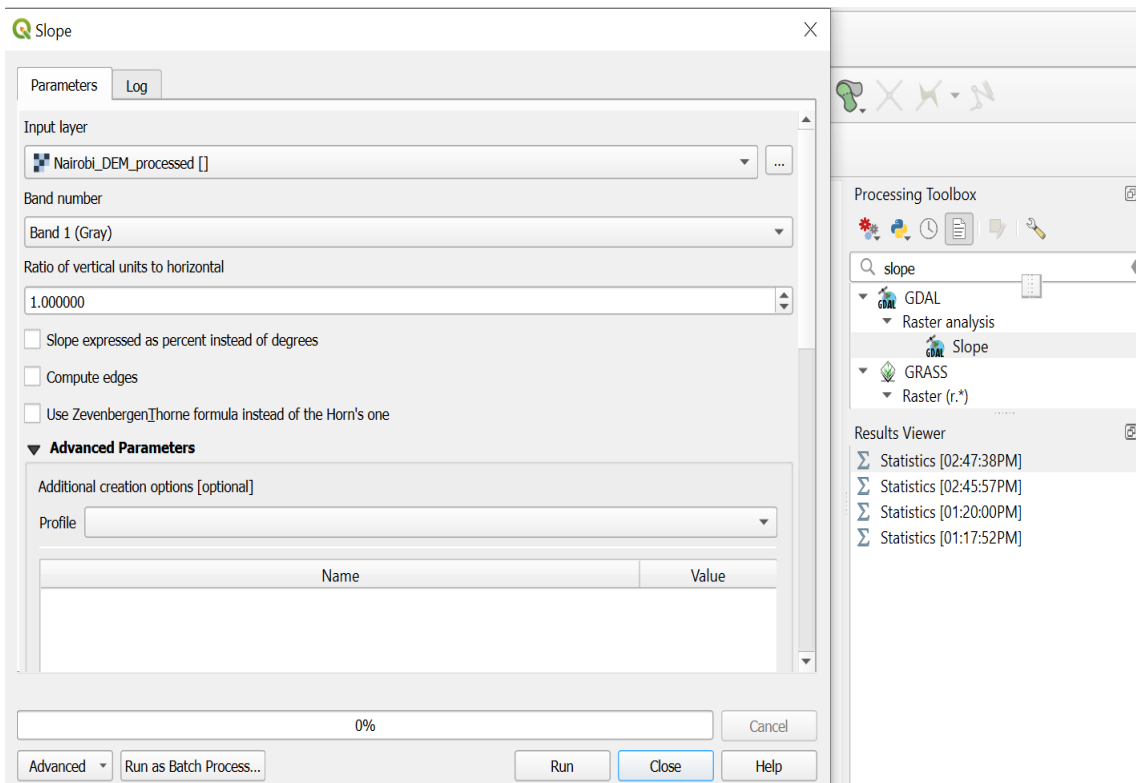
called Slope which can be accessed in Raster > Analysis > Slope which calculates the slope degree for each pixel. This process created the slope raster presenting the gradients within the city, thus indicating areas of largely elevated steepness. Symbology was used in slope raster to differentiate between low, medium and high slopes with a sharp focus on steep slopes represented in red. So as to assess slum areas with regards to slope, the boundary shapefiles of the slum study areas were superimposed on the slope layer. The mean slope for slum and residential area was calculated using the Zonal Statistics tool of the QGIS software which would help in comparing both the scenarios. The findings provided knowledge regarding the influence of slope to slum growth, where slums are usually built on hazard prone steep slopes, which make it difficult to establish infrastructures and environment people live.

- **Fill No-Data:** Use QGIS's built-in Slope tool. For that firstly the DEM has to be pre-processed to have no gaps and empty data.

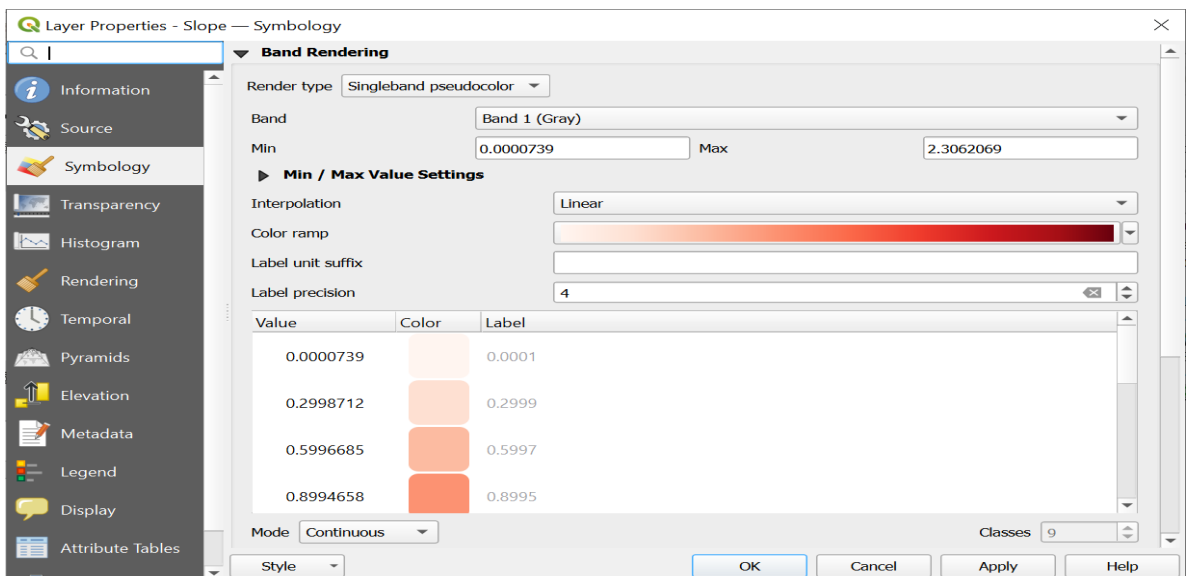




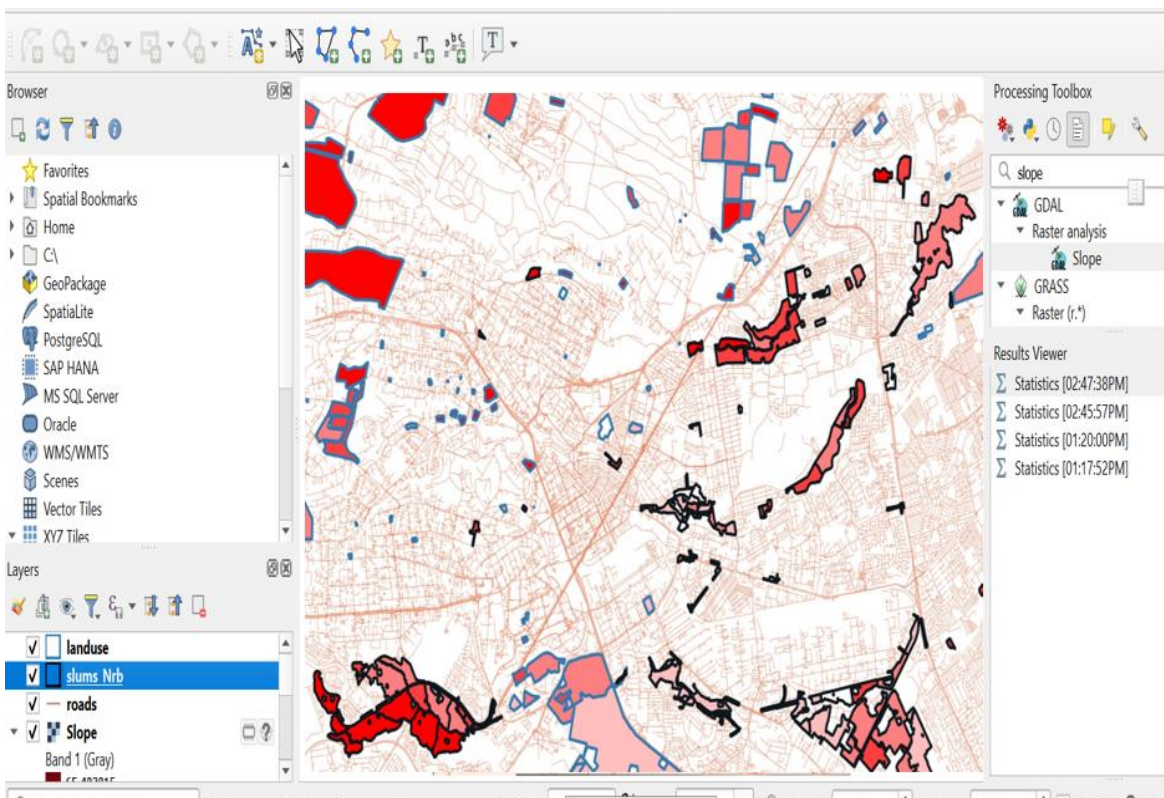
- **Slope Analysis Tool:** Navigate to Raster > Analysis > Slope, selecting the DEM as the input layer. This will compute the slope for each pixel.



- **Symbology Setup:** Apply color symbology to distinguish between slope levels. Steeper areas can be marked in red to visualize risks of landslides, especially in slum areas.



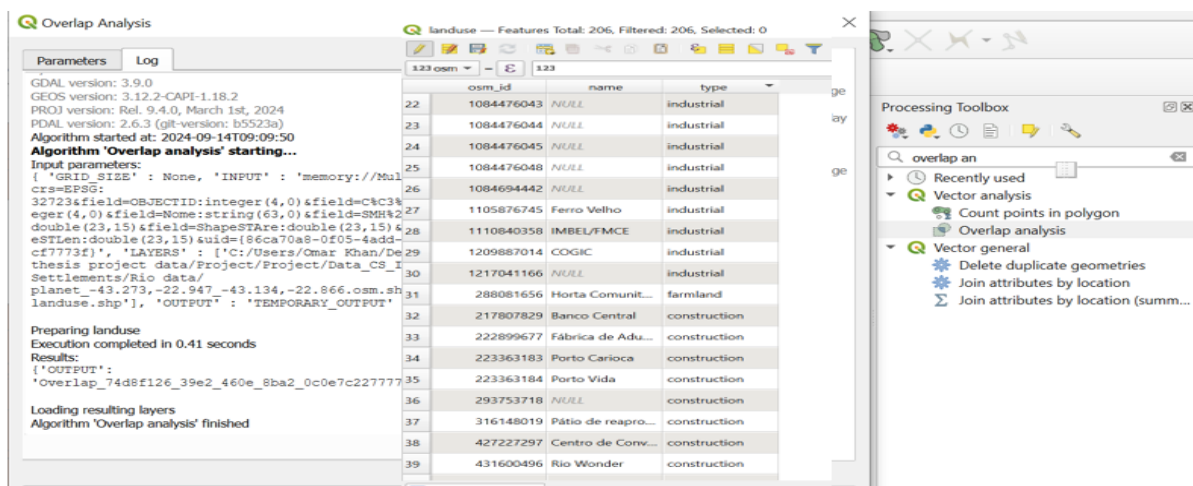
- **Segregating Residential vs. Slum Areas:** Overlay the slum boundary and residential shapefiles with different boundary color to differentiate and calculate the mean slope within slum vs. residential areas for comparison.



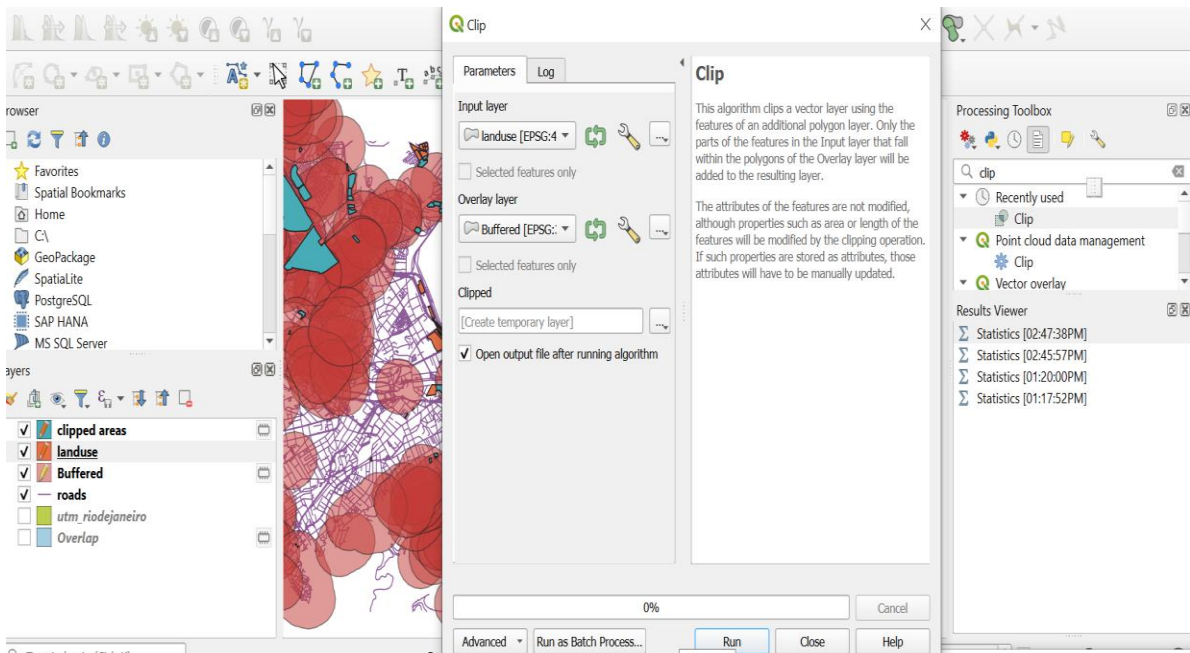
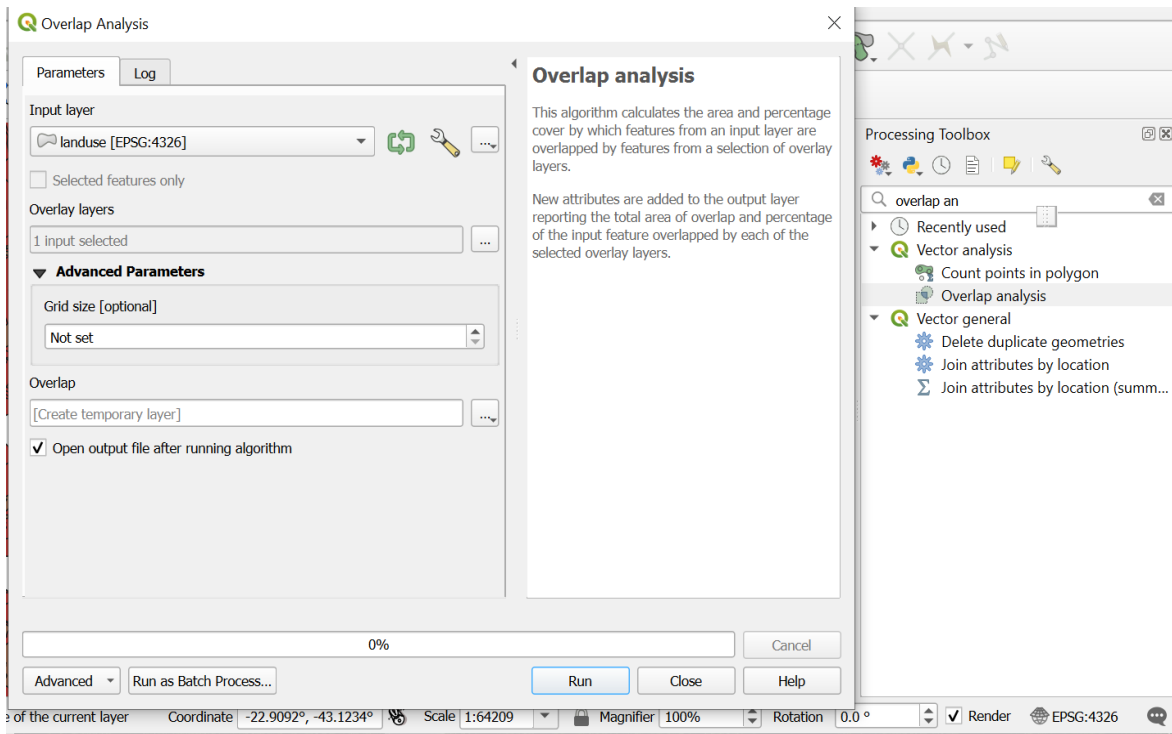
- **Proximity/Buffer Analysis:** The **proximity analysis** is done to determine how close the slum areas are to socio-economic activities like industries; trade areas and other important land-use types. This facilitates in identifying the economic potential and environment/the ecological hazards provided in the area/and known as slums. The first

step involved filtering land-use data in QGIS to isolate five specific classes: many buildings and structures including allotments, commercial areas, construction sites, farmland, and industries. This was done by putting attribute filters on the land-use vector data. After the classes were chosen, a 500-meter buffer was created around the limit of the slum areas with the help of the Buffer function in QGIS. This gave the basic way of evaluating the distance of the slums by establishing a buffer zone around them. With the help of the Overlay and Clip tools, the buffer was overlay on the land-use features to determine which socio-economic activities were located in the buffer area. After overlaying, the Basic Statistics tool was applied to find out the percentage of the slum areas that fall in the buffer zones. This assisted in establishing the measure to which the slum populace is accessible to economic activities on foot. The findings by this study revealed that the slums in Nairobi are relatively closer to economic centers compared to the slums in Rio de Janeiro which gave a socio-economic background to inhabitants of the slums in each city

- **Filtering Land-Use Classes:** Filter land-use data for the five categories: allotments, commercial areas, construction sites, farmland, and industries.



- **Overlay and Clip Analysis:** Use the Clip tool to extract the land-use features within the slum boundaries and buffer zone. This identifies the proximity of slums to economic activities.



- **Buffer Tool:** Apply a 500m buffer to slum boundary shapefiles by using the Vector > Geoprocessing Tools > Buffer option in QGIS.

Overlap — Features Total: 1017, Filtered: 1017, Selected: 0

OBJECTID	Código	Nome	SMH*RIO02	ShapeSTAre	ShapeSTLen	Buffered_area	Buffered_pc	
31	31	464	Asa Branca	76215.2850873...	76215.2850874...	1732.64336605...	76225.1851974...	100
32	32	915	Caminho da Ca...	18760.3344814...	18760.3344815...	1529.92590230...	18762.9661935...	100
33	33	924	Caminho Novo ...	8749.39928644...	8749.39928646...	583.096363635...	8750.58604948...	100
34	34	916	Caminho do Fin...	13332.9017636...	13332.9017636...	923.536706842...	13334.7597181...	99.9999999999...
35	35	661	Curicica II	8760.70034596...	8760.70034594...	482.008688840...	8761.85694066...	100
36	36	468	Vila Calmete	19535.3417512...	19535.3417512...	1016.55721311...	19537.8927710...	100
37	37	869	Vila União (RA - ...	21181.7925830...	21181.7925830...	685.749569280...	21184.5615545...	100
38	38	469	Vila União da C...	37045.0781587...	37045.0781587...	1395.82532276...	37049.8119945...	100
39	39	591	Parque Dois Ir...	180796.803526...	180796.803526...	2827.51726870...	180820.237788...	100
40	40	429	Curicica	2587.00799048...	2587.00799048...	220.029453199...	2587.33700693...	100
41	41	650	Antiga Creche	91531.6717500...	91531.6717499...	2288.50563376...	91543.3892101...	100
42	42	434	Comunidade Sã...	40961.0497656...	40961.0497657...	2322.29888218...	40965.8038865...	100
43	43	255	Outeiro (RA - Ja...	34649.8114689...	34649.8114688...	2034.65485702...	34653.7466677...	100
44	44	870	Rua André Rocha	4128.25927357...	4128.25927354...	290.037906655...	4128.74507929...	100
45	45	262	Vila Sapê	83953.0648834...	83953.0648833...	2152.70980897...	83962.6889553...	100
46	46	590	A.M. do Vale do...	73690.8324193...	73690.8324194...	2223.50740215...	73699.8777632...	100
47	47	470	Santa Anastácia	33203.1263437...	33203.1263437...	3458.88097151...	33207.0003267...	100
48	48	254	Nova Aurora	25120.6891668...	25120.6891668...	776.407754634...	25123.5515970...	100
49	49	431	Vila Santa Mõni...	13044.8375444...	13044.8375445...	641.664818272...	13046.3548387...	100

Show All Features

➤ **Calculating Percentage Overlap:** Apply the Basic Statistics tool to determine the percentage of slum areas overlapping with the buffer zones, offering insights into socio-economic proximity.

Basic Statistics for Fields

Parameters Log

Execution completed in 0.35 seconds

Results:

```
{'COUNT': 68,
'CV': 3.4326447814119443,
'EMPTY': 0,
'FILLED': 68,
'FIRSTQUARTILE': 3452.37,
'IQR': 12800.0285,
'MAJORITY': 251.093,
'MAX': 691242.491,
'MEAN': 30308.20102941178,
'MEDIAN': 8426.902,
'MIN': 251.093,
'MINORITY': 251.093,
'OUTPUT_HTML_FILE': 'C:/Users/Omar '
'Khan/AppData/Local/Temp/processing_toCJFw/
e59c2ffdb4de4bcabe8ad5b10bdfdf48a/
OUTPUT_HTML_FILE.html',
'RANGE': 690991.398,
'STD_DEV': 104037.28809759446,
'SUM': 2060957.670000001,
'THIRDQUARTILE': 16252.3985,
'UNIQUE': 68}
```

Loading resulting layers
Algorithm 'Basic statistics for fields' finished
HTML output has been generated by this algorithm.
Open the results dialog to check it.

Complete

Advanced Run as Batch Process...

Basic Statistics for Fields

Parameters Log

Execution completed in 0.27 seconds

Results:

```
{'COUNT': 206,
'CV': 3.3115984718626557,
'EMPTY': 0,
'FILLED': 206,
'FIRSTQUARTILE': 3474.837,
'IQR': 11259.044,
'MAJORITY': 184.968,
'MAX': 691242.491,
'MEAN': 19685.02083009708,
'MEDIAN': 7081.8655,
'MIN': 184.968,
'MINORITY': 184.968,
'OUTPUT_HTML_FILE': 'C:/Users/Omar '
'Khan/AppData/Local/Temp/processing_toCJFw/
2d618f5480104196b5f223215bfd7bef/
OUTPUT_HTML_FILE.html',
'RANGE': 691057.523,
'STD_DEV': 65188.88489953404,
'SUM': 2055114.290999999,
'THIRDQUARTILE': 14733.881,
'UNIQUE': 206}
```

Loading resulting layers
Algorithm 'Basic statistics for fields' finished
HTML output has been generated by this algorithm.
Open the results dialog to check it.

Complete

Advanced Run as Batch Process... Change Parameters Close Help

Basic statistics for fields

This algorithm generates basic statistics from the analysis of a values in a field in the attribute table of a vector layer. Numeric, date, time and string fields are supported.

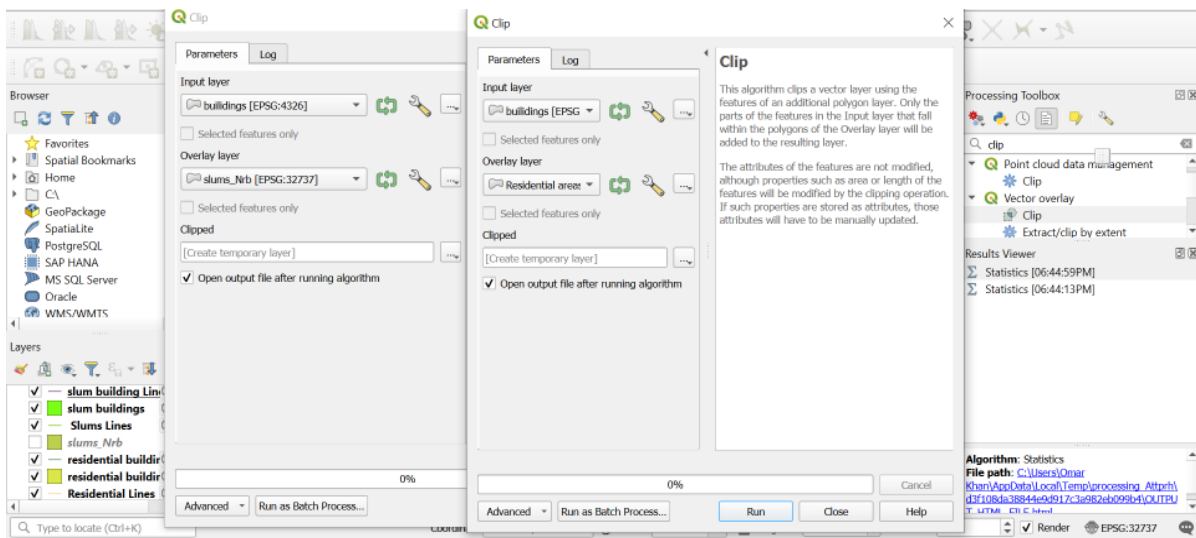
The statistics returned will depend on the field type.

Statistics are generated as an HTML file.

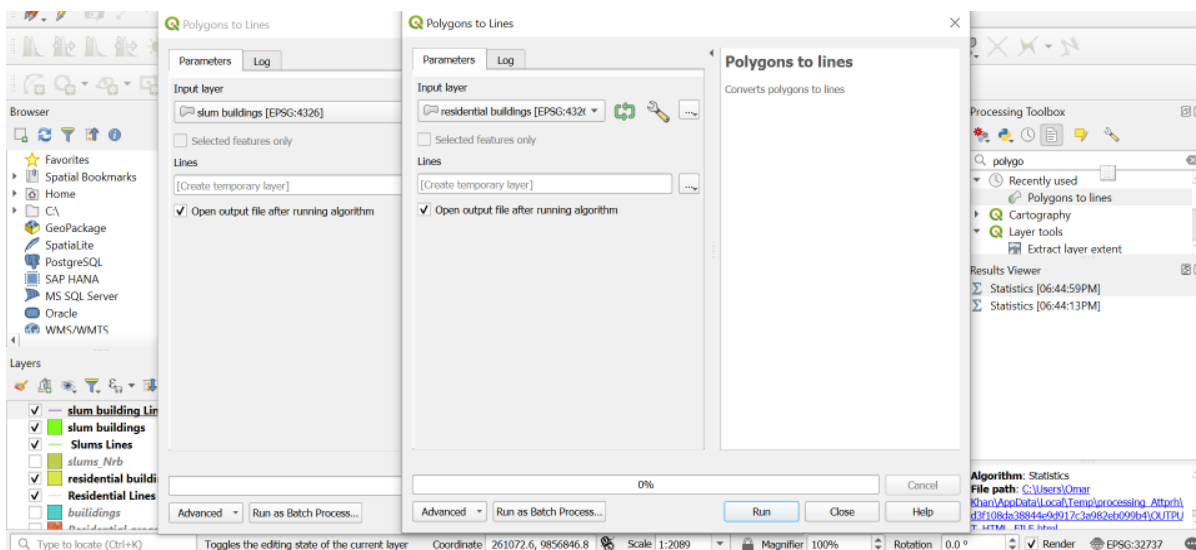
• **Fractal Dimension Calculation:** Slum polygons were rasterized and converted to line string in the first place and then the **minkowski DimCalculator-2.0** was used to

calculate mink dimension which further help in determining the fractal dimension being helpful in managing complexity of the shape of slum. Fractal dimension is a mathematical concept which describes the degree of detail and self-similarity of the geometrical or real structures, and which can be helpful to explain the irrational and random construction of slums. The plugin used in calculating **fractal dimensions** was Minkowski Dimension for which the deviation of slum areas from the standard Euclidean geometry, where simple geometrical shapes such as squares and rectangles have comparatively low fractal dimensions. First, the slum and the residential polygons were transformed to the **LineString** format using Vector > Geometry Tools > Polygons to Lines on QGIS. This made it possible to identify the building line within the slum areas. Subsequently, the slum polygons were buffered with building footprints to extract structures within the slum as well as the neighboring residential region. The Minkowski Dimension tool was used in both datasets whereby the mean fractal dimension for each area was computed. On an overall note, the mean fractal dimension was lower for the slum areas which means that they are more complex in nature and there are many gaps and crannies in the structures as compared to the identified regular areas as compared to planned areas having value closer to **1** indicating a stability in geometry. They created the added benefit of offering a quantitative means of comparing slum complexity within and between cities. For instance, by comparing the two cities, higher fractal dimensions were apparent in Nairobi with the slum areas experiencing more decentralization and higher extent of urban sprawl than the slums of **Rio de Janeiro**.

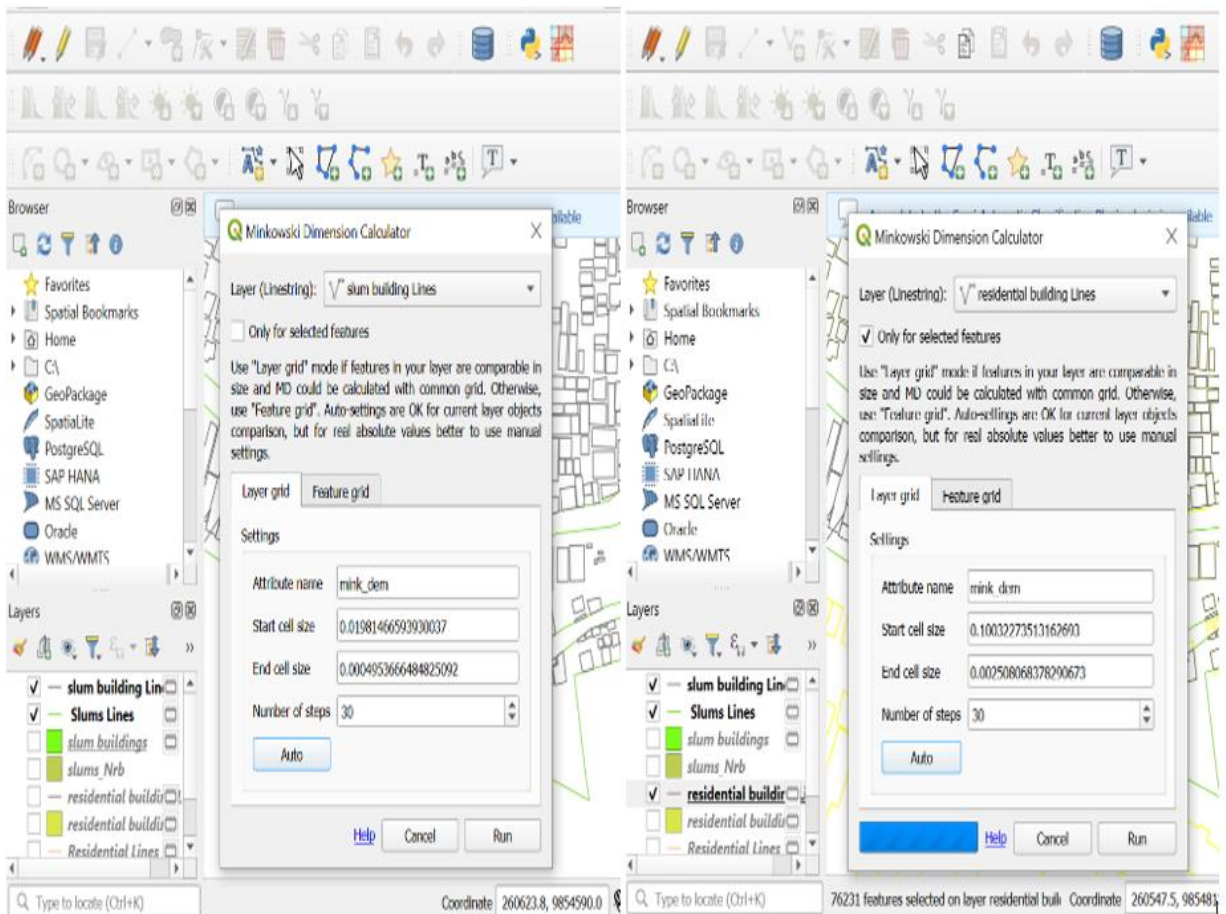
- **Clip Analysis:** Use the Clip tool to extract the land-use features within the slum boundaries and residential areas were clipped with building footprints to isolate structures within slum and residential areas



- **Converting to LineString:** Convert slum and residential polygons into LineString format using the Vector > Geometry Tools > Polygons to Lines.



- **Minkowski Dimension Calculation:** Run the Minkowski Dimension tool to compute fractal dimensions for both slum and residential areas in Nairobi and Rio. This reveals the complexity and disorganization typical of slum layouts compared to planned areas.



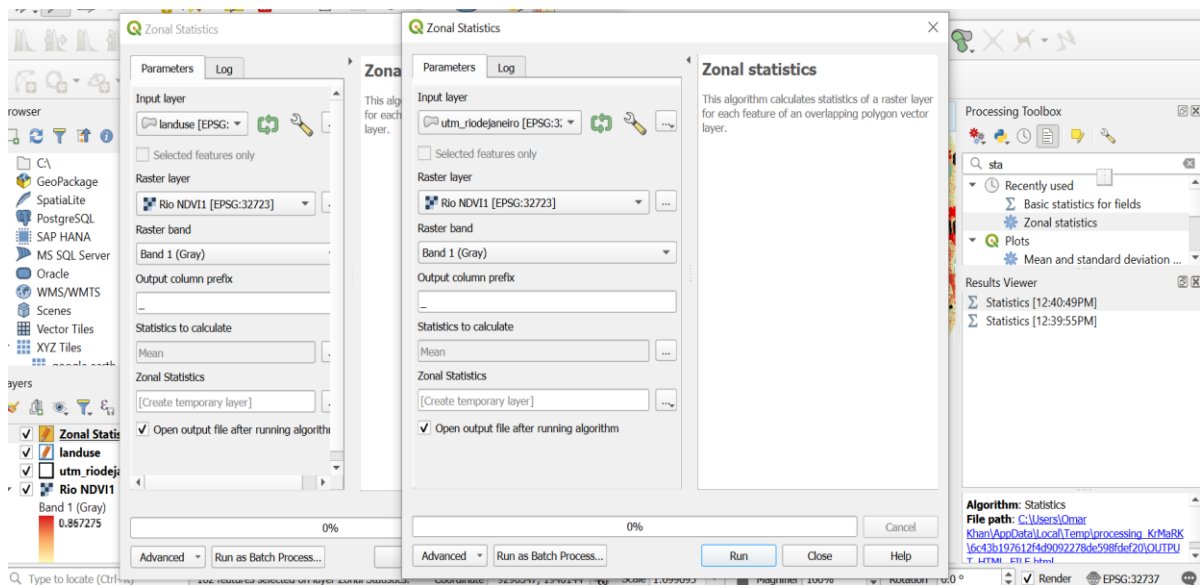
osm_id	name	type	area	mink_dem
1	NULL	***** 540...	69763.927	0.56435904239
2	NULL	** 540131159	96262.294	0.40559676833
3	NULL	***** 686...	41.248	0.77170489153
4	NULL	***** 686...	22.912	-0.0048471778
5	NULL	***** 686...	158.248	0.49475376740
6	NULL	***** 686080121	85.665	0.10392955144
7	NULL	* ***** 686	75.800	0.37717048915
8	80122	NULL *****	109.790	0.30150966845
9	NULL	**** 686080125	78.394	0.47717048915
10	NULL	***** 686...	42.670	0.00000000000
11	NULL	NULL ***** 68	15.730	0.00000000000
12	80223	NULL *****	35.242	0.00000000000
13	NULL	**** 686080225	25.791	0.80974258703...
14	NULL	***** 686...	14.668	0.00000000000
15	NULL	***** 686...	66.632	0.69415030532

osm_id	name	type	area	mink_dem
1	8869	ouse	431.639	0.73149374377...
2	NULL	commercial ... Towers	570.394	0
3	0	commercial ...	7.296 10315641	0.90392955144...
4	366519972	NULL **	1294.450	1.10392955144...
5	NULL	**** 489795324	466.301	0.80392955144...
6	NULL	***** 48...	459.935	0.62675906228...
7	NULL	***** 48...	359.911	0
8	NULL	***** 48... 8	183.453	0
9	NULL	***** 489795330	280.902	0
10	NULL	NULL ***** 48	275.229	0
11	795331	NULL *****	268.876	0.54322554625...
12	NULL	**** 4897953...	504.656	0.86913076190...
13	NULL	***** 48...	482.575	0.80974258703...
14	NULL	***** 48...	511.733	0
15	NULL	***** 48... 41	460.246	0

- Green Roof Coverage Estimation:** Green roof coverage is another way used to determine the vegetation density in the urban environment, especially in the distinction between spaces without essentially any vegetation and those that do have vegetation. For landscape heterogeneity examination, the Normalized Difference Vegetation Index (NDVI) was employed to measure the vegetation physical density.

Sentinel-2 imagery was loaded into QGIS, and the **Raster Calculator** was used to compute NDVI values with the formula: $NDVI = (B8 - B4) / (B8 + B4)$ where B8 is the Near-Infrared (NIR) band, and B4 is the Red band. The resulting NDVI layer was then overlaid with slums and residential areas. Using the **Zonal Statistics** tool, the mean NDVI values were calculated for both slum and residential zones. A threshold value of $NDVI > 0.35$ was applied to classify areas with substantial vegetation (green roofs). In the **Field Calculator**, a new field named "**Green_Roof**" was created, assigning a value of 1 to areas with $NDVI > 0.35$ and 0 to areas with lower values. This method enabled separation of vegetated areas from other non-vegetated built-up areas based on the Greenness. The final outcomes were displayed in the form of symbols to depict the areas of green roofs in slums and residential places. In relation to green roofs coverage, it was observed that slum areas were characterized by overcrowded environment with congestion resulting to little or no open spaces.

- **Zonal Statistics:** Apply Zonal Statistics to calculate NDVI for slum and residential areas separately.



- **Setting of Green Roof Threshold:** Use a threshold of $NDVI > 0.35$ to define green roofs. Add a new field in the attribute table to classify areas with $NDVI > 0.35$ as 1 (green roof) and ≤ 0.35 as 0 (non-green).

Zonal Statistics — Features Total: 1017, Filtered: 1017, Selected: 0

OBJECTID	Código	Nome	SMH'RIO/02	ShapeStAre	ShapeStLen	_mean	
1	1	1010	Comunidade N...	17702.8330821...	17702.8330821...	1123.79862490...	0.26147741035...
2	2	646	Estrada do Pont...	28541.6904427...	28541.6904427...	1948.46489082...	0.48657950099...
3	3	649	Vila Doutor Cre...	2534.09523208...	2534.09523208...	354.867722199...	0.23748011248...
4	4	371	Restinga	13986.4035760...	13986.4035761...	640.887395007...	0.22541711380...
5	5	794	Avenida dos Eu...	3035.98047626...	3035.98047626...	253.906092205...	0.09799357276...
6	6	663	Servidão D	1033.00634906...	1033.00634908...	203.178404709...	0.66591642300...
7	7	974	Avenida Guiom...	1215.24628437...	1215.24628439...	164.415121438...	0.14604528124...
8	8	548	Rua RW, 500	19448.0865181...	19448.0865181...	1350.22880086...	0.41456687427...
9	9	457	Vila Amizade	14238.9620771...	14238.9620771...	656.375296492...	0.09651755346...
10	10	367	Canal das Tachas	78894.4562005...	78894.4562006...	2461.68487553...	0.10422561688...
11	11	556	Parque Chico M...	75659.4052320...	75659.4052320...	2938.94150149...	0.11185186484...
12	12	253	Morro do Piolho	160831.623482...	160831.623482...	2527.29814088...	0.27671512794...
13	13	368	Canal do Cortado	110214.025172...	110214.025172...	5164.91127611...	0.18100261609...
14	14	799	A.M. Barra Amé...	4313.63857485...	4313.63857486...	284.396244451...	0.06691666282...
15	15	795	Bosque Mont S...	42225.1640520...	42225.1640519...	1351.98219715...	0.25448445763...
16	16	458	Santa Luzia	42080.2240917...	42080.2240916...	3083.59407647...	0.20949331664...
17	17	922	Estrada do Pau ...	15430.0084185...	15430.0084184...	935.003716772...	0.70712742954...
18	18	577	Parque da Pedr...	75002.5046283...	75002.5046283...	2716.81491742...	0.65075873654...
19	19	366	Caminho do M...	24510.3889569...	24510.3889570...	947.110706003...	0.30930061183...

Zonal Statistics — Field Calculator

Only update 0 selected features

Create a new field Update existing field

Create virtual field

Output field name: green roof

Output field type: 1.2 Decimal Number (real)

Output field length: 10 Precision: 3

Expression: `case when "_mean" > 0.35 then 1 else 0 end`

Feature: 27 de Setembro

Preview: 0

You are editing information on this layer but the layer is currently not in edit mode. If you click automatically be turned on.

- **Basic Statistics:** Compute the percentage of green roof areas using the Basic Statistics tool to show variations in vegetation cover between slum and non-slum areas.

Zonal Statistics — Features Total: 1017, Filtered: 1017, Selected: 162

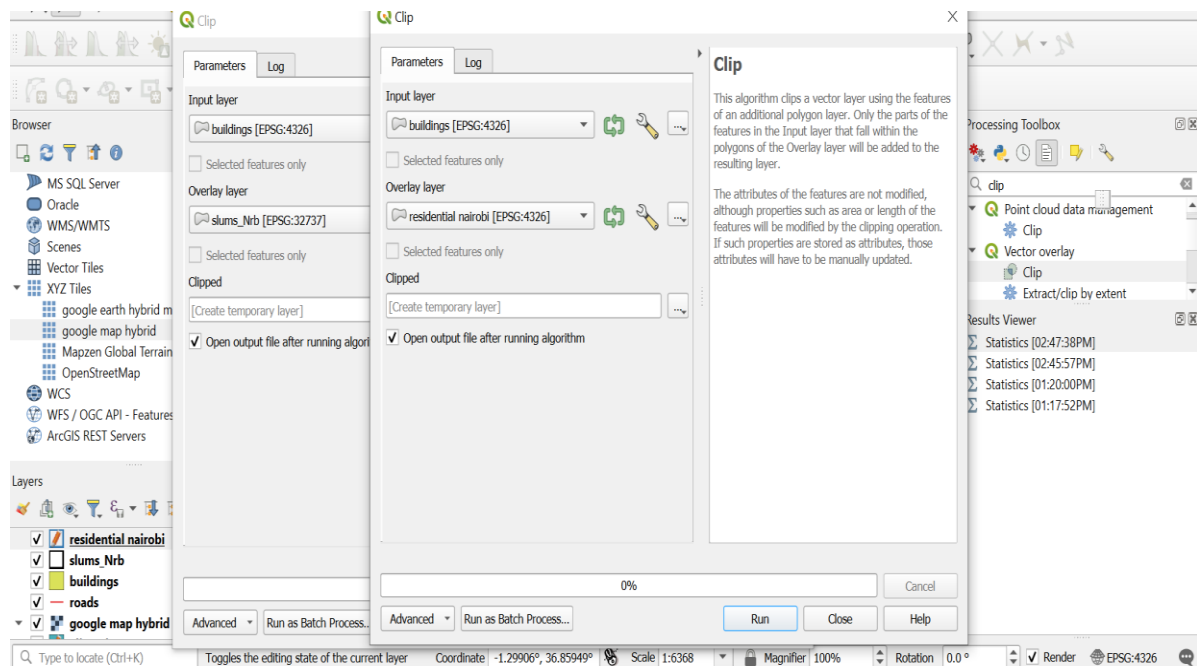
123 OBJ = 123

OBJECTID	Código	Nome	SMH'RIO/02	ShapeStAre	ShapeStLen	_mean	green roof	area
150	918	1008	Beco da Coruja	5731.09131631...	5731.09131629...	452.462889206...	0.56386501554...	5731.105
151	929	624	Vila Elza	13824.0782686...	13824.0782686...	774.067970458...	0.38269027652...	13823.569
152	932	15	Morro Santos R...	47023.9892407...	47023.9892406...	1679.75634846...	0.5003955812...	47022.042
153	936	24	Guararapes	28567.4784364...	28567.4784364...	1032.84150212...	0.38085282425...	28566.457
154	940	20	Sumaré	45753.2690526...	45753.2690526...	1222.35417930...	0.45179361627...	45752.064
155	949	993	Rua São Francis...	2617.93248927...	2617.93248925...	334.637551655...	0.50592205425...	2617.918
156	952	74	Salgueiro	171821.084004...	171821.084004...	3351.42794837...	0.37772643172...	171818.163
157	955	72	Morro da Liber...	105989.992540...	105989.992540...	3305.58350948...	0.35248132579...	105987.306
158	969	709	Beco do Carcará	24079.4360814...	24079.4360815...	1166.85521369...	0.38688932120...	24087.182
159	990	884	Morro da Foice	25255.0697520...	25255.0697520...	1695.32529849...	0.39760541206...	25263.415
160	999	877	Estrada da Pedr...	19364.4607894...	19364.4607893...	1856.92118544...	0.41464128862...	19370.889
161	1007	80	Morro dos Mac...	190143.664770...	190143.664770...	4233.43409935...	0.44530580204...	190144.907
162	1015	365	Caminho do Bic...	307.415086719...	307.415086714...	129.415834655...	0.51441091299...	307.465
163	1	1010	Comunidade N...	17702.8330821...	17702.8330821...	1123.79862490...	0.26147741035...	17706.647
164	3	649	Vila Doutor Cre...	2534.09523208...	2534.09523208...	354.867722199...	0.23748011248...	2534.608
165	4	371	Restinga	13986.4035760...	13986.4035761...	640.887395007...	0.22541711380...	13989.254
166	5	794	Avenida dos Eu...	3035.98047626...	3035.98047626...	253.906092205...	0.09799357276...	3036.557
167	7	974	Avenida Guiom...	1215.24628437...	1215.24628439...	164.415121438...	0.14604528124...	1215.491

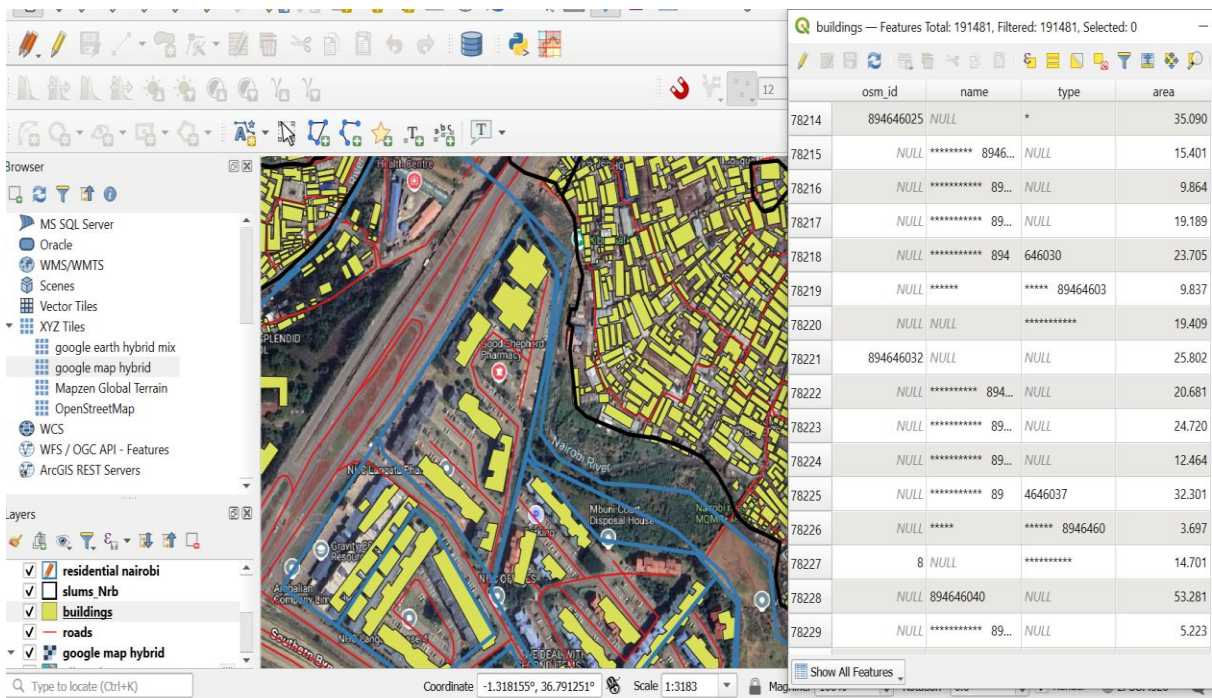
- **Building Size Estimation:** Building size is the most effective way to measure urban compactness and dwellings' quality, especially the quality of the buildings in slum areas where the buildings are small, and the density of the buildings is high. To estimate building sizes, OpenStreetMap (OSM) building footprint data was clipped to isolate

buildings within slum and residential areas using the **Clip tool** (Vector > Geoprocessing Tools > Clip). After the buildings were clipped, a new field named "Area" was added in the **Field Calculator** using the formula \$area to compute the area of each building polygon. This offered the sizes of the building in terms of the area in square meters of the slum and the residential areas. The average building size was then determined from the **Basic Statistics tool** for each area identified. These results agree with the overcrowded and enclosed slum settlements with limited available space and prevailing nature of informal construction.

- **Clipping buildings in Slum Areas:** Use the Clip tool to extract building footprints within slum and residential areas.

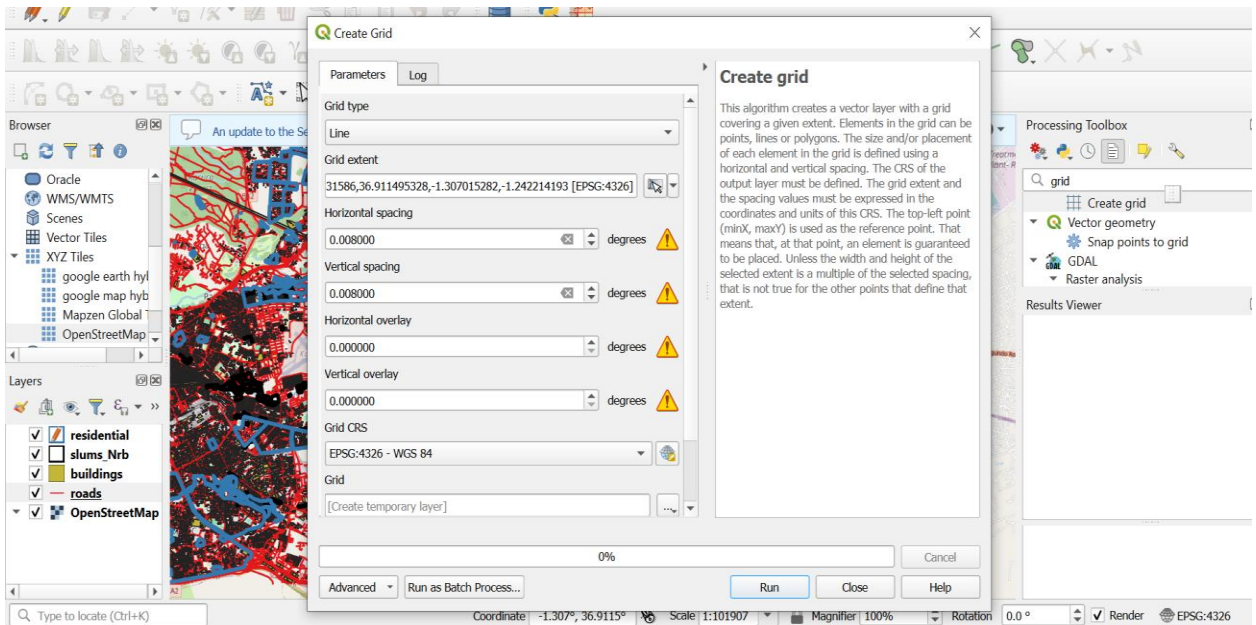


- **Area Calculation and Basic Statistics:** Add a new field in the attribute table using the Field Calculator, and compute building areas using the formula. Calculate average building size for both slum and residential areas. This reveals smaller, overcrowded structures in slums compared to planned areas

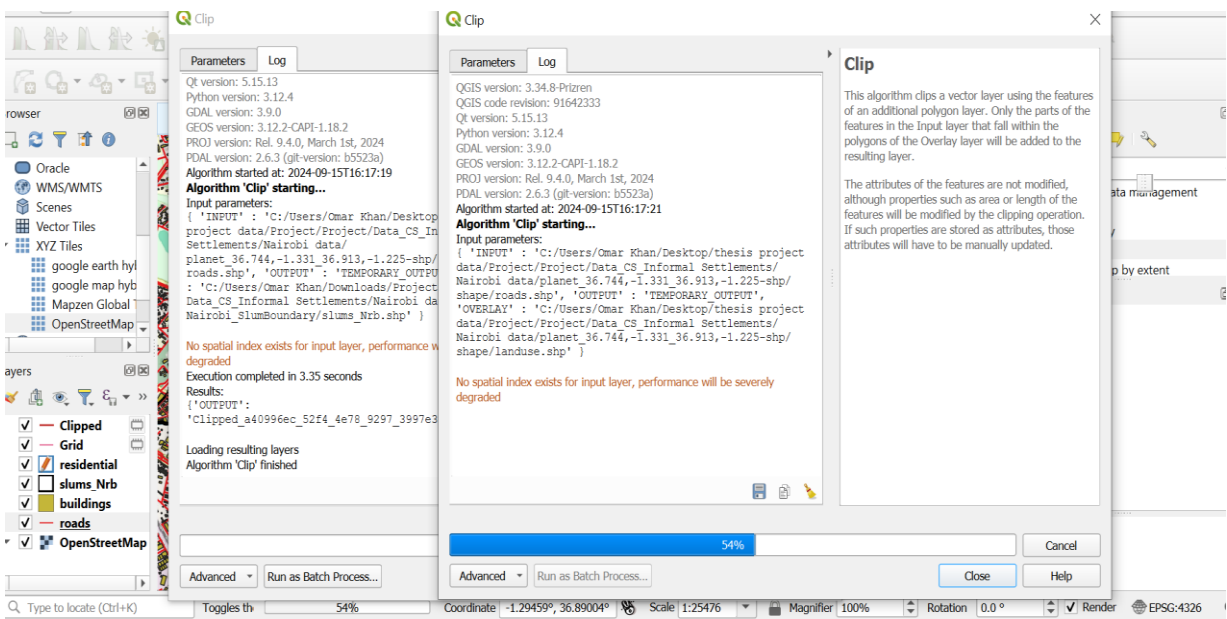


- Road Network Irregularity Calculation:** Road irregularity is an indicator of the lack of planning in slum areas, and telling how unplanned the area is particularly the slum area where the roads are characterized by a small, irregular and twisting path. To calculate road irregularity, the road network data for slum and residential areas was first clipped using the **Clip tool**. This separated the roads within slum areas from those in more structured, planned residential zones. Next, the **Extract Vertices** tool was used to identify the nodes or intersections within the road network. This step was essential for measuring road complexity. To provide a more structured analysis, a 1x1 km grid was added to the map to calculate node density per kilometer of road. Two node counts were calculated: one per road segment and another per grid unit using the **Count Points in Polygon** tool. The same was observed in this study where the node densities tended to be higher in the slum areas signifying much disorganized patterns of network and fragmentation of roads compared to homogeneity of the neighborhood of the residential zones. This metric aids in measuring the number of infrastructural barriers that people living in slums suffer from, especially in the areas of service delivery such as response to disasters or accessibility of strategic resources such as roads.
- **Adding a Grid:** Add a 1x1 km grid to the map to calculate node density both per road

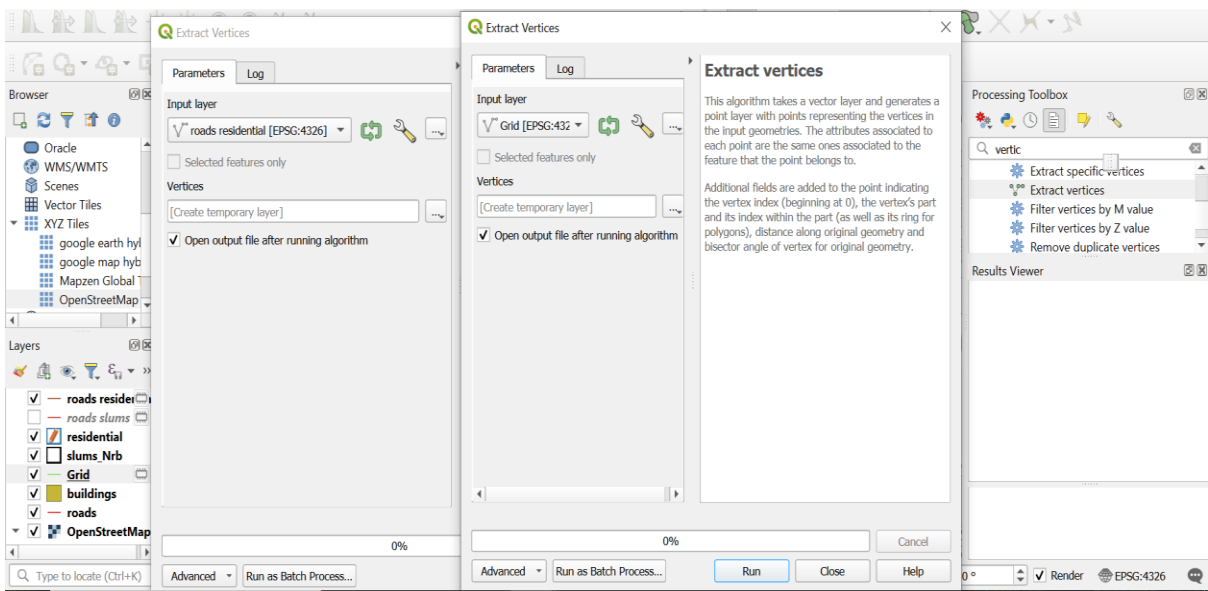
segment and per km². This provides a measure of road irregularity, which is generally higher in slum areas.



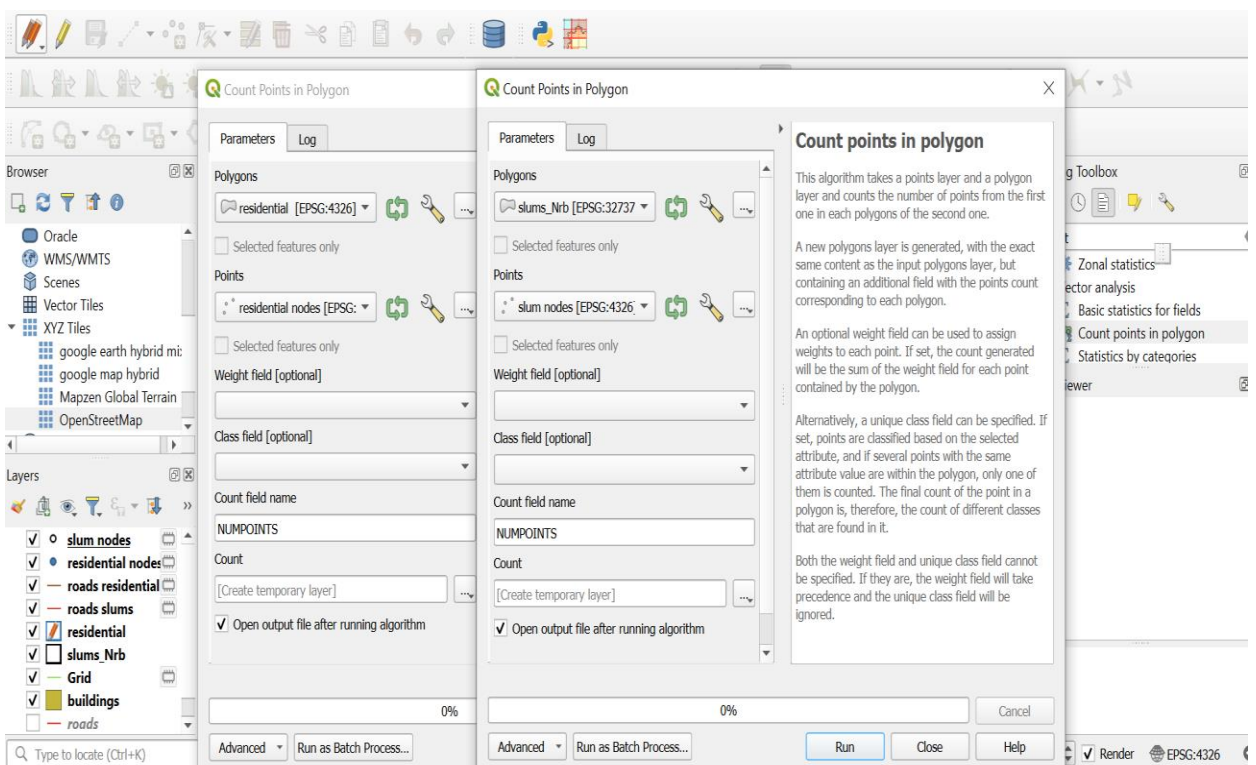
- **Clipping Roads:** Use the Clip tool to separate road networks within slum and residential boundaries.



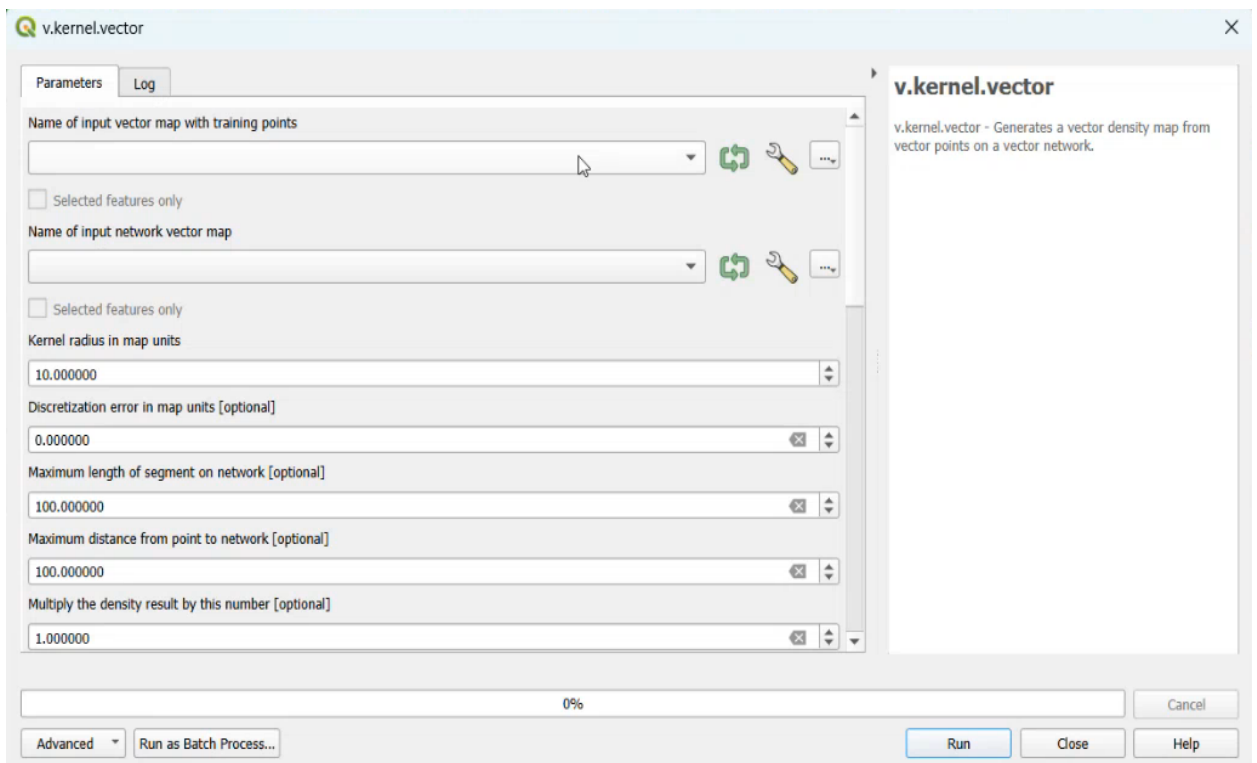
- **Extract Vertices:** Apply the Extract Vertices tool to identify road junctions and vertices, which will be used to measure road irregularity.



- **Node Count Tool:** Use the Count Points in Polygon tool to calculate the number of nodes per road.



- **kernel vector tool:** to count the density in a grid, showing the fragmented nature of slum infrastructure.



The below table summarizes which datasets and geospatial processes were used for the calculation of above physical characteristics:

Physical Characteristic	Dataset Used	Geospatial Processes
Slope	SRTM DEM 30m	The calculation of minimum, mean and maximum percentage slope of slum and non-slum areas
Proximities to industries and other socio-economic activities	OSM Places and land-use data	500m Buffer around slum areas and then the classification of this buffer into land use to calculate the proximities to industries
Fractal Dimension	Vector data provided for slums.	Fractal Dimension calculation
Roof coverage	Sentinel-2 Images	Area of slum footprints / area of total pixels
Building size	OSM Building data	Area calculation of footprints of slum buildings and non-slum building
Road's irregularity	OSM roads data	Calculation of nodes / km in slums and non-slums areas

Table 2 Summary Table of datasets and geospatial processes

4.7. Intracity Slum Comparative Analysis

Slum areas are highly heterogeneous, even within the same city, due to varying environmental, social, and economic conditions. To capture this variability, a comparative analysis was conducted to examine the differences in slum characteristics

within each city.

Approach

The comparative analysis involved comparing the calculated indicators for different slum areas as compared to residential areas within each city. The analysis focused on identifying patterns and trends in the physical characteristics of slums, such as differences in slope, building size, and roof coverage, which could indicate varying levels of development and infrastructure quality.

Findings

The findings from the intracity analysis revealed significant variation in slum characteristics within both cities. In Nairobi, slums located closer to the city center tended to have smaller building sizes and higher roof coverage, indicating higher population density and more intense land use. In contrast, slums located on the periphery of the city exhibited larger building sizes and lower roof coverage, suggesting less dense development. In Rio de Janeiro, slums on steeper slopes had more irregular shapes and road networks, reflecting the challenging topography and unplanned nature of these settlements.

4.8. Intercity Slum Comparative Analysis

The final phase of the methodology involved a comparative analysis of slum characteristics between the two cities. This analysis aimed to determine the extent to which the identified GSO indicators are applicable across different urban contexts and to assess the potential for global application of these indicators.

Approach

The intercity comparative analysis involved comparing the calculated indicators for slum areas in Rio de Janeiro and Nairobi. The analysis focused on identifying similarities and differences in slum characteristics between the two cities and

understanding the factors driving these differences. The analysis also explored the thresholds for each indicator, assessing whether these thresholds differed significantly between the cities.

Findings

The intercity analysis revealed both similarities and differences in slum characteristics between Rio de Janeiro and Nairobi. Both cities exhibited slums with high roof coverage, small building sizes, and irregular road networks, reflecting the common challenges of informal settlements in urban areas. However, significant differences were observed in the slope and shape indicators. Slums in Rio de Janeiro were generally located on steeper slopes and exhibited more complex shapes, likely due to the city's mountainous terrain. In contrast, slums in Nairobi were more likely to be located on flatter terrain, with less complex shapes.

4.9. Data Management Plan

To ensure the systematic organization and management of the datasets used in this research, a comprehensive data management plan was developed. This plan involved creating a structured file directory and maintaining detailed metadata for each dataset.

File Structure

The top-level directory for the project was named "Project" and was organized into the following subdirectories and is to be uploaded via google drive link along with all the necessary data related to the project:

- **Sentinel-2 Images:** This subdirectory contained the raw and pre-processed Sentinel-2 images for both cities, with filenames indicating the city, satellite, and processing level (e.g., "Nairobi_S2A_L2C_Image.tif").
- **SRTM DEM:** This subdirectory contained the raw and pre-processed DEM files for both cities, as well as slope maps generated during the analysis (e.g., "Slope_Rio.tif").

- **OSM Data:** This subdirectory contained the OSM vector data for both cities, including layers for buildings, roads, places, and land use (e.g., "Buildings_Nairobi.shp").
- **Slum Boundaries:** This subdirectory contained the shapefiles for the slum boundaries in each city (e.g., "Slum_Nairobi.shp").
- **Administrative Boundaries:** This subdirectory contained the shapefiles for the administrative boundaries in each city (e.g., "Adm_Rio.shp").

Metadata

A metadata table was created to provide detailed information about each dataset, including the data source, year of creation, filenames, and specifications. The metadata ensured that all datasets were properly documented, facilitating reproducibility and transparency in the research.

Data	Process step	Source	Filenames	Specification
2 Sentinel-2 Images	Pre-processing	Open source	{city}_{satellite}_{level}_Image.tif	10m spatial resolution and 13 bands each
DEM	Pre-processing	Open source	{city}_DEM.tif	1 Arc Second/30m
Slope	Slope calculation	Processing	Slope_{city}.tif	Slope for each pixel in percentages
OSM	Used in geospatial processes	BB Bikes	Places_{city}.shp Buildings_{city}.shp Roads_{city}.shp Landuse_{city}.shp	Vector data representing different features
Slum Boundary	Used in calculation of spatial proxies	Open source	slum_{city}.shp	Vector data of slum boundaries
Administrative boundaries	Used in calculation of spatial proxies	Open source	Adm_{city}.shp	Vector data of administrative boundaries

Table 3 Summary Metadata table

The methodology outlined in this section provides a comprehensive framework for analyzing the physical characteristics of slum areas using remote sensing and geospatial data. The systematic approach to data collection, indicator calculation, and comparative

analysis ensures that the research findings are robust and applicable across different urban contexts. By identifying and quantifying key slum characteristics, this study contributes to a better understanding of the spatial dynamics of informal settlements and their potential implications for urban planning and policymaking.

5. Results

The results presented here provide a comprehensive analysis of the physical characteristics of slum areas in Nairobi and Rio de Janeiro. The analysis would primarily be drawing on geospatial processes applied to calculate key indicators such as slope, proximity to socio-economic activities, fractal dimension, roof coverage, and building size. These results are discussed in the context of urban planning. Furthermore, these also lay a special emphasis on how these physical characteristics influence the living conditions and development potential of slum areas.

5.1. Slope Calculation

Nairobi

In Nairobi, therefore, looking at the slope of areas that are considered slums and comparing them with other areas that are considered non-slum we find a difference. The mean slope for slum areas was then based determined as 10.19%, compared to 6.39% for non-slum areas. What distinguishes graduate symbol map is the slope of the line in planned settlements as conveyed in blue-lined areas and in slum areas depicted in black.

From this it can be deduced that the slum areas usually are situated on the steep slopes of the city, and this has several implications for the inhabitants. Slopes were also found to be a major threat to the structures due to increased rate of soil erosion and landslides during the rainy season which is frequent in Nairobi. The higher slopes in slum areas also make it difficult for one to construct a strong and durable structure, thus, there is use of temporary or even semi temporary houses which could not so

well resist the stresses of the environment. Further, some of the slopes may act as barriers in accessing needs such as water, sanitation and transport, as these regions do not have proper infrastructure.

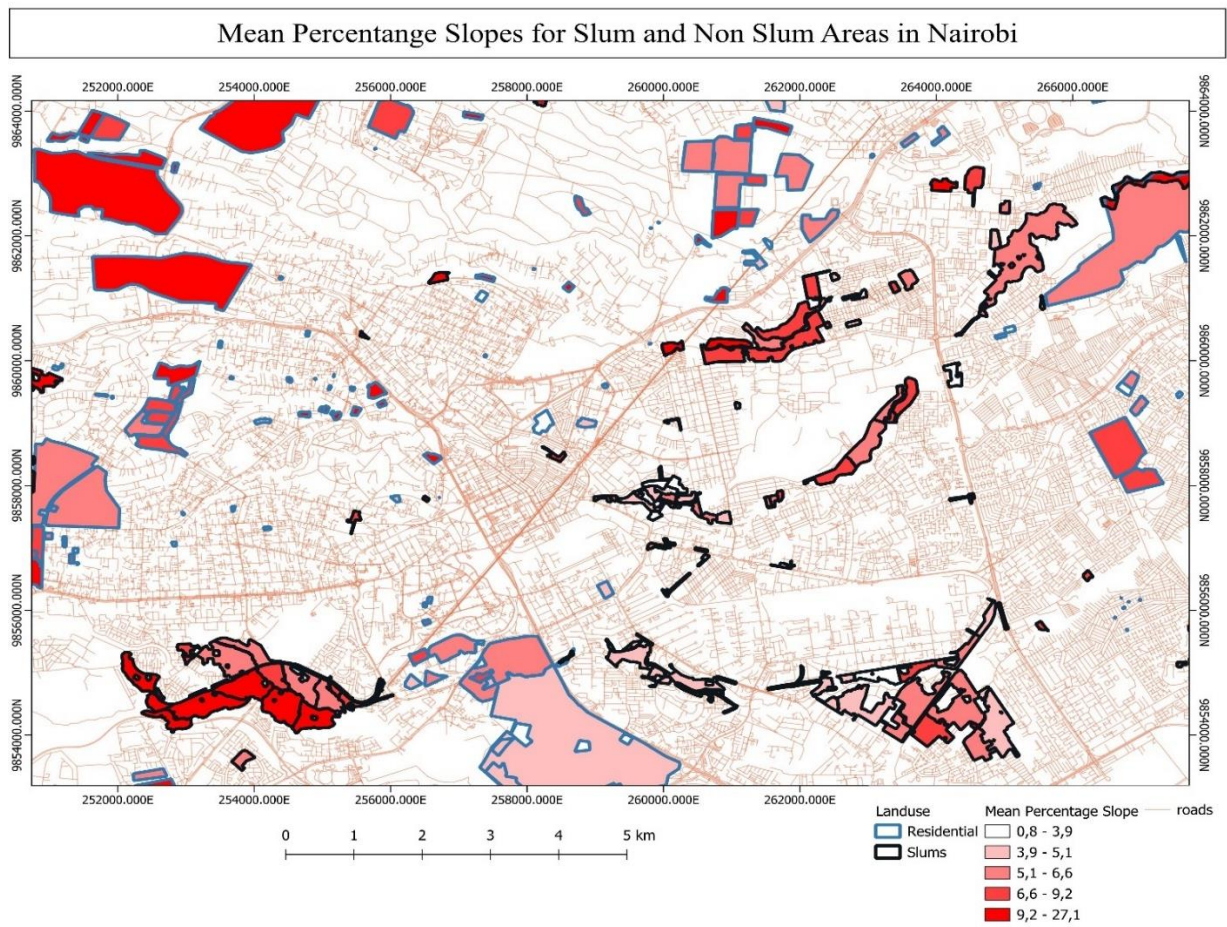


Figure 7 Mean Percentage Slopes for Slum and Non-Slum Areas in Nairobi (QGIS)

Land Feature	Mean Slope	Colour Notation
Slum Areas	10.19	Black
Residential (non-slum)	6.39	Blue

Table 4 Key Statistical metrics extracted for Slum and Non-Slum Areas in Nairobi

Rio de Janeiro

In the same way, the slum areas in Rio de Janeiro have steeper slopes with higher mean compared to planned settlements. This steepness is illustrated in the accompanying map in which the symbology scheme used is similar to that employed for Nairobi but with the color of the roads being different. This is especially very evident in Rio de Janeiro where steep slopes have been experienced mainly due to the rugged terrain. These areas are commonly called ‘favelas’, and usually, they are situated on steep slopes that also imply the difficulties

of the official construction. The slopes are extremely steep hence increasing the danger of landslides, where harms that arise from such disasters have been catastrophic to some of the favelas in the past. These physical characteristics also affect the land use since people construct their houses wherever they find space, which may well be on unstable ground.

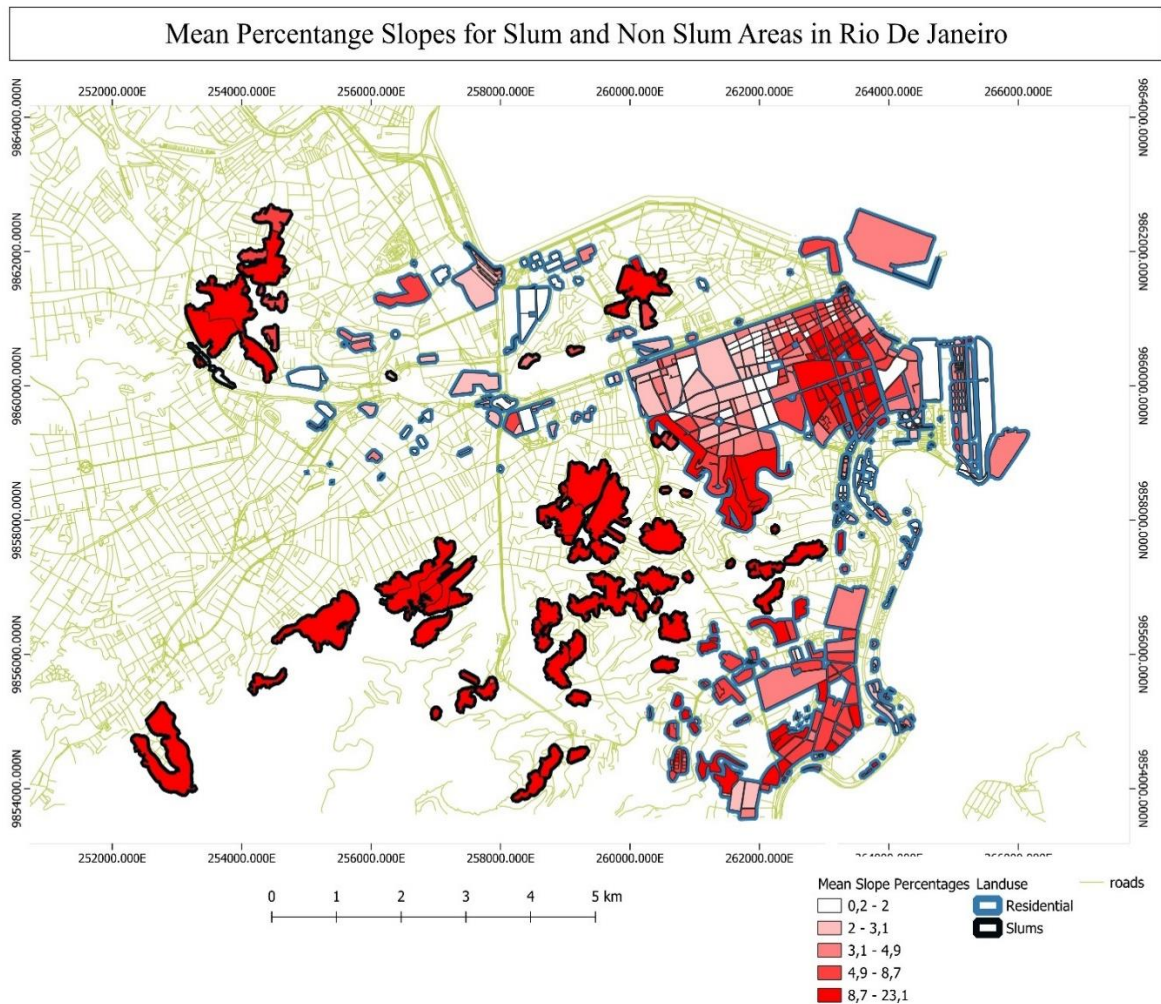


Figure 8 Mean Percentage Slopes for Slum and Non-Slum Areas in Rio (QGIS)

Land Feature	Mean Slope	Colour Notation
Slum Areas	13.08	Black
Residential (non-slum)	6.54	Orange

Table 5 Key Statistical metrics extracted for Slum and Non-Slum Areas in Rio

Comparing Nairobi and Rio de Janeiro, it can be seen that slum areas are more likely to be located in areas with steeper slopes, which is not a coincidence from socio-economic point of view. As famously explained, the flat terrain remains preferred for the rich or planned developments, while the steep and dangerous slopes are for the

poor or the squatters. Such spatial inequality means that interventions have to be made to cater for the high risks involved in slum environments and the people occupying them.

5.2. Proximity to Industries and Socio-Economic Activities

Nairobi

Analyzing Nairobi, the proximity of slum areas to industries and other socio-economic activities was analyzed by examining the distance from slum areas to five key classes: residential areas, industries, commercial areas, farmland-level opioid construction sites and institutional areas. The proximity analysis showed us that 83% of the slum areas are located within a 500-meter radius of one or more of the socio-economic activity zones as illustrated in the proximity analysis map above. This level of proximity can be construed to mean that slum areas in Nairobi are well placed in areas of economic incomes, which can be an advantage/ disadvantage. While on the other hand the areas provide the residents with easy access to employment, markets, and other essential services that are vital in their daily lives. On one hand, living close to industries and construction areas has some disadvantages; one can be affected by pollution, noise, and traffic jam. Furthermore, competition for space especially around such socio-economic activities means that increased population densities are witnessed in slum areas and hence problems such as overcrowding and poor physical infrastructure are further prone.

Industries and Socio-Economic activities inside the 500m of Slums of Nairobi

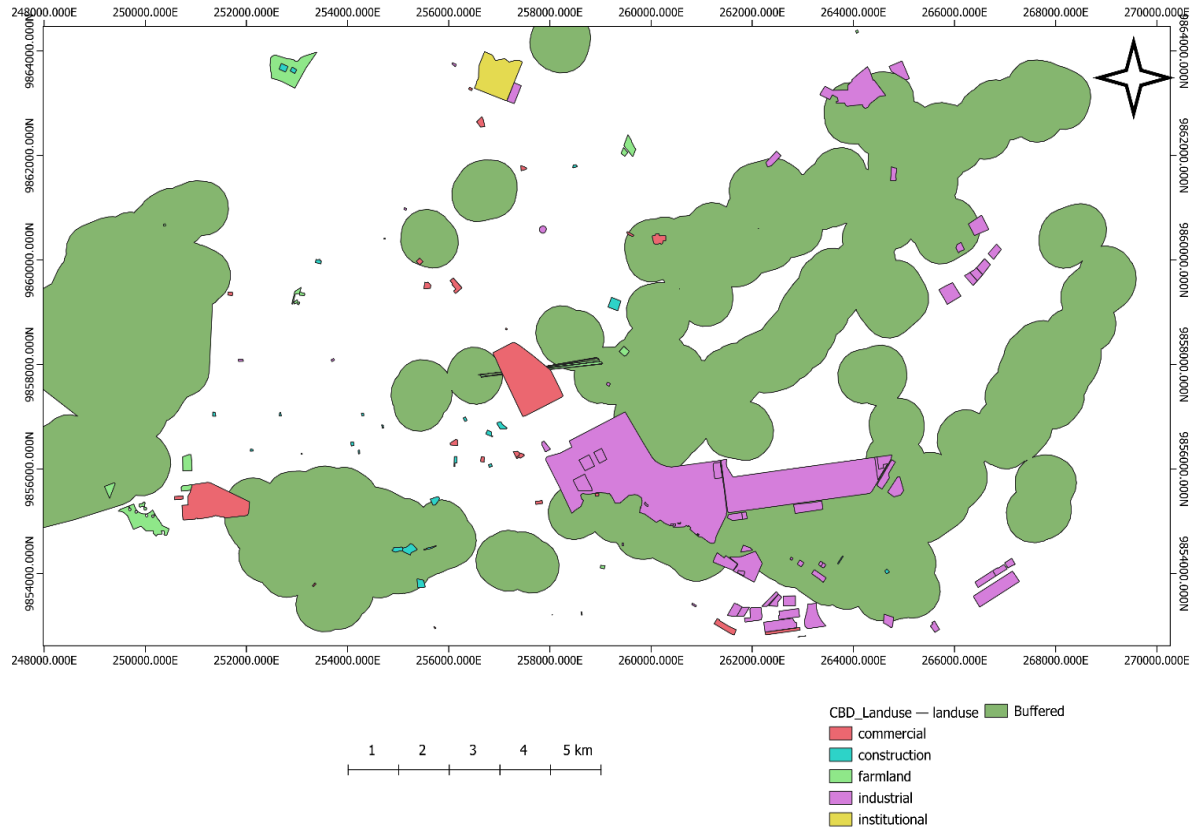


Figure 9 Buffer Analysis of Nairobi with 500m proximity for Slum areas as with reference to Industries

Land Feature	Overlapped Areas %	Buffer Parameters
Slum Areas	83.5	500m
Residential (non-slum)	52	500m

Table 6 Key Statistical metrics extracted for Slum and Non-Slum Areas in Nairobi

Rio de Janeiro

In contrast, the analysis for Rio de Janeiro indicated that only 20-30% of slum areas are located within 500 meters of the five socio-economic activity zones: - allotments, commercials, constructions, farms, industries and many others. With this smaller percentage it is therefore safe to infer that slum areas in Rio de Janeiro are relatively more pulled back from these zones of economic activity as compared to those in Nairobi.

In view of this, isolation may have various repercussions to the dwellers of the favelas in Rio de Janeiro. Lack of employment opportunities and services continue to set up a poverty and social exclusion cycle, due to long distances likely to be travelled to

areas of economic activities. This also means that the slum areas are not located close to the socio-economic centers which in effect isolates the slum dwellers from the mainstream economy of the city.

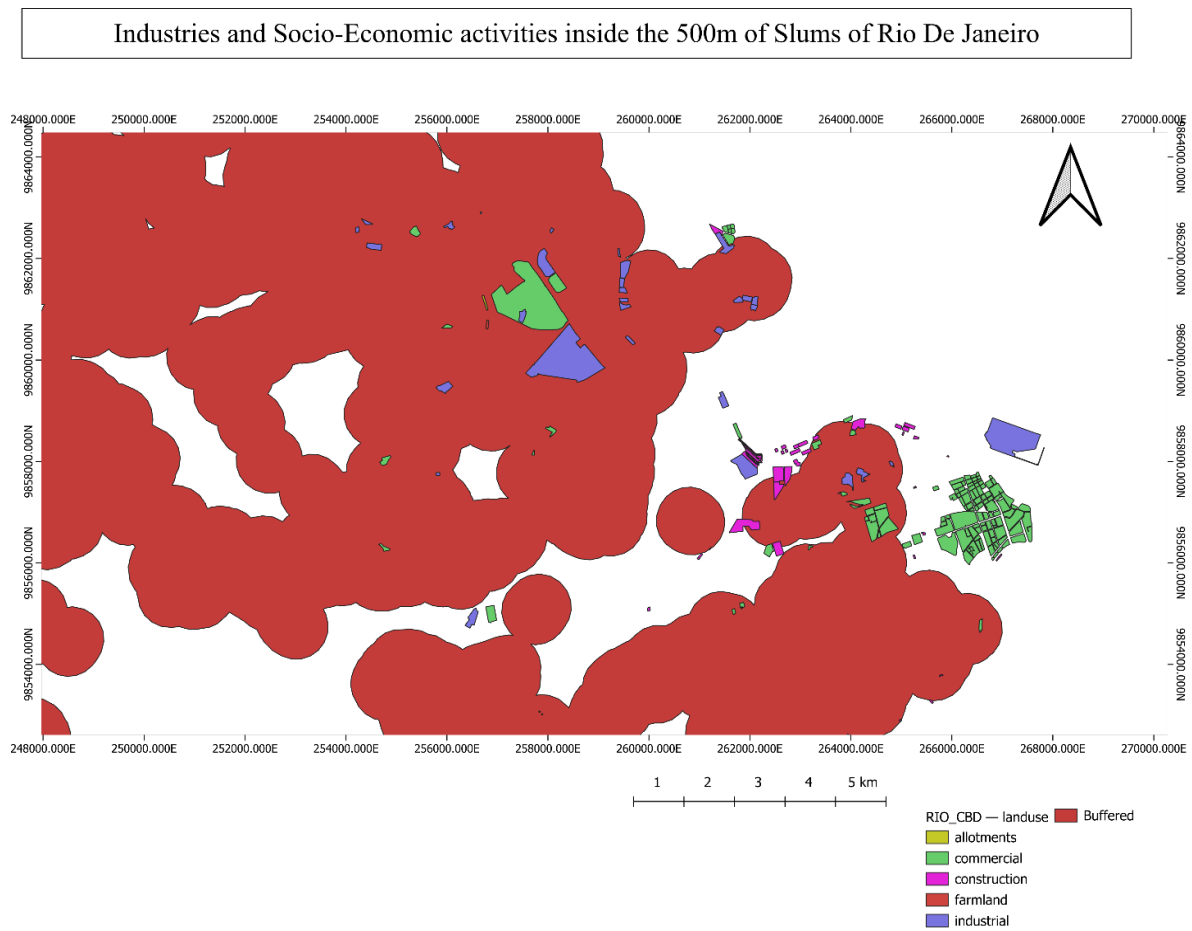


Figure 10 Buffer Analysis of Rio with 500m proximity for Slum areas as with reference to Industries

Land Feature	Overlapped Areas %	Buffer Parameters
Slum Areas	24.6	500m
Residential (non-slum)	45.4	500m

Table 7 Key Statistical metrics extracted for Slum and Non-Slum Areas in Rio

A comparison between Nairobi Slum and Rio de Janeiro shows that the locations of the slum with regard to economic activities differ, resulting from different urban planning past and present societal characteristics. While in Nairobi, the-slum areas are relatively being incorporated into the mainstream economy with its attendant risks, the opposite is the case of Rio de Janeiro hence the need to improve connectivity of the-slum areas.

5.3. Fractal Dimension

The fractal dimension is a measure of the complexity of the shape of slum areas, with higher values indicating more irregular and complex shapes. Mean fractal dimension that was found in the slum areas of Nairobi was estimated to be between 0.5 and 0.6; This is a very less score, showing a lack of richness in the shape geometry and meaning very complex and irregular shapes.

Fractal Dimension (Nairobi)



Figure 11 Building Fractal dimensions for Slum and Non-Slum Areas in Nairobi (QGIS)

Land Feature	Mean mink dimension	Colour Notation
Slum Areas	0.56	Yellow
Residential (non-slum)	0.78	Orange

Table 8 Key Statistical metrics extracted for Slum and Non-Slum Areas in Nairobi

This is due to the fact that slums in Nairobi have developed haphazardly due to the lack of systematic planning and development and people construct a house for a variety of reasons without much concern to how the other people will lay out their homes.

Results – Fractal Dimension (Rio de Janeiro)

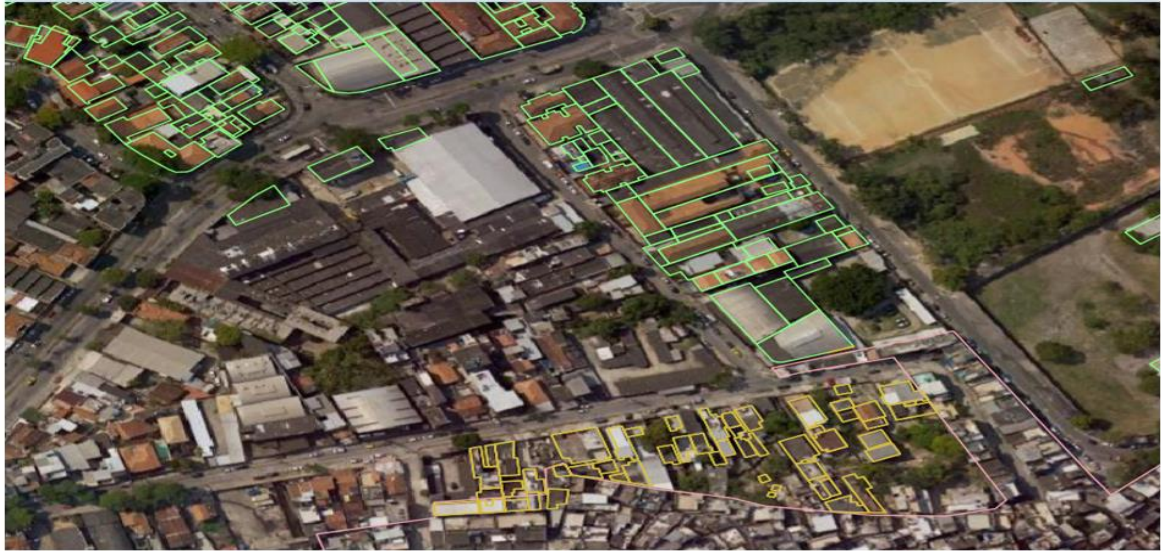


Figure 12 Building Fractal dimensions for Slum and Non-Slum Areas in Rio (QGIS)

Land Feature	Mean mink dimension	Colour Notation
Slum Areas	0.67	Yellow
Residential (non-slum)	0.89	Green

Table 9 Key Statistical metrics extracted for Slum and Non-Slum Areas in Rio

The overall mean F was observed to be of the order of 1 for the slum regions in the city of Rio de Janeiro between 0.5-0.7, which while still showing some extent of a shift from basic and simplistic geometrical forms is slightly lower than that of Nairobi.

This means that while the slum formation in Rio de Janeiro is also irregular as in Nairobi it may be less complex implying that it has at least a slightly more order structure.

This difference may be attributed to various factors such as the history of the favelas in Rio de Janeiro is relatively older as compared to the favelas in other cities, hence there could have been possibility for some form of order to have evolved overtime. The higher fractal dimension could also be attributed to the growth of population in Nairobi as well as the resultant pressure towards enhancement of shelter development. Slums are areas that are occupied by new migrants on arrival in the city, and because they are not in a systematic order, they expand the size of the slum in a haphazard manner. This results in very complex shapes of the slum structures in

Nairobi due to the fact that new structures are built in a haphazard manner as and when space is available. Rio de Janeiro favelas exhibited slightly lower fractal dimension, which may be related to the fact that they are more mature settlements in which people have longer time to arrange their territory. Though, as earlier mentioned when describing Rio de Janeiro's favelas, the existence of steep slopes may serve to increase the general level of irregularity in these regions since people have to construct their houses according to these realities.

5.4. Green Roof Coverage

Green Roof coverage is one of the best ways of determining the amount of concentration in slum areas and the degree of development fitting the area. In Nairobi, roof cover was estimated using NDVI data where it was possible to distinguish between vegetation and non-vegetation. The factor analysis showed that there could be a significant variation in terms of roof coverage percentage in the slum areas minimum 2. It ranges from 7% to a maximum of 53%. This implies that there are relatively large disparities in the extent to which roof coverage has prevented slums areas from extending across the rest of Nairobi. It is expected that slums with higher roof coverage also have a higher population density and more constructions and less open space available. They have suggested that these areas are likely to also be more affected with matters to do with overcrowding problems of a severe nature such as shortage of basic needs, poor hygiene practices and easy prey to diseases. Slums with small roof area may have large unbuilt areas which could be put to productive use for social purposes or for farming or any other activity which may be beneficial to the poor residents of the slums.

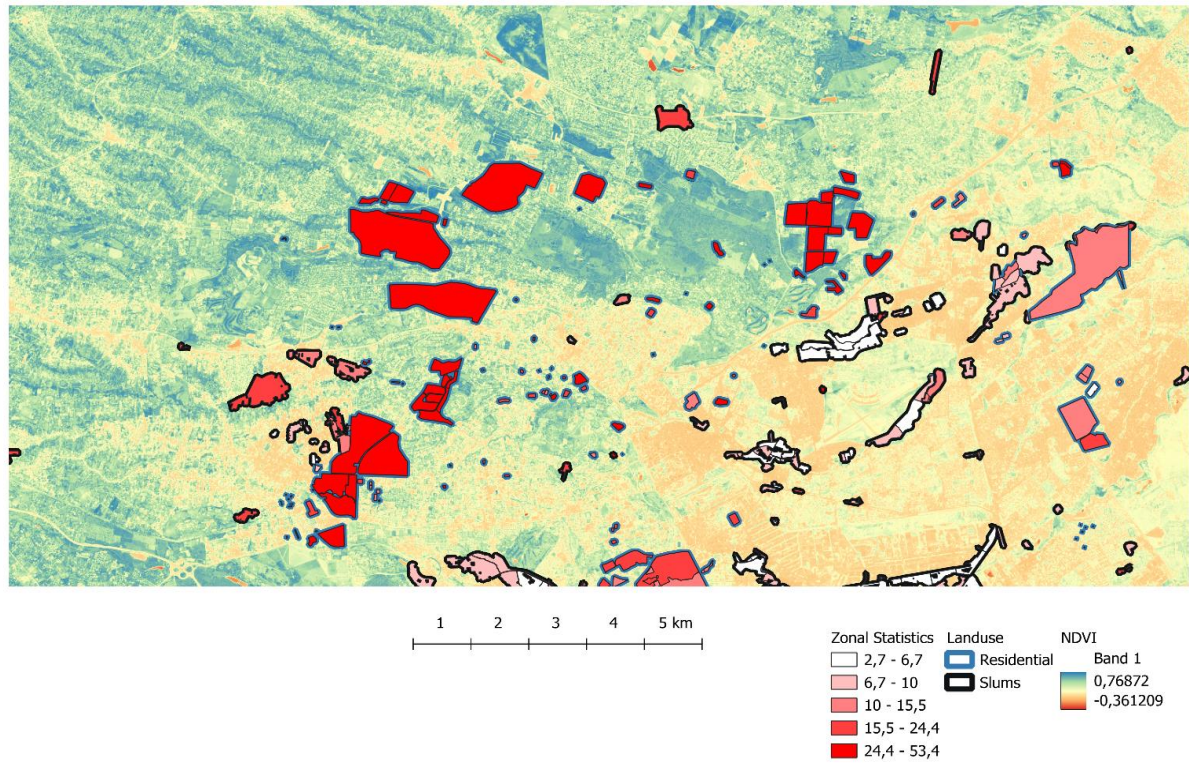


Figure 13 Roof Coverage w.r.t NDVI for Slum and Non-Slum Areas in Nairobi (QGIS)

Land Feature	Green Roof Area Count	Green Roof Coverage % Area	Colour Notation
Slum Areas	162	8.3	Black
Residential (non-slum)	855	47.9	Blue

Table 10 Key Statistical metrics extracted for Slum and Non-Slum Areas in Nairobi

This study was conducted in Rio de Janeiro and the estimated total coverage of the roofs for the slum areas differed as follows; 2. 8% to 83. 5 % of its human resources. This shows a wider variation than the one recorded in Nairobi. Such variable range is attributed to disparities in urban development and growth of various zones within city areas. Some favelas are formed by a set of buildings located closely packed with very little empty spaces between them while in others the houses are more spaced out with perhaps large areas of vegetation or other structures.

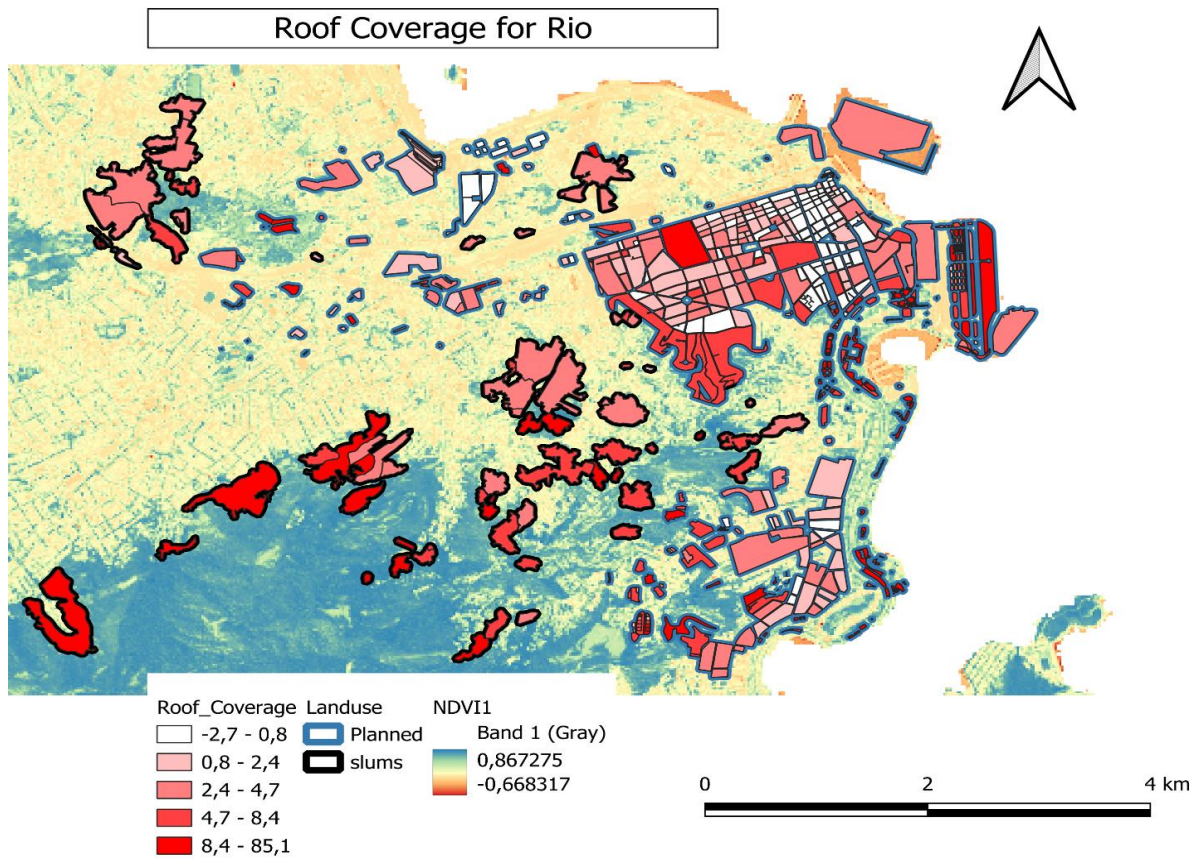


Figure 14 Roof Coverage w.r.t NDVI for Slum and Non-Slum Areas in Rio (QGIS)

Land Feature	Green Roof Area Count	Green Roof Coverage % Area	Colour Notation
Slum Areas	97	13.7	Black
Residential (non-slum)	653	58.3	Blue

Table 11 Key Statistical metrics extracted for Slum and Non-Slum Areas in Rio

Higher maximum roof coverage in Rios' slum as compared to Nairobi indicates that this in fact implies some areas in Rios are more congested and badly stretched in terms of infrastructure and overcrowd. Nevertheless, San Juan and Manila illustrate diverse slum roofs: the former has a higher proportion and better roof protection compared with the latter but is still characterized by substandard living conditions.

5.5. Building Size Road Irregularity

The analysis of building size and road irregularity in slum areas of Nairobi and Rio de Janeiro reveals common characteristics and these can be termed as typical of informal settlements.

Building Size (Nairobi)

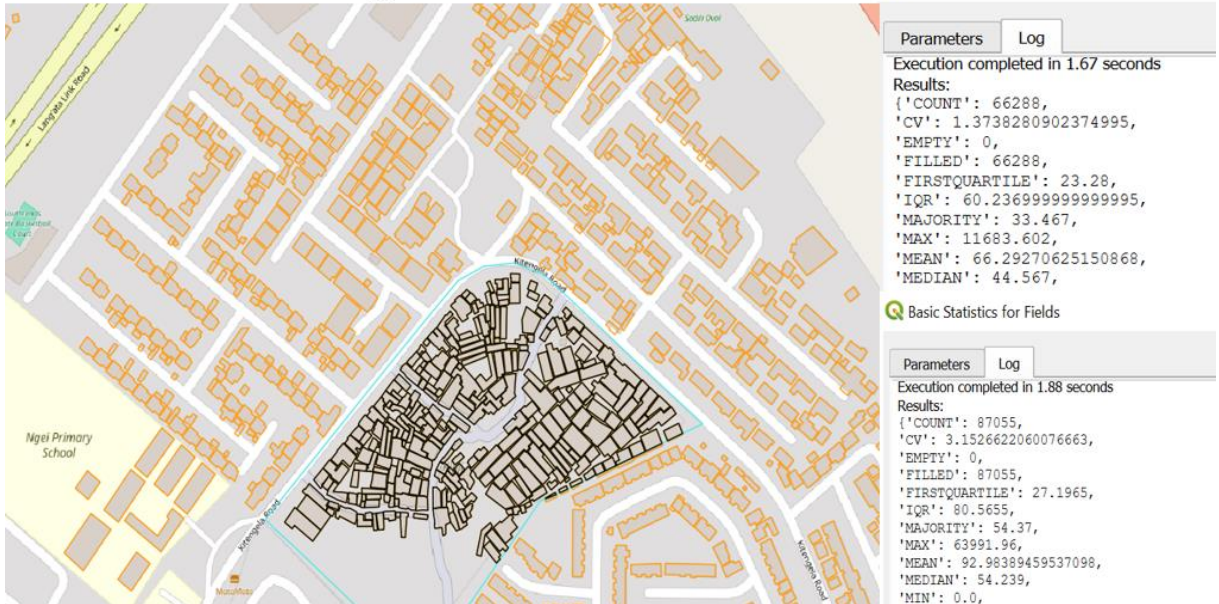


Figure 15 Building Sizes for Slum and Non-Slum Areas in Nairobi (QGIS)

Land Feature	Mean	Median	Colour Notation
Slum Areas	66.2	44.5	Black
Residential (non-slum)	92.8	54.2	Orange

Table 12 Key Statistical metrics extracted for Slum and Non-Slum Areas in Nairobi

The structures in both the city slum areas which are used for residential purposes are on an average of 40-60 square-meter floor area.

Building Size (Rio)

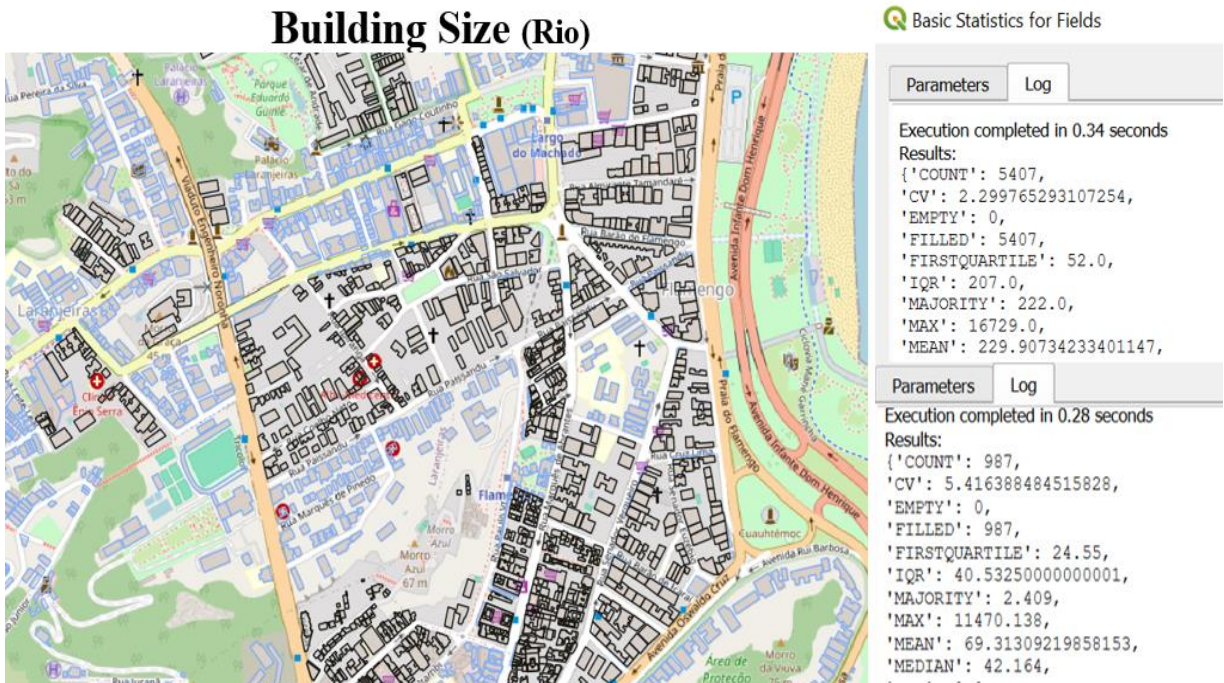


Figure 16 Building Sizes for Slum and Non-Slum Areas in Rio (QGIS)

Land Feature	Mean	Median	Colour Notation
Slum Areas	69.3	42.1	Blue
Residential (non-slum)	229	125	Black

Table 13 Key Statistical metrics extracted for Slum and Non-Slum Areas in Rio

This is partly due to the small space and where most slum dwellers are subjected to poor economy hence their ability to build homes from scrap or poor-quality material which is easily accessible.

5.6. Road Irregularity

Another characteristic of slum areas is the disconnection of their road networks; they are fairly patchy. Thus, main roads in slum areas are narrow and curved and pave way for relatively random patterns unlike those found in more classy regions with more appropriately designed planned and systematic layouts of roads. In order to measure road irregularity, the coordinates of the vertices of the road lines were obtained by using GIS analysis tools.

Roads Irregularity (Nairobi)



Figure 17 Road Nodal Network analysis with 1x 1 km grid for Slum and Non-Slum Areas in Nairobi (QGIS)

Land Feature	Mean Nodes per km ²	Mean Nodes per Road
Slum Areas	225	37
Non-Slum Areas	45	9

Table 14 Key Statistical metrics extracted for Slum and Non-Slum Areas in Nairobi

These were the vertices, which are the points through which roads junction or where the direction changes. Before the vertices were counted, they were divided by the

total number of kilometers of roads in each of the slum areas. From this it is possible to obtain the nodes per kilometer which is a measure of the level of complexity and irregularity of the network. Research has it that the correlations of nodes per kilometer are higher for slum areas because it is a common thing for such neighborhoods to have evolved haphazardly.

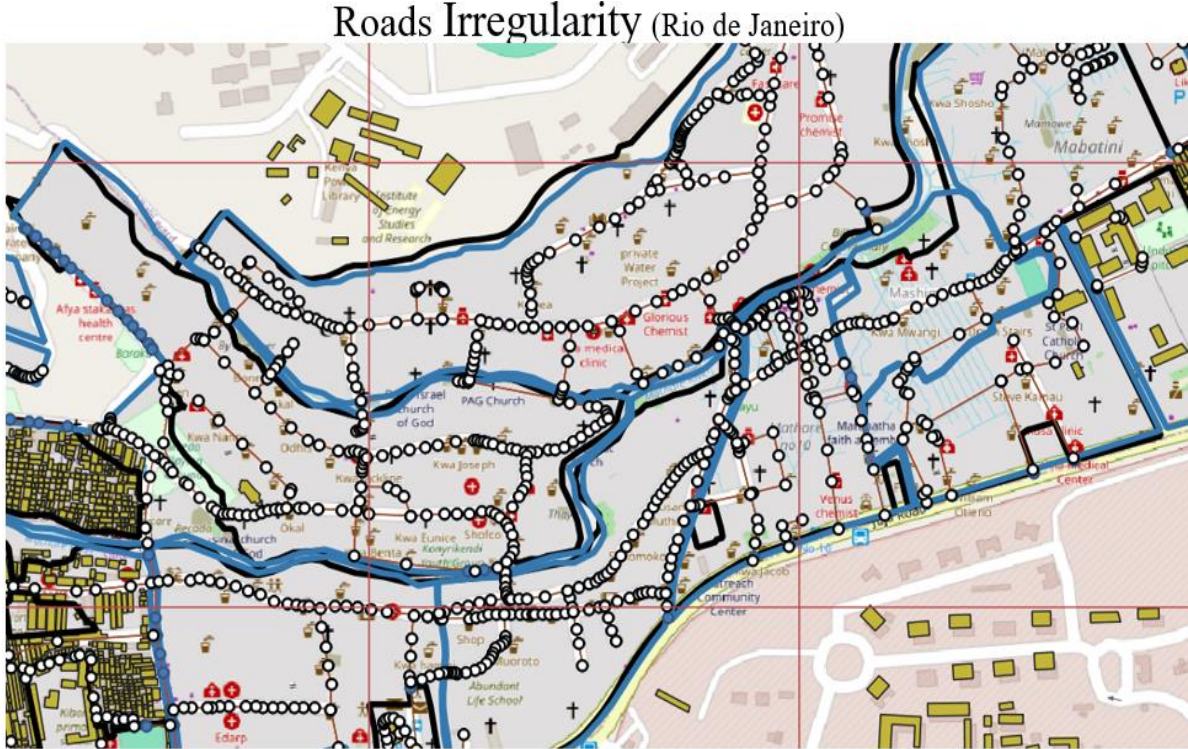


Figure 18 Road Nodal Network analysis with 1x 1 km grid for Slum and Non-Slum Areas in Rio (QGIS)

Land Feature	Mean Nodes per km ²	Mean Nodes per Road
Slum Areas	127	25
Non-Slum Areas	25	5

Table 15 Key Statistical metrics extracted for Slum and Non-Slum Areas in Rio

The high node density in slum areas also affects the accessibility of services and infrastructures since roads organization in slum areas may sometimes lead to the restriction of free movement of emergencies such as ambulances, garbage collection etc. This irregularity of navigating makes the separation process of those communities by depriving them of resource or service chances. Altogether, the small building sizes and irregular road patterns evidence the socio-economic problems and unordered nature inherent to the slum areas of Nairobi and Rio de Janeiro. When aggregated and analyzed these characteristics give useful information on the spatial distribution of

slum areas and thus the importance of designing urban interventions for enhancing living standards in these areas.

6. Discussion and Challenges

This thesis reveals the diverse nature of the physical environment of slums in Nairobi and Rio de Janeiro and shows that the structure of slum areas is diverse and unique, both in terms of potential for development and in terms of difficulties. The understanding of slope, socio-economic activities proximity, fractal dimension, roofed area, building area and road ruggedness helps in understanding spatial characteristics of slum areas for effective formulation of urban planning and policies. It further depicts the patterns and economic nature of slums of Nairobi and Rio de Janeiro to elucidate the issues and future of urbanization in the given areas. This means that the geographical setting of slums in Nairobi where many of them slopes and population density is high, which enhances the possibility for slippage as well as enhancing in fractional challenges. The general gradient of the slum regions of Nairobi is 10 percent. 19%, compared to 6. 39% in non-slum areas. Whereas, in Rio, the mean slope in slums is about 13. 8 percent, increasing exposure to the threats and responding to development propulsive endeavors. They provide that 83% of the slum areas, in Nairobi are within 500 meters of socio-economic activities, which are economic zones for instance the industrial or the commercial zones. However, Rios slum areas are closer to such zones in only 20-30% of the areas proving more tendency towards detachment from society. According to this analysis, fractal dimensions of Nairobi's slum is higher than Rio's slum that reveals decentralized and disordered urban growth pattern and challenging for city planning.

Roof coverage data shows temporal fluctuation for both Cities: Nairobi roof slum area: 7% to 53%, and Sao Paulo's favelas shows an even wider variety of numbers ranging between 2. 8% to 83. 5%. These values represent the density and pressure

on the living conditions in specific areas of the United States, and therefore where a high roof coverage represents crowding and poor living conditions. Small building sizes such that most buildings range between 40-60 sq.m and fragmented road networks make service delivery even harder in both cities. Factors such as variation in resolution of images retrieved and subjectivity in the analysis of images also lead to error and uncertainties while identifying a slum. The future work would involve adopting better satellite data for the analysis together with better classification methods to increase the accuracies of the results. In details, therefore, the study calls for development specific urban planning strategies that fit the infrastructural, environmental and economic characteristics of slums in Nairobi and Rio de Janeiro.

7. Conclusion

The research aims to give an overall view on their geographical features as well as physical and socio-economic characteristics which define slum areas as informal settlements and differentiate them from the planned cities. The research reveals marked differences between slum and non-slum areas such as slope, distance to socio-economic activity, fractal dimension, and roof area density to provide indications of the spatial characteristics of these cities. Nairobi is a city characterized by steep slopes with slum areas developed on steep slopes which is unfortunately associated with high risks of landslides and great challenges in development. The closeness of the slums to socio-economic activities points to strategic, albeit risky, location in the flow of city's economy. On the other hand, the remaining isolated slum zones in Rio are discussed in terms of completely different urban experience – social and spatial marginality keeps people poor and deprives them of contact with easier lifestyles. The fractal dimension analysis shows that slum formation is Decentralized, disordered and has a different pattern in both cities with higher slum complexity level in Nairobi due to factors such as urbanization

pressure and population density. Roof coverage also shows the heterogeneity of slum density in the urban context, especially as it relates to the degree of development and population density in the slum areas. This pattern of residential buildings also shows the problem of accessing basic human needs such as proper housing and other essentials in slum areas; they are also informality that complicates the integration of the slum areas into the formal city. These attributes call for planning that takes into consideration the characteristics of slum areas and aims at the fair development of such areas.

The study concludes that there is still a need to adopt methodological approaches to slum definition and Urban Development. Although, the individual assessments like slope or fractal dimension are informative; the complex relationship between these metrics provide enhanced comprehension required for accurate slum boundary definition and consequent application of corrective measures. Moreover, the comparison of Nairobi with Rio de Janeiro on these indicators shows that there is still a gap that has to be closed at the same time that proves that the approaches have to be contextualized. Local socio-geographical factors must be taken into account by urban planners and policymakers in the process of choosing strategies for slum upgrading and development. This kind of approach is crucial in the realization of Sustainable Development Goal 11. 1 which focuses on the strategies to promote adequate, safe and affordable shelter for all, especially for the people living in the informal sector. Summing it up, this study argues that apropos to the physical and socio – economic characteristics of slum territories can use geospatial histories, which this work has developed, as a useful map for understanding the regions applicability to the general questions of urban planning and policy making. Employing these findings, cities can work towards a more enhanced and appropriate technique on slum upgrading, which will therefore foster improved and improved urban development.

Recommendations for Future Work

1. Integrate socio-economic factors with spatial analysis to provide a holistic view of living conditions.
2. Utilize high-resolution imagery and advanced algorithms to minimize errors in slum mapping.
3. Explore temporal analyses to track slum growth and inform adaptive urban planning strategies.

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9. Appendix

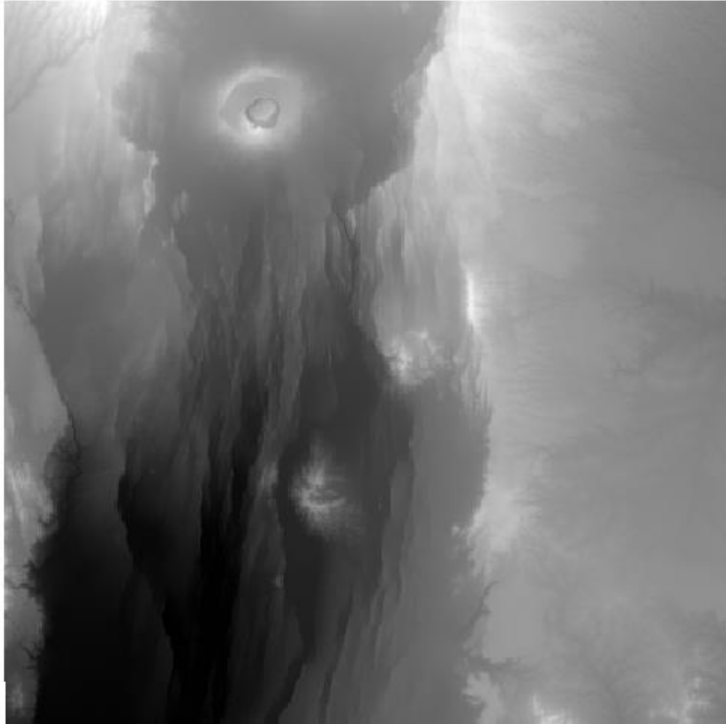


Figure 19 DEM without pre-processing from SRTM

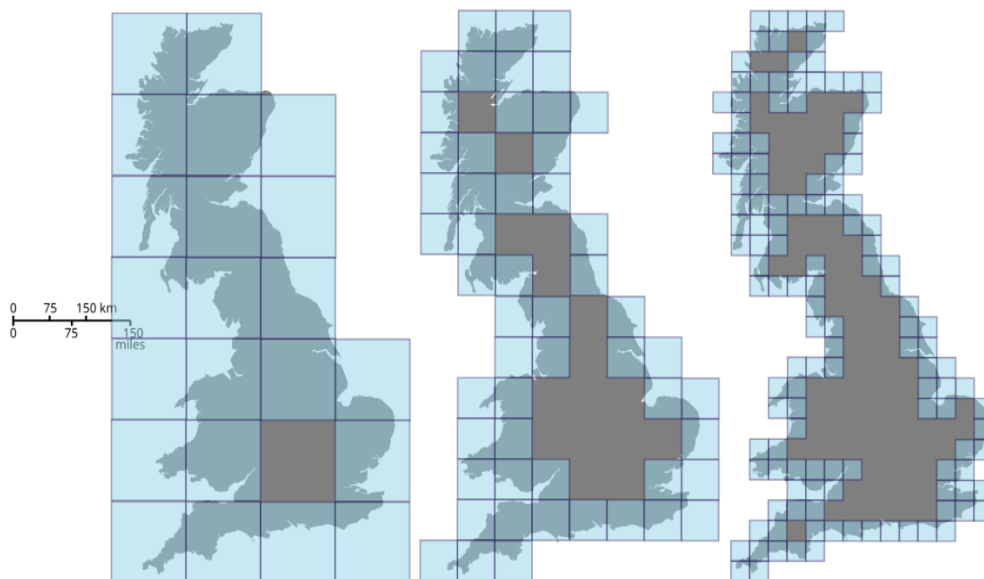


Figure 20 Estimating the box-counting (Minkowski–Bouligand) dimension of the coast of Great Britain

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Minkowski Dimension Calculator

Plugin ID: 910

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★ (14) votes

Plugin calculates Minkowski dimension (also known as Minkowski–Bouligand dimension, box-counting dimension) for features of vector layer.

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2.0	no	2.99.0	3.99.0	3148	ekazakov	Jan 7, 2019, 01:53 AM GMT+1
1.0	no	2.0.0	2.99.0	2726	ekazakov	Dec 23, 2015, 11:29 AM GMT+1

Figure 21 Minkowski Dimension Calculator in QGIS Plugins Repository