An extent analysis of Freetown’s informal settlements in 2021

Author: Ostap Fedyshyn

Contents

Introduction

Problem discussed

According to the UN, in 2018, a quarter of the world's population lived in slums (UN-Habitat, 2018), defined as settlements where access to necessary resources is limited (Ward, 2016). For sub-Saharan Africa, that number is well above 50 per cent, and for Sierra Leone, nearly 60% or almost 2 million people resided in slums as of 2018 (UN-Habitat, 2018).

The complex and diverse structure of informal settlements makes it challenging to define and detect a potential slum through standard methods. Moreover, data on informal settlements are often messy and unorganized, which further complicates slum monitoring and evaluation (Kuffer et al., 2016).

In his influential book "The Mystery of Capital", Hernando De Soto points out that slum dwellers accumulate enormous resources and significantly contribute to the economies of their countries. However, the problem is that most of this economic activity happens in the so-called 'grey area', which prevents the capital from growing (De Soto, 2001).

Over the last two decades, many governments have recognized that "slums disappear not through being removed, but by being transformed" (Cobbett, 2013, p. 1) and that the most effective way in dealing with informal settlements is in situ upgrading. Hence, it is essential to have up-to-date information on the changing locations, extent, and densities of informal settlements, as it is crucial in the difficult task of slum dwellers economic inclusion and slum upgrading (Kuffer et al., 2016). Knowing the exact extent of informal settlements within the city is also crucial for urban development, planning, and decision support.

Study area

This study was conducted using the data for Freetown, Sierra Leone, or more specifically, the Western Area Urban District of the country (Statistics Sierra Leone, 2021). For simplicity, the name Freetown will be used to refer to Western Area Urban District (figure 1).

Figure 1. Position of Sierra Leone on the African continent (left), dark grey highlights countries belonging to ECOWAS. Location of Freetown in Sierra Leone (right).

Freetown is a medium-sized capital of 1,236,425 million people (World Population, 2021), with an annual increase of almost 3% this population, however, is projected to double by the year 2050 (United Nations, 2021). Freetown faces severe overcrowding problems. According to UN criteria, up to 75% of the city can be considered as slums (UN-Habitat, 2003). This, in many ways, is the result of a civil war (1991-2002) that forced nearly half a million people to relocate to Freetown, which has rapidly transformed the urban realities of the capital (Monica, 2021) (figure 2).

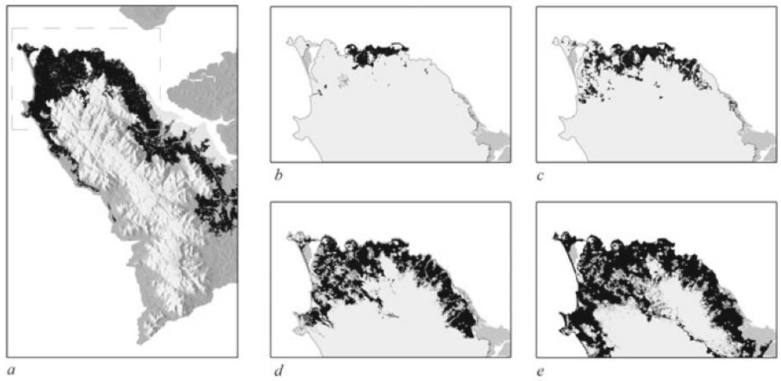


Figure 2. Spatial evolution of Freetown: a) the greater Freetown area in 2017 (build-up areas shown in black), b) Freetown in 1958 (before independence), c) 1977, d) 2006 (after the war), and e) 2016. Credit: Monica, 2021, p.114.

Expansion of the city and her informal settlements causes severe problems. As slums are often located along the waterways and on the slopes of numerous hills, they cause serious water pollution and massive deforestation. To make matters worse, floods and landslides claim casualties and cause economic damage annually. In 2017 a vast landslide resulted in the death of 1,141 people (Monica, 2021). This is one of the reasons why it is so important to accurately map the extent of Freetown slums as they are often located in the most prone to natural disasters areas of the town.

Brief literature review

There is some impressive research on slum detection using various methods. One example is a worldwide detection of informal settlements carried out by scientists of the University of Chicago (Satej et al., 2020). This recent research utilises Open Street Map building and road network data to analyse the connectivity of building blocks of the Global South. This project is undoubtfully beneficial for city planners; however, it is probably not the most effective method for mapping informal settlements in cities like Freetown, where the connectivity is generally poor across broad areas with different levels of wealth (figure 4).

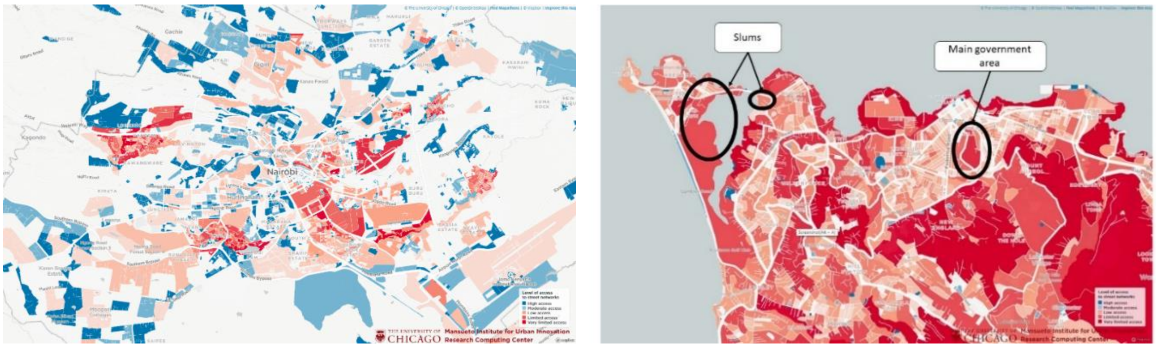


Figure 4. Choropleth of street blocks by connectivity in Nairobi, Kenya (left) and Freetown, Sierra Leone (right). Blue represents better-connected street blocks, and red represents poorly connected ones. Maps are of identical scale. Adopted from: MillionNeighborhoods, 2021.

There has been a lot of work that focused on identifying slums, specifically in Freetown; however, it rarely resulted in exact boundary identification of informal settlements. Besides a couple of most significant and most famous slums, few of them are mapped more than with a point (Monica, 2014).

The only map that shows the exact extent of Freetown slums found by the author was published by Dr Monica in 2014 (figure 5). Although it is very informative and can be used by decision-makers, many informal settlements have grown since 2014, and many are missing. This is mainly due to the dynamic evolution and spread of Freetown slums and the difficulty of slum identification (figures 6,7). This research attempts to update Dr Monica’s informal settlement map (Monica, 2014, p. 131), relying on different methodologies and more recent data.

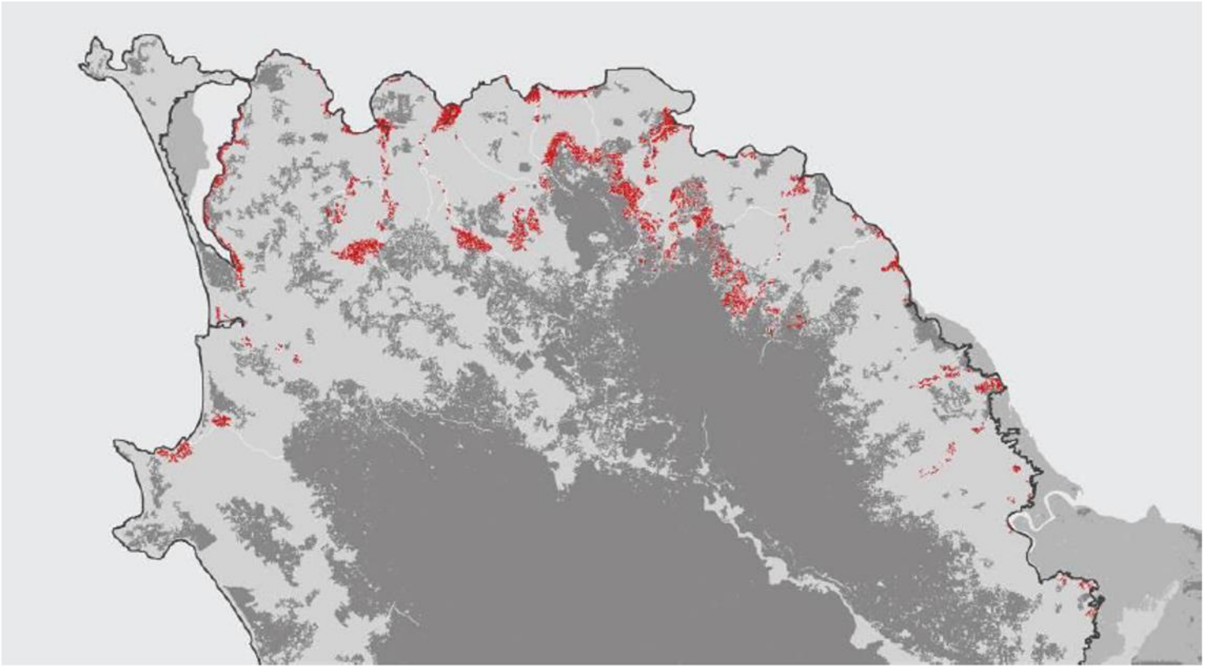


Figure 5. Map of the informal settlements of the city of Freetown, 2014. Credit: Monica, 2014, p. 131.

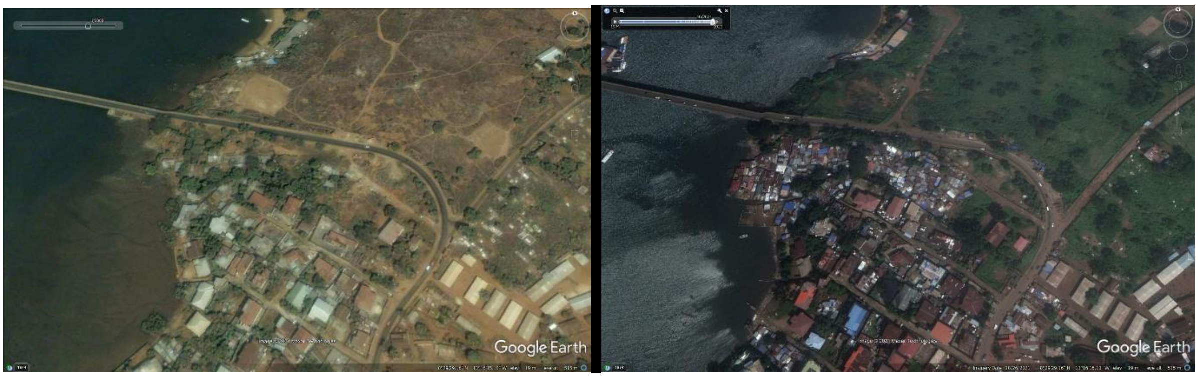


Figure 6. Informal settlement near Aberdeen Rd., Freetown over time. Left 2008, right 2021. Photo Source: Google Earth.

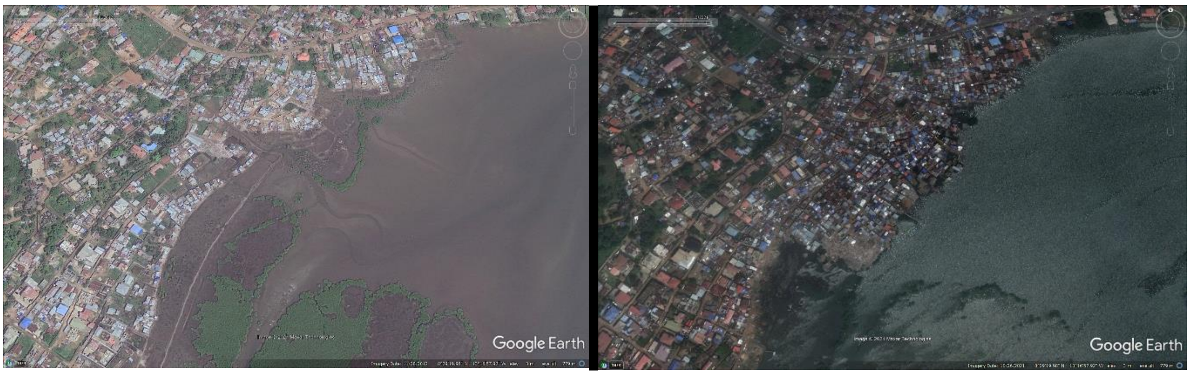


Figure 7. Land reclamation on Aberdeen peninsula, Freetown over time. Left 2012, right 2021. Photo Source: Google Earth.

Methods

Data description

This analysis used the Open Buildings dataset of detected footprints of buildings in Freetown. The dataset was created in 2021 by a model training pipeline for detecting structures that used 50 cm satellite imagery (Maxar Technologies and CNES/Airbus). Open Buildings dataset contains 516 million building footprints detected across Africa; however, for the purposes of this analysis, only buildings located within the Wester Urban Area of Sierra Leone were extracted (Sirko et al., 2021).

A deep learning model was used to identify building footprints that classified each pixel of a satellite image as building or non-building. A confidence score threshold was then developed to find connected components and produce a building polygon (figure 8) (Sirko et al., 2021).

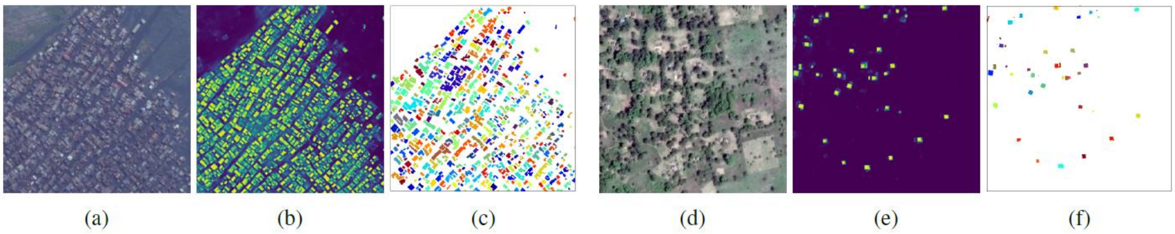


Figure 8. Examples of building detection: (a,d) test images; (b,e) semantic segmentation confidences; (c,f) instances of buildings found. Credit: Sirko et al., 2021.

The data is subject to both omission and commission errors. Some areas did not have up-to-date satellite imagery, or there was a high level of cloud cover. However, most of the downloaded data still obtains an estimated 70% precision levels (figure 9). This should be sufficient to detect informal settlements' extent in Freetown accurately.

Figure 9. Building footprints confidence level in Kroo Bay, Freetown. Credit: Sirko et al., 2021.

Procedure

According to the literature review on slum identification conducted by Kuffer et al., there are four main morphological characteristics that are common for slum areas (2016). These include high roof coverage density, organic patterns, small building sizes, and hazardous locations (table 1). All of these are typical of Freetown slums (Monica, 2014).

Table 1. Morphological features typical for slum areas. Adapted from Kuffer et al., 2016, p. 4.

Features	**Slum Areas**	**Formal Built-Up Areas**
Size	• Small building sizes.	• Generally larger building sizes.
Density	• High roof coverage densities. • Lack of public (green) spaces within or in the vicinity of slum areas.	• Low to moderate density areas. • Provision of public (green) spaces within or in vicinity of planned areas.
Pattern	• Organic layout structure (few roads).	• Regular layout pattern (planned regular roads)
Site Characteristics	• Often at hazardous locations (e.g., flood prone, steep slope).	• Land has basic suitability for being built-up.

	• Proximity to infrastructure lines and livelihood opportunities.	• (Basic) infrastructure is provided

This analysis is based on two above morphological characteristics of informal settlements (Table 1). It is assumed that the high density of small area buildings constitutes a slum. Hence, an object-based method was combined with an area-based identification method to locate them. The open building data was used to locate all identified buildings in Freetown. Next, this data was processed, and the area-based analysis was conducted to detect clusters of informal settlements (Kuffer et al., 2016).

This analysis was conducted in ArcGIS Pro software licenced by the University of Manchester. There were three main stages of the analysis:

- Upload and clearance of necessary data
- Slum extent detection analysis
- Comparison of the results to available raster map from 2014

The original 'Africa buildings' layer that contained nearly four million building features was cropped to the extent of Freetown. Resulting 245,621 features were used in the analysis. The data was corrected as some ships were incorrectly classified as buildings; these were removed, all other features with confidence over 60% were included. A necessary polygon for the Western Urban Area boundary was uploaded from Esri's Living Atlas.

In order to quickly understand the clustering situation, 'Global Moran's I' was used. This tool evaluates whether a set of features is clustered, dispersed, or random (Esri, 2021). The report (figure 10) indicated that there was significant clustering of the data.

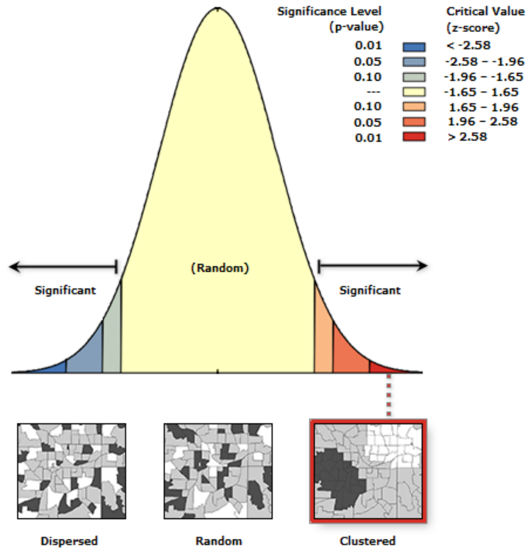


Figure 10. Global Moran's I Spatial Autocorrelation Report.

Three main methods were used to detect slum extent (figure 11).

1. Density-based clustering.
2. Cluster and outlier analysis (Anselin Local Moran's I).
3. Optimized hot spot analysis.

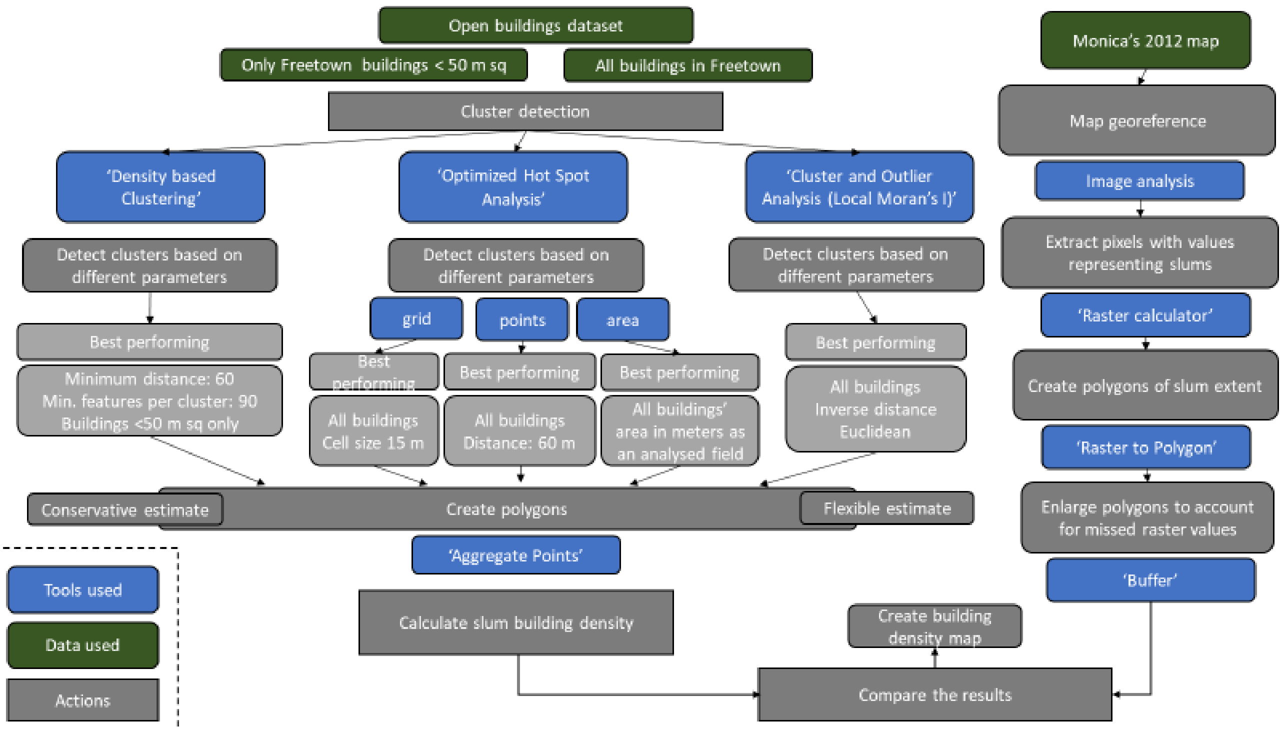


Figure 11. Flow chart summary.

The density-based clustering finds clusters of point features based on their spatial distribution (Esri, 2021). In other words, it detects areas where points are concentrated and where empty or spare spaces separate them. All the points in the outcome that are not clustered are classified as noise. This method was used because it allows finding clusters solely based on the input points' location.

Local Moran's I offer much more sophisticated analysis. It is a measure of spatial correlation that identifies spatial clusters and assigns points with high or low values. It calculates a z-score and p-value, which help to assess how statistically significant a certain point is (Esri, 2021). Moran's I was used to find clusters based on building locations giving each building a weight associated with its area in square meters. Hence, this method helps to measure the magnitude of clustering, showing the strength of the connection between different features (Ritvikmath, 2020). This tool was used to identify the concentration of large and small buildings.

Optimised hot spot analysis uses the Getis-Ord Gi* statistic to weight points and highlight statistically significant hot and cold spots (Esri, 2021). It was used because it evaluates the characteristics of the input feature (building area in our case) and produces results that highlight differences between different neighbourhoods.

Local Moran's I and Getis-Ord Gi* both are statistical techniques that appear to be quite similar. However, they can help answer different questions as they calculate values of the features differently based on the influence of neighbourhood on the feature. Basically, the Getis-Ord Gi* determines *whether each feature's neighbourhood is significantly different from the study area* and categorises the feature as a hot/cold spot if it is. Local Moran's I, on the other hand, removes the feature from its neighbourhood and determines *whether each feature is significantly different from its neighbourhood*. Hence, Local Moran's I allow to find the outliers within hot/cold spots, like large buildings in a densely built-up slum (Esri, 2021).

Before running any of the above tools for all the buildings in Freetown, they were tried on a smaller sample first in order to find out the parameters that work best. As a sample, buildings located on the Aberdeen peninsula and near the Aberdeen bridge were used (6856 buildings or 3% of total Freetown buildings). The author assessed this area in the fall of 2019 and determined two neighbourhoods that can be clearly defined as slums. As nothing was found about these specific slums in the literature, they were called ‘Aberdeen West’ (figure 7) and ‘Aberdeen Road’ (figure 6), all other slum names used in this analysis were taken from the literature (Monica, 2014). Images from Google Earth were also used as a reference. Mentioned slums are coastal and relatively easy to identify; hence if the resulting output did not show their realistic extent, the parameters were changed until satisfactory results were obtained. Next, best-performing parameters were used on all the buildings in Freetown.

To compare the results with other studies, Monica’s 2014 map of Freetown slums (figure 5) was georeferenced using imagery analysis capabilities of ArcGIS Pro. Next, the ‘Raster calculator’ was used to extract only pixels with values that corresponded to the colours of informal settlements (figure 12). Different colour value combinations were tried, and eventually, the following code was used:

```
Con("Green.tif", 1, 0, "Value<130")*Con("Blue.tif", 1, 0,
"Value<140")*Con("Red.tif",1,0, "Value>100")
```

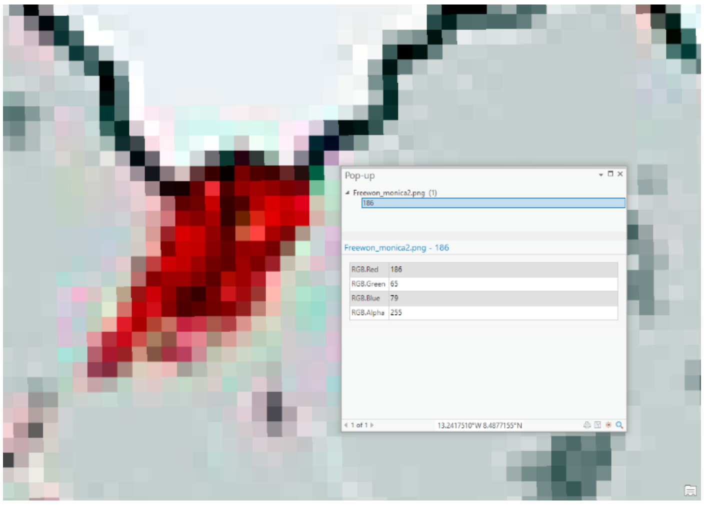


Figure 12. Band values broadly represent the extent of a slum. Adopted from Monica, 2014, p. 131.

In the binary raster outcome, only values equal to ‘one’ were extracted, and selected values were then turned into polygons. Resulted polygons represented informal settlements on the original image well; however, due to the poor quality of the picture, some surrounding rasters cells were left outside of the polygon features. To correct this, ‘Buffer’ tool was used, and polygons were enlarged by 30 meters, which yielded very close results to the slums on the original image (figure 13).

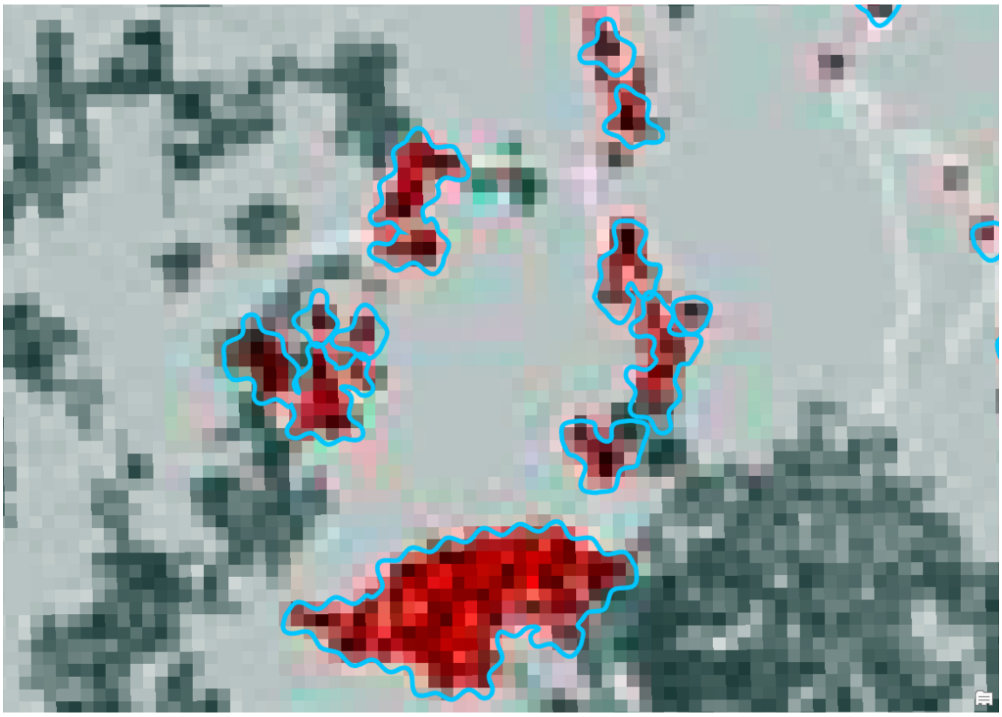


Figure 13. Buffer polygons are outlined in yellow. Slums on the original image (Monica, 2014, p. 131) are mostly red.

Results

Each of the geoprocessing tools discussed above was run numerous times with different parameters, and the outcomes of best-performing parameters are shown below. Figure 14 shows the extent of slums based on buildings (points) locations, where densely built-up areas were classified as slums.

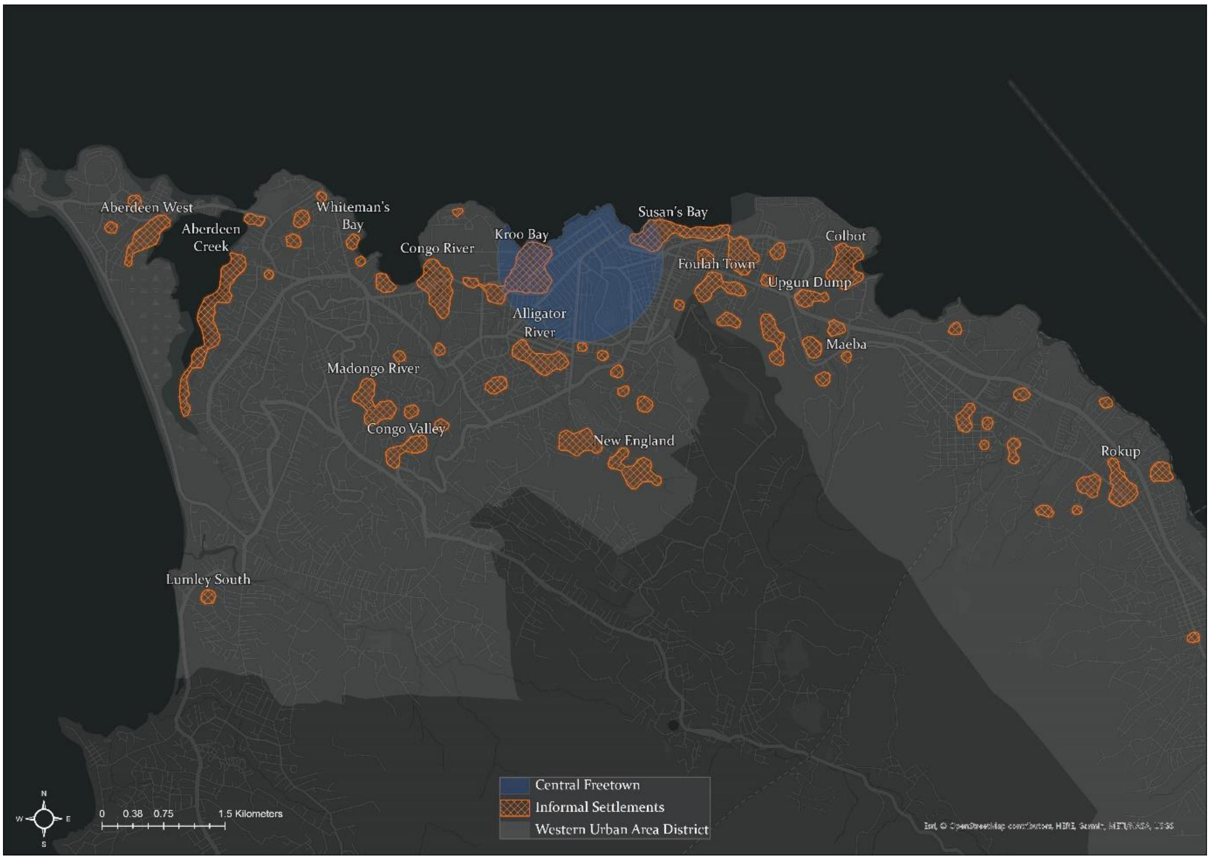


Figure 14. Informal settlements' extent in Freetown derived using Density-based clustering method. The radius of Central Freetown circle = 1 kilometre.

Local Moran's I result yielded a very broad estimate of slums' extent (figure 15). According to this outcome, areas around the city centre are almost exclusively occupied by informal settlements.

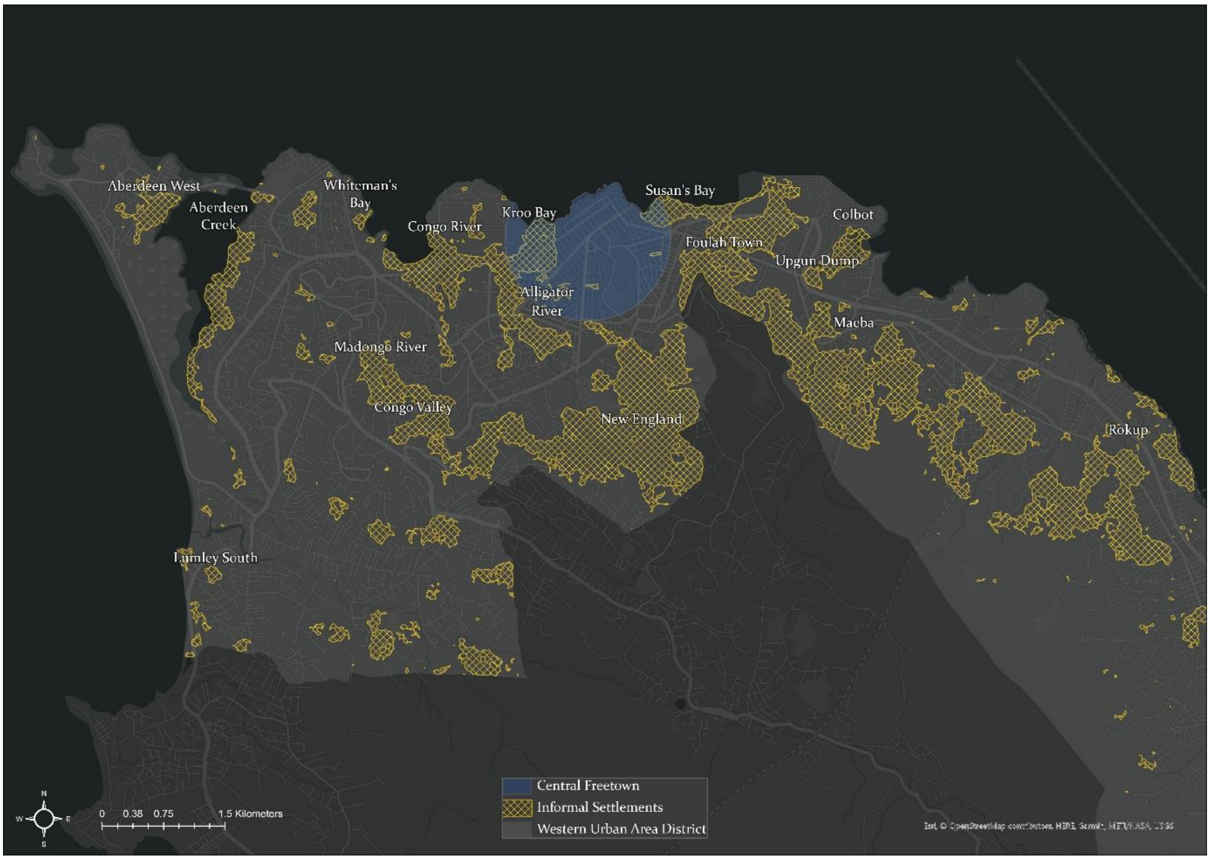


Figure 15. Informal settlements' extent in Freetown derived using Local Moran's I method.

However, the most realistic outcomes were obtained using Optimized Hot Spot Analysis. The grid map highlights the slum areas with high building numbers per cell (figure 16). And the results visualized in figure 17 were produced based on analysis of each building footprint area and their locations.

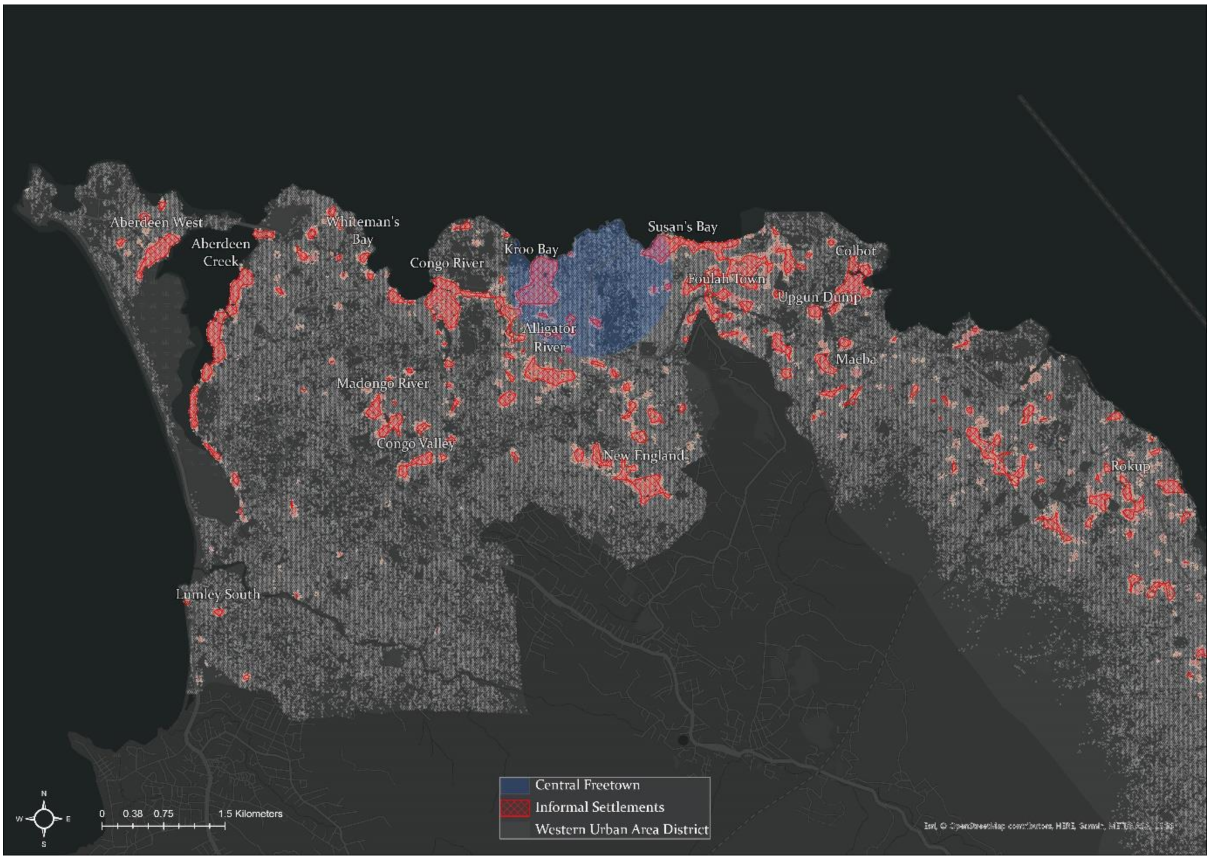


Figure 16. Informal settlements' extent in Freetown derived using Optimized Hot Spot Analysis grid method. Each hexagon cell = 15 meters squared.

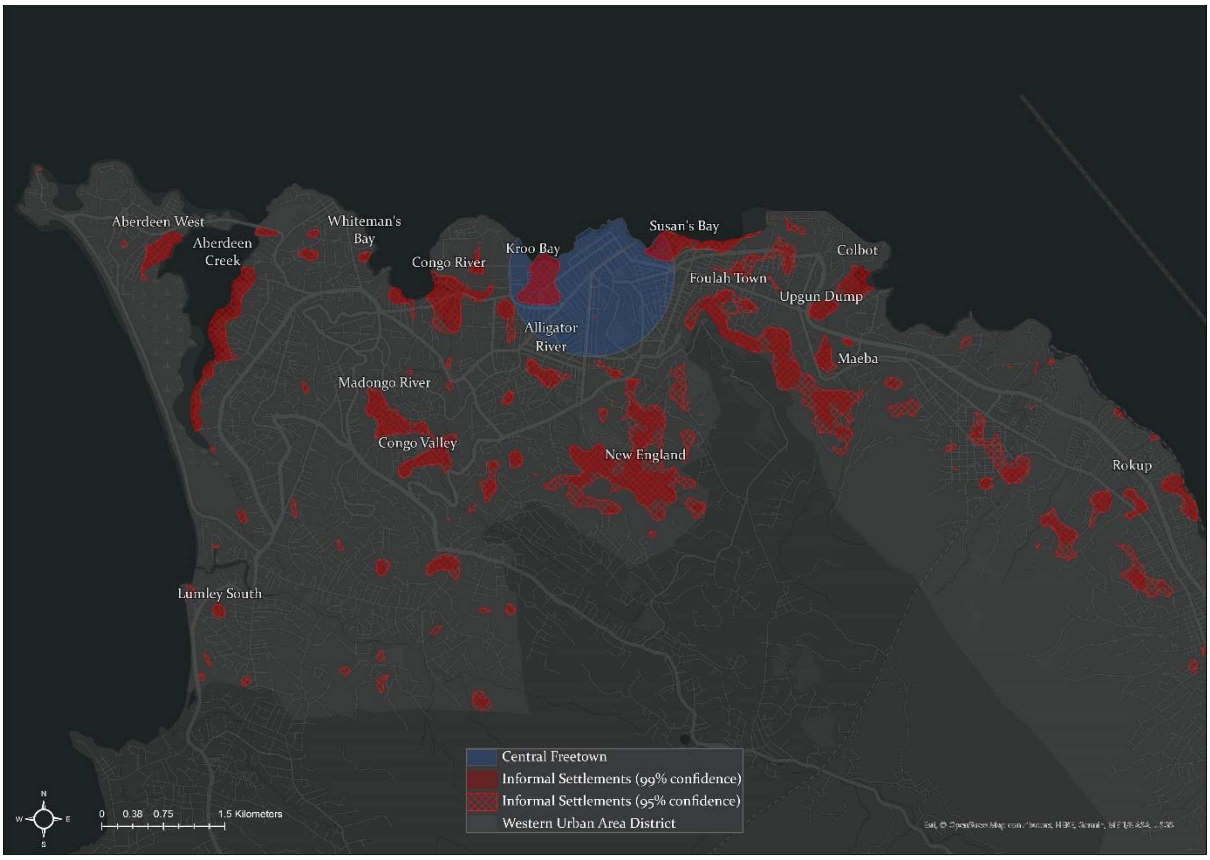


Figure 17. Informal settlements' extent in Freetown derived using Optimized Hot Spot Analysis area method.

The more conservative (figure 17) and broader (figure 15) estimates of slum extents were compared to informal settlements mapped by Dr Monica in 2014 (figure 18).

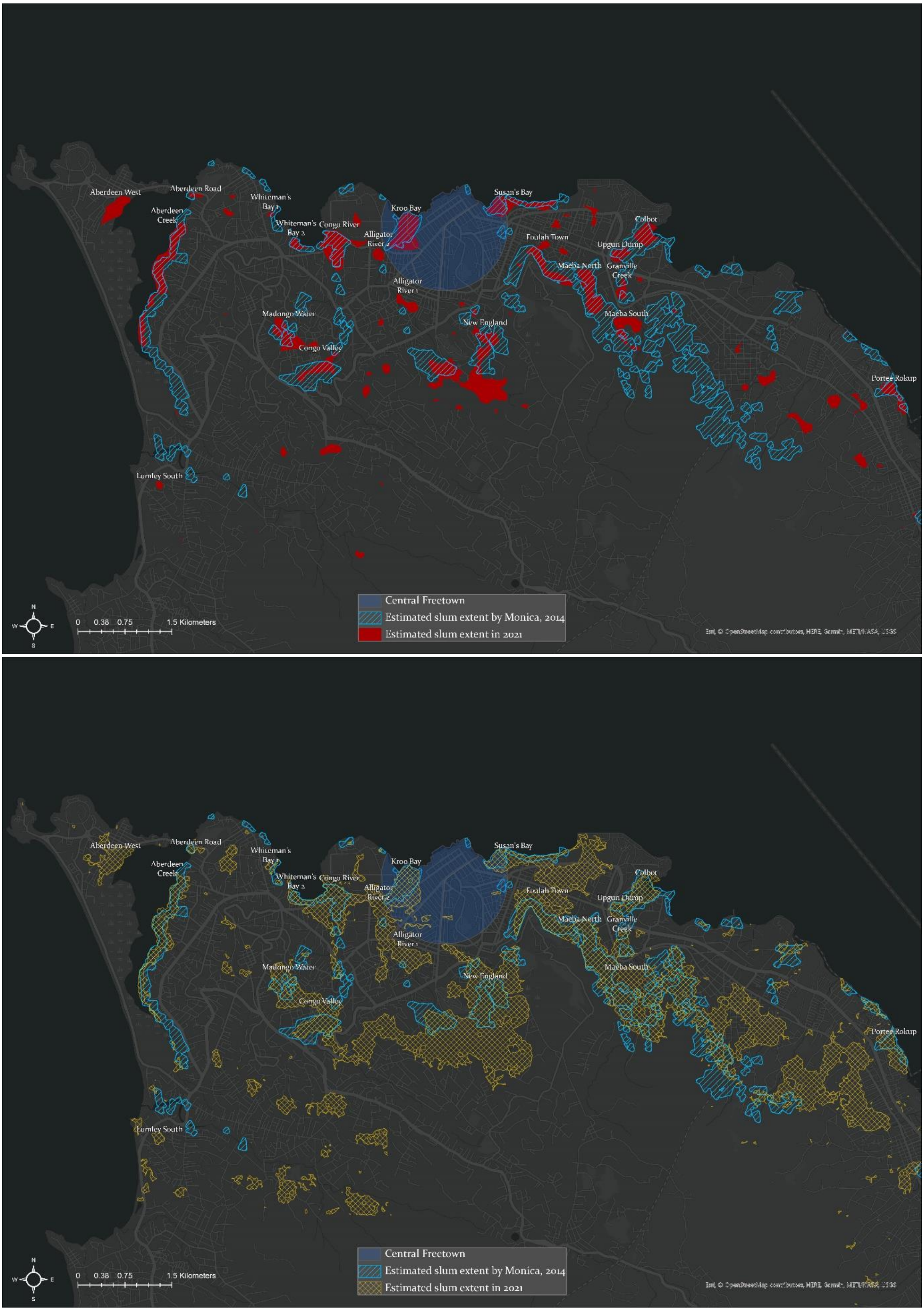


Figure 18. Informal settlements' extent comparison with 2014 map composed

by Dr Monica (blue areas) (Monica, 2014, p. 131). Conservative estimate (upper), broad estimate (lower).

The largest slums from the conservative estimate were extracted, and their building density was calculated based on polygon area and number of identified buildings within each polygon (figure 19).

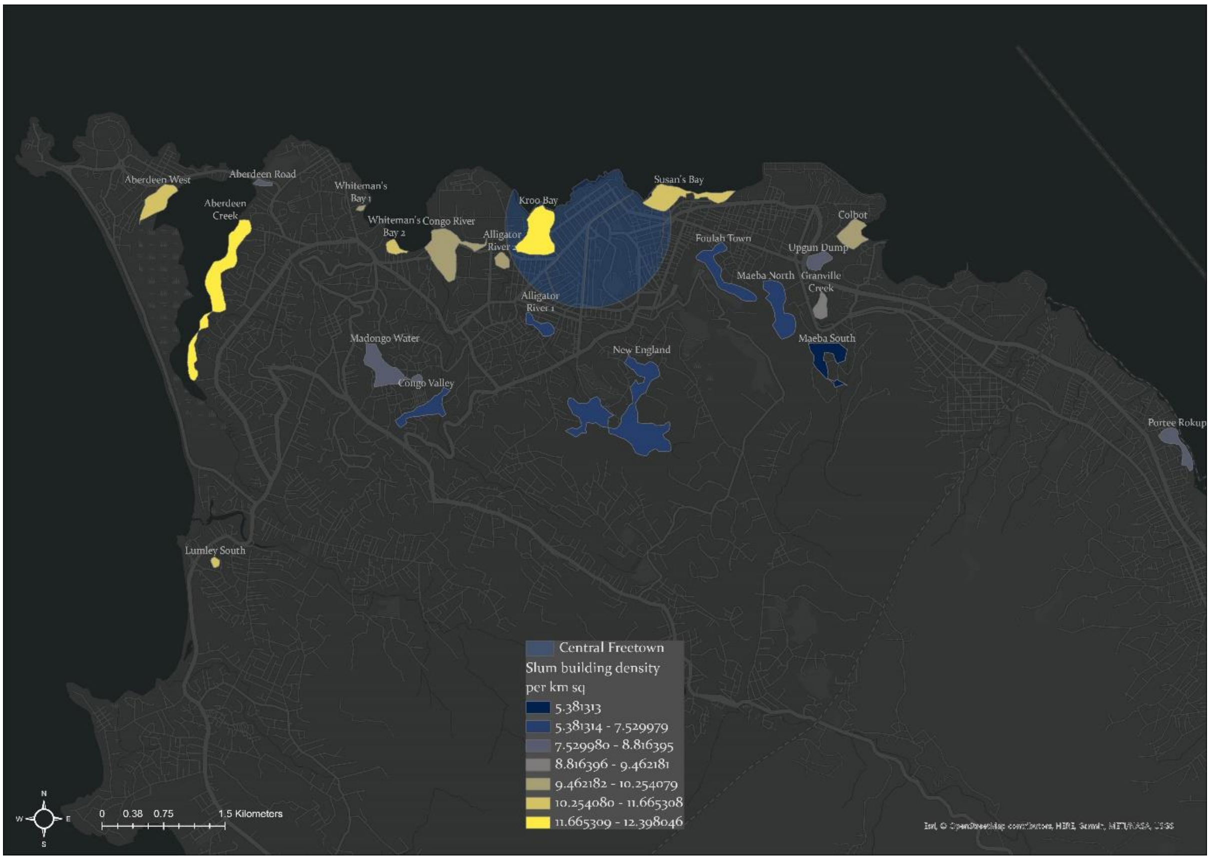


Figure 19. Building density in Freetown's largest slums.

Next, the population of each of the largest identified slums was calculated. The following formula was used:

slum population	=	number of buildings	*	average number of people per household

The average slum household in Freetown was assumed to have four people (Statista, 2020). The population estimates for Kroo Bay slum were compared with known figures, and results were satisfactory for a broad population estimate (Kabba et al., 2014).

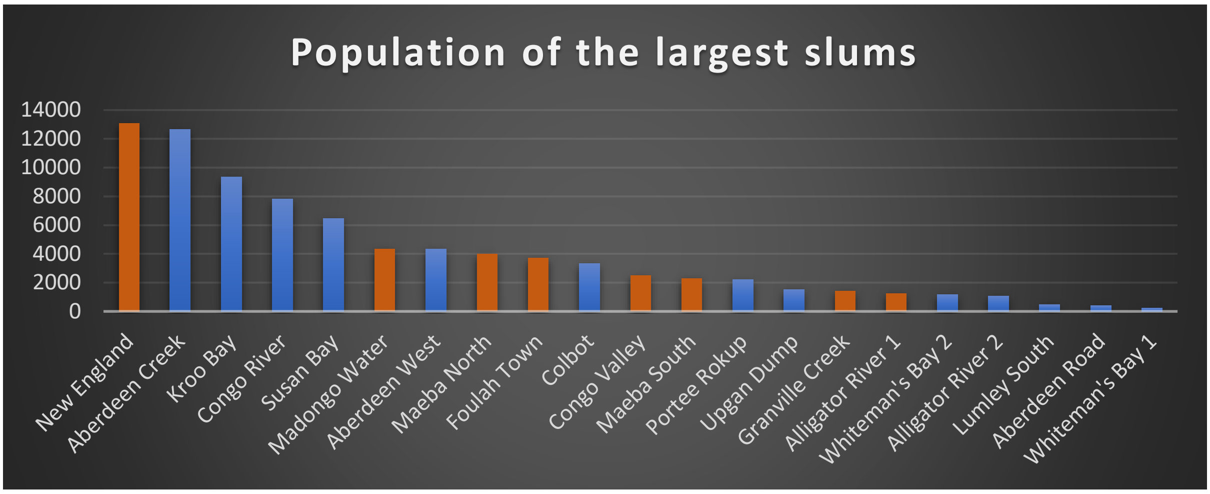


Figure 20. Population estimates of the largest slums in Freetown. The number of dwellers is shown on the left. Slums located on the slopes of the hills are orange, and coastal slums are blue.

Discussion and limitations

The Local Moran's I method resulted in a broader estimate of slum areas (figure15), which can be true depending on the definition of what constitutes a slum. This estimate is closer to the UN definition of informal settlements (UN-Habitat, 2003). However, considering local realities in Freetown, the Optimized Hot Spot Analysis yielded more valuable results for the city planners in Sierra Leone (figure 17).

The comparison of results with Dr Monica's map shows many similarities of our estimates, as many core slum areas were identical. However, some areas clearly differ due to different methodologies and different data used. For example, the area south of the Aberdeen Creek slum (figure 18) was not detected as a slum because the open building data used did not identify buildings in this area correctly. The results of slums located inland (on the slopes of the hills) were also significantly different. This potentially is due to dense vegetation cover; hence, it was more challenging to identify buildings there correctly.

The density map (figure 19) demonstrates a very interesting trend. Almost all coastal slums (Kroo Bay, Susan's Bay, etc.) have much higher densities of buildings than slums located on the slopes of the hills (New England, Madongo Water, Maeba, etc.). This can be explained by the difficulty of building houses on the slopes. Another explanation, however, can be better identification of buildings near coastal areas, as these areas generally are more urbanized and have lower tree cover. The population estimates of coastal slums are also generally higher (figure 20).

One serious limitation is the small sample used while selecting parameters. The sample size included two slums: Aberdeen West and Aberdeen Road (figure 19), which are both coastal slums. Hence, the results for inland slums might be less reliable. The building data used was also not always exact, and some slums might be much larger than they were shown above.

Overall, the results can be useful for city planners and decision-makers in Freetown, as the core extent of the largest slums was identified with high confidence. Given more time and data, it would be very interesting to incorporate other factors in this analysis, such as street layout structure, proximity to the road infrastructure, hazardous locations, schools, water sources, electricity usage, etc.

Acknowledgements

This analysis was based on work of Dr Monica. The data used was derived from 'Open Buildings' dataset created by Dr Sirko and other scientists of the University of Chicago. Google Earth were used to compare satellites images over time.

Google Earth, (2021). Available at: https://earth.google.com/web/search/freetown/@8.45535847,-13.22428229,415.90200404a,18399.27385726d,35y,0h,0t,0r/data=CnIaSBJCCiQweGYwNGMyNTZiM2U2MDYzMzoweDk3YjdjOGM4YWYwMTNjMWUZDwh0Jm3uIEAhpn7eVKR2KsAqCGZyZWV0b3duGAIgASImCiQJvLQDEQvPSEARCItXV0i9SEAZ34SbAC3ROUAhpCU2q9RgOUA (Accessed 11 December 2021)

Monica, F. (2014). 'Scrap cities. Strategies and tools for the development of Freetown's slums', Università degli Studi di Parma. Dipartimento di Ingegneria Civile ed Architettura, Available at: https://www.repository.unipr.it/handle/1889/2538 (Accessed: 1 December 2021)

Sirko, W., et al. (2021). 'Continental-scale building detection from high resolution satellite imagery'. arXiv:2107.12283, 2021. Available at: https://sites.research.google/open-buildings/ (Accessed: 15 November 2021)

References

Cobbett, W. (2013), 'How Cities Can Get Rid of Slums By Supporting Them', Informal City Dialogues, 22 April 2013, Available at: https://nextcity.org/informalcity/entry/how-cities-can-get-rid-of-slums-by-supporting-them (Accessed: 5 December 2021)

De Soto, H. (2001), 'The Mystery Of Capital', Black Swan.

Esri (2018) 'Spatial Data Mining: A Deep Dive into Cluster Analysis'. Available at: https://www.esri.com/videos/watch?videoid=m6wFsgQUbM8&title=esri-2014-uc-tech-session-spatial-data-mining-a-deep-dive-into-cluster-analysis (Accessed: 2 December 2021)

ESRI (2021). 'How Cluster and Outlier Analysis (Anselin Local Moran's I) works'. Available at: https://pro.arcgis.com/en/pro-app/2.8/tool-reference/spatial-statistics/h-how-cluster-and-outlier-analysis-anselin-local-m.htm (Accessed: 2 December 2021)

ESRI (2021). 'How Density-based Clustering works'. Available at: https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/how-density-based-clustering-works.htm (Accessed: 9 December 2021)

ESRI (2021). 'How Optimized Hot Spot Analysis works'. Available at: https://pro.arcgis.com/en/pro-app/2.8/tool-reference/spatial-statistics/how-optimized-hot-spot-analysis-works.htm (Accessed: 10 December 2021)

ESRI (2021). 'How Spatial Autocorrelation (Global Moran's I) works'. Available at: https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-how-spatial-autocorrelation-moran-s-i-spatial-st.htm (Accessed: 10 December 2021)

Google Earth, (2021). Available at: https://earth.google.com/web/search/freetown/@8.45535847,-13.22428229,415.90200404a,18399.27385726d,35y,0h,0t,0r/data=CnIaSBJCCiQweGYwNGMyNTZiM2U2MDYzMzoweDk3YjdjOGM4YWYwMTNjMWUZDwh0Jm3uIEAhpn7eVKR2KsAqCGZyZWV0b3duGAIgASImCiQJvLQDEQvPSEARCItXV0i9SEAZ34SbAC3ROUAhpCU2q9RgOUA (Accessed 11 December 2021)

Kabba, R., et al. (2014). 'Slum Mapping Report for Congo Town, Kroo Bay, Susan‟s Bay and Mabella in Freetown', Research and Evaluation Unit BRAC Sierra Leone.

Kuffer, M., et al. (2016). ‘Slums from Space—15 Years of Slum Mapping Using Remote Sensing’, Remote Sens. 2016, 8(6), 455. Available at: https://www.mdpi.com/2072-4292/8/6/455 (Accessed: 6 December 2021)

MillionNeighborhoods, (2021). Available at: https://millionneighborhoods.org/#13.33/8.47732/-13.26338 (Accessed: 2 December 2021)

Monica, F. (2014). ‘Scrap cities. Strategies and tools for the development of Freetown’s slums’, Università degli Studi di Parma. Dipartimento di Ingegneria Civile ed Architettura, Available at: https://www.repository.unipr.it/handle/1889/2538 (Accessed: 1 December 2021)

Monica, F. (2021). ‘Slums as Opportunities? Spatial Organisation, Microeconomy and Self-made Infrastructures in Freetown Informal Settlements’, “African Cities Through Local Eyes”, Springer, pp. 111-126.

Ritvikmath, (2020). Moran's I : Data Science Concepts [YouTube]. Available at: https://www.youtube.com/watch?v=OJU8GNW9grc (Accessed: 9 December 2021)

Satej S. et al. (2020) ‘Worldwide Detection of Informal Settlements via Topological Analysis of Crowdsourced Digital Maps’

Sirko, W., et al. (2021). ‘Continental-scale building detection from high resolution satellite imagery’. arXiv:2107.12283, 2021. Available at: https://sites.research.google/open-buildings/ (Accessed: 15 November 2021)

Statista, (2020). ‘Average size of slum households in India in 2001 and 2011’, Available at: https://www.statista.com/statistics/619587/average-slum-household-size-india/ (Accessed: 13 December 2021)

Statistics Sierra Leone, (2021). ‘Stats SL Datasets’, Available at: https://www.statistics.sl/index.php/what-we-offer/open-data-free-datasets.html (Accessed: 29 November 2021)

UN-Habitat, (2003). ‘The Challenge of Slums - Global Report on Human Settlements’, Available at: https://unhabitat.org/the-challenge-of-slums-global-report-on-human-settlements-2003 (Accessed: 12 December 2021)

UN-Habitat, (2018). ‘Proportion of Urban Population Living in Slum Households by Country or Area 1990-2018 (Percent)’, Available at:

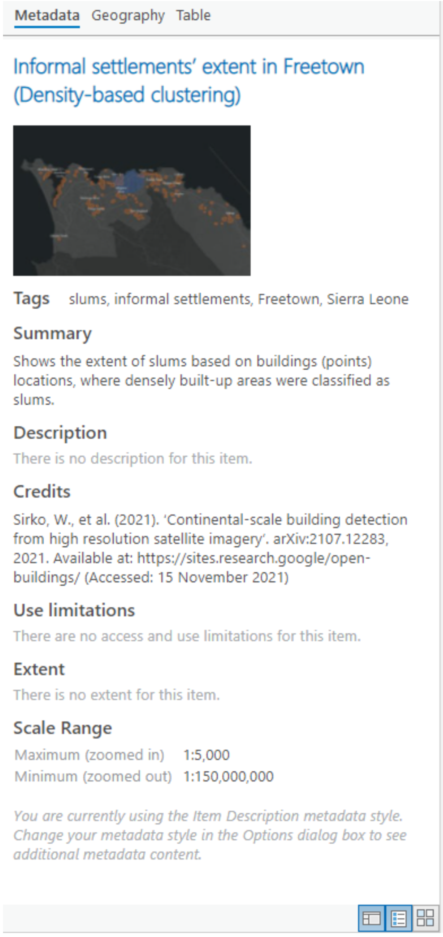
https://data.unhabitat.org/datasets/proportion-of-urban-population-living-in-slum-households-by-country-or-area-1990-2018-percent/explore (Accessed 2 December 2021).

United Nations, (2021). 'The 2019 Revision of World Population Prospects', Available at: https://population.un.org/wpp/ (Accessed: 8 December 2021)

Ward, P.M. (2016). 'HOUSING REHAB FOR CONSOLIDATED INFORMAL SETTLEMENTS: A NEW POLICY AGENDA FOR 2016 UN-HABITAT III', Available at: https://www.lahn.utexas.org/wp-content/uploads/2021/03/Pre-publication-Habitat-International-Ward-paper-5.pdf (Accessed: 11 December 2021)

World population, (2021). 'Freetown Population 2021', Available at: https://worldpopulationreview.com/world-cities/freetown-population (Accessed: 12 December 2021)

Metadata



Metadata Geography Table

Informal settlements' extent in Freetown (Density-based clustering)

Tags slums, informal settlements, Freetown, Sierra Leone

Summary

Shows the extent of slums based on buildings (points) locations, where densely built-up areas were classified as slums.

Description

There is no description for this item.

Credits

Sirko, W., et al. (2021). 'Continental-scale building detection from high resolution satellite imagery'. arXiv:2107.12283, 2021. Available at: https://sites.research.google/open-buildings/ (Accessed: 15 November 2021)

Use limitations

There are no access and use limitations for this item.

Extent

There is no extent for this item.

Scale Range

Maximum (zoomed in) 1:5,000
Minimum (zoomed out) 1:150,000,000

You are currently using the Item Description metadata style. Change your metadata style in the Options dialog box to see additional metadata content.

Figure 21. Informal settlements' extent in Freetown derived using Density-based clustering method.

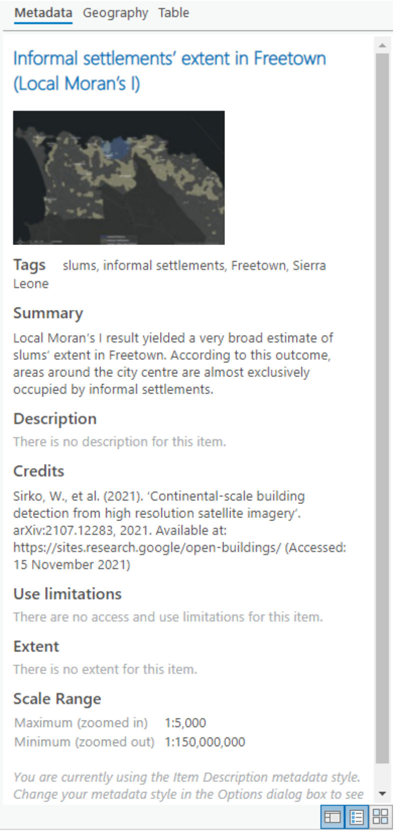


Figure 22. Informal settlements' extent in Freetown derived using Local Moran's I method.

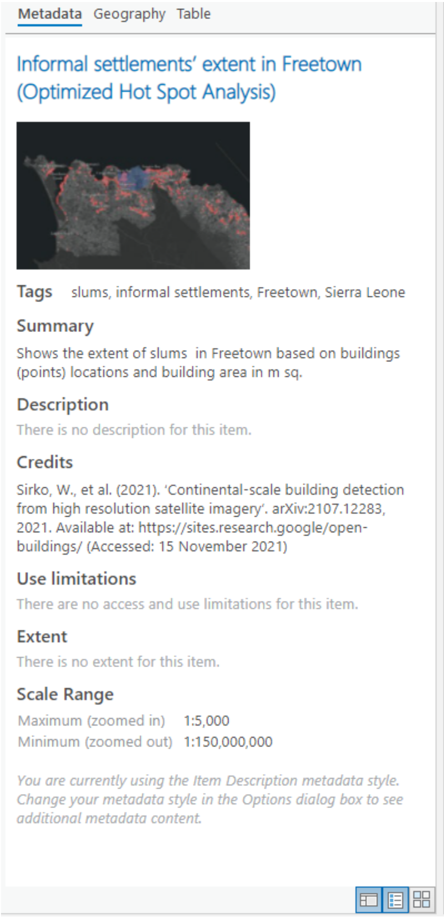
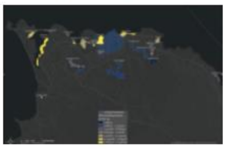


Figure 23. Informal settlements' extent in Freetown derived using Optimized Hot Spot Analysis method.

Metadata Geography Table

Building density in Freetown's largest slums



Tags slums, informal settlements, Freetown, Sierra Leone, density

Summary

Building density in Freetown's largest slums in 2021.

Description

There is no description for this item.

Credits

Sirko, W., et al. (2021). 'Continental-scale building detection from high resolution satellite imagery'. arXiv:2107.12283, 2021. Available at: https://sites.research.google/open-buildings/ (Accessed: 15 November 2021)

Use limitations

There are no access and use limitations for this item.

Extent

There is no extent for this item.

Scale Range

Maximum (zoomed in) 1:5,000
Minimum (zoomed out) 1:150,000,000

You are currently using the Item Description metadata style. Change your metadata style in the Options dialog box to see additional metadata content.

Figure 24. Building density of Freetown's largest slums.

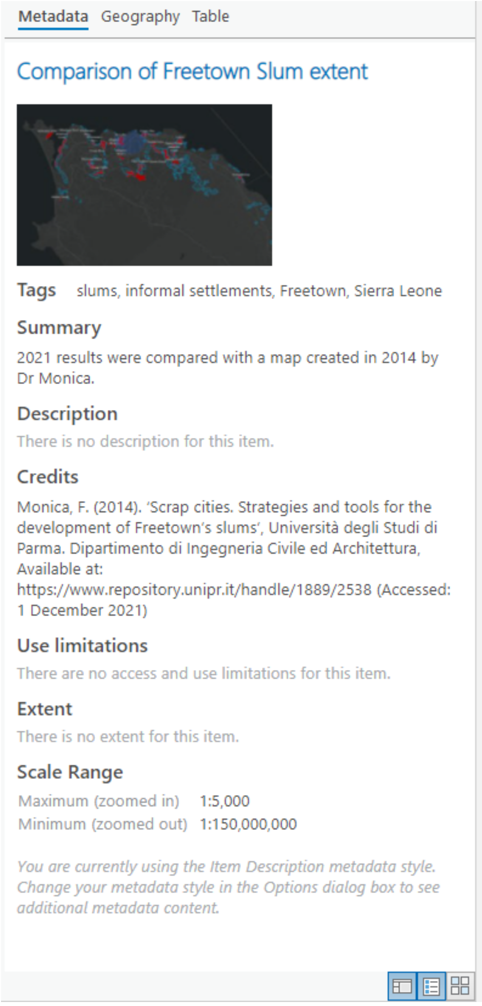


Figure 25. Comparison map of slum detection with Dr Monica's map.