Internship report - CEAT

Performance Assessment of Remote Sensing Algorithms to Extract Building Footprints in Informal Settlements

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Sincerely,

Jordane Provin

Abstract

Cities in Sub-Saharan Africa are experiencing significant demographic and spatial expansion, mostly characterized by “informal” urbanization, i.e., the extralegal construction of human settlements that often face material and social precarity. In this context, keeping track of how the form and extent of cities evolve – a basic condition for urban planning – is a challenge. Recently, several remote sensing algorithms have been developed, from open and commercial sources, to detect urbanization and building footprints. The purpose of this study was to assess the accuracy of a selection of such algorithms to extract building footprints in informal settlements through different performance indicators based on spatial analyses. The originality of this research lies in the fact that we have ground-truth data of the selected informal settlements (which is often unavailable), allowing us to confront the outputs given by the algorithms to the actual building footprints. Ultimately, this study raised awareness regarding limitations of remote sensing algorithms when conducting detailed analyses (at small geographic scales). If disregarded, these limitations can have important social impact and consequences for the planning and modernization of these areas.

Key words: Remote sensing; Informal settlements; Urban morphology; Urban planning; Sub-Saharan Africa.

Contents

1 Introduction

Cities in Sub-Saharan Africa are experiencing significant demographic and spatial expansion [1]. Despite the substantial increase in population, the supply of affordable housing does not meet the demand rate [2,3]. Consequently, we witness the emergence of "informal settlements" on the outskirts or within urban areas. These settlements are defined by the United Nations [4] as : « Residential areas where inhabitants are deemed by the authorities to have no legal claim to the land they occupy and the system of occupation ranges from squatting to informal rental housing. In most cases, the housing is insecure and poor quality and does not comply with current planning and building regulations. Informal settlements are also often situated in the most precarious urban areas where basic services and infrastructure including public or green space are limited. » This definition englobes a variety of settlements such as "bidonvilles", "favelas", "barrios marginals", or "slums", which are characterized by material and social precarity.

Fig. 1: Photo, Mukuru kwa Njenga, Nairobi. Geoffrey Mboya.

Given the extralegal, "informal" nature of the construction of these settlements, it is challenging for local planning authorities to keep track of their development (e.g., map them) and there are important knowledge gaps on their social and built fabrics. Previous studies have described the physical morphology of informal settlements ('Arrival Cities') [5, 6]. These studies relied on high-resolution optical satellite data in combination with street-level imagery. With the recent and substantial increase in the availability of Earth observation sensors (EO sensors), remote sensing data has become crucial for capturing urban inequalities in space. Notably, the development of automated methods, such as the use of 'MVII (Manual Visual Image Interpretation),' provides more reliable precision, especially in areas with unclear textural patterns.

Today, numerous algorithms have been developed for analysing the geospatial characteristics of cities for various purposes, including mapping morphology, density, and the number of dwellings [7]. However, these algorithms are often trained on data from North planned neighbourhoods where the building structure is mostly regular, such as developed cities in Europe and America [8, 9,10,11]. Their application in informal settlements, frequently found in low- and middle-income countries, and less commonly in Western countries, can result in significant deviations from reality. Several studies highlight the imprecision and challenges of cartographic interpretation in informal settlements [7, 12, 13]. Recent research suggests alternative methods to achieve higher spatial resolution in these areas, such as using multi-resolution analysis (MRA) and texture analysis [13]. However, these studies investigating spatial disparities are directly based on the algorithms' ability to detect building morphology and its spatial arrangement.

The performance assessment of remote sensing algorithms has often been conducted through global indicators (such as the. Intersection over Union) that allow to test if the general built-up area is detected, but does not address the ability to detect individual building footprints. Furthermore, the assessment of those algorithms in the context of informal settlements is limited due to the lack of ground truth data. We addressed these gap by obtaining detailed ground truth data (maps of building footprints) through field studies in Abidjan and Nairobi, two cities marked by the prevalence of informal settlements [14, 15, 16]. This allowed us to assess the performance of remote sensing algorithms both through "conventional" (global) and detailed indicators.

The underlying hypothesis was that remote sensing algorithms perform well in global indicators (detection of overall buit-up area), but less so in detailed indicators (at the level of the single building footprint). Scale was indeed a critical element in this analysis. We aim to emphasize the importance of considering the accuracy of data depending on the spatial resolution and purpose of the analysis, as the use of inaccurate data in planning may have significant social consequences.

2 Method

2.1 Geographic scope

The study was conducted within informal settlements located in Abidjan, Côte d'Ivoire, and Nairobi, Kenya. We selected these two cities due to their relevance in illustrating recent urbanization trends in sub-Saharan Africa. Indeed, significant population growth has led to a substantial concentration in geographically limited areas. Consequently, in addition to an increase in housing demand and a shortage of affordable options, the formal sector is overshadowed by informal settlements where most of the population is forced to reside [17]. In 2020, studies highlighted that more than half of the urban population in both Côte d'Ivoire and Kenya lived in these informal settlements, making them the predominant type of urban housing [18], particularly notable in Abidjan and Nairobi.

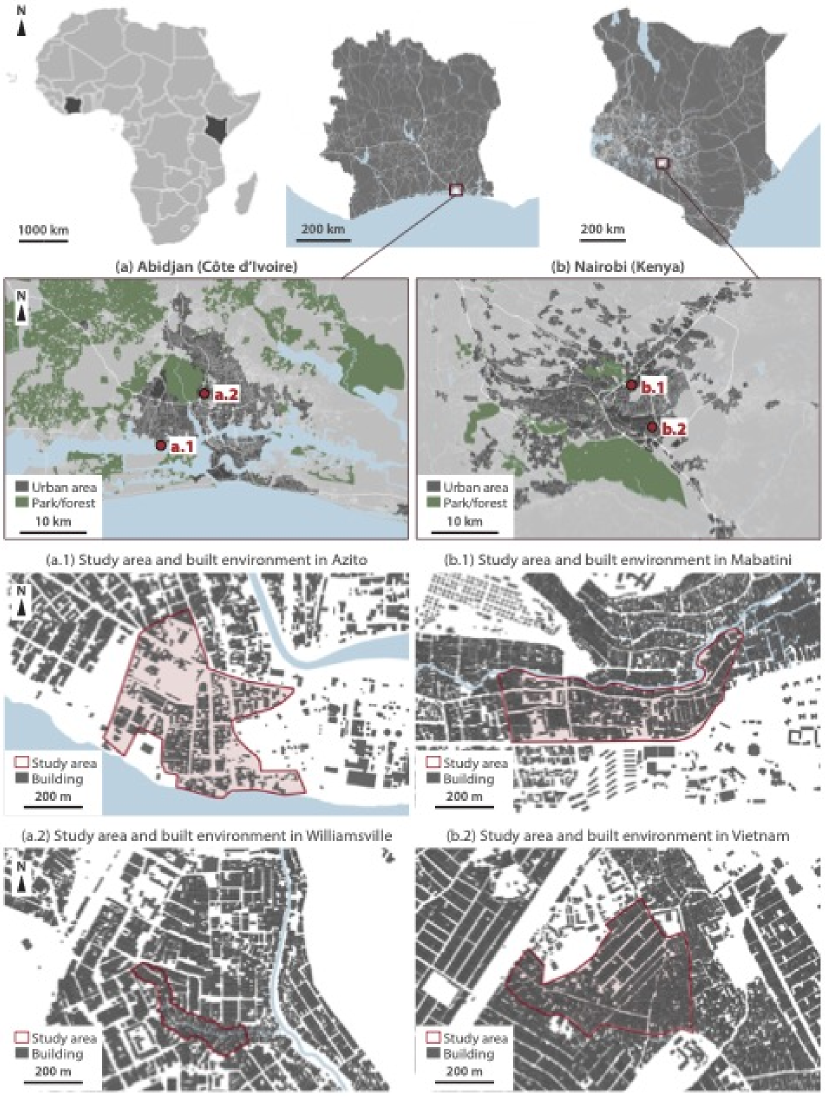

Fig. 2: Studied informal settlements. Côte d'Ivoire and Kenya

To conduct this analysis, we have chosen four informal settlements in Africa: two in Abidjan (Azito and Williamsville) and two in Nairobi (Mathare and Mukuru). Following field investigations, in-depth spatial analyses, and detailed housing mapping in these areas, we have obtained precise data regarding the housing conditions. In Abidjan, Azito is a fishing village located on the outskirts, bordering the lagoon, while Williamsville is situated not far from the central business district of Abidjan. In Nairobi, Mathare is located in a former quarry along the Mathare River, not far from the heart of downtown Nairobi, while Mukuru borders the Nairobi National Park in the southern part of the city.

2.2 Ground truth data

We obtained data on the individual building footprints of 4 informal settlements. Two were in Abidjan (Côte d'Ivoire), Azito with 782 buildings footprints and Williamsville with 493 buildings. The other two settlements were in Nairobi (Kenya), Mathare with the number of buildings of 1309 and Mukuru with 1473 buildings footprints. This ground truth data was obtained in a combination of remote sensing (manual digitization of building footprints with the software QGIS) based on high resolution satellite imagery (30 cm), and on-site verifications with a global positioning system (GPS). Annotations were made on-site, and then used to update the digitized building footprints on QGIS.

2.3 Algorithms used

Regarding the data and methods employed, we used cartographic information describing the footprints of buildings in each site. These data were extracted from very high-resolution satellite images (approximately 50 cm per pixel) from various providers, such as Ecopia (in 2022), Microsoft (2014-2020, the neighborhood already existed during this period), and Google (in May 2023, the latest version). To ensure data accuracy, we compared the results with manually corrected building footprint maps following field verifications, using the Geographic Information System (GIS) software QGIS. Each building was represented by a unique polygon in these building footprint maps.

2.4 Data harmonization

Furthermore, before conducting the analysis on the data set, we harmonize every data that we have in the same coordinate, referential... in the Pre-processing part. Indeed, the buildings footprints data of the different algorithms were not extracted with the same satellite imagery. Extraction of the data from algorithms were from 2 sets of satellite imagery, i.e., ESA for the ground truth and Ecopia outputs, and Maxar for Google and Microsoft outputs. To take in consideration this gap, spatial analyses were done separately for the data from ESA and MAXAR satellite imagery.

2.5 Statistical Analysis

In addition to the common performance analyses of morphological detection of built structures, such as the proportion of true building area and the proportion of built area detected compared to reality, we conducted several other statistical analyses to compare algorithm performance in terms of the precision of building arrangement within the neighborhood. Then, we evaluated three different remote sensing algorithms, namely those developed by Google, Microsoft, and Ecopia. To compare the algorithmic outputs with the ground truth data, we employed several spatial indicators.

We used Python scripts to run descriptive statistical analyses of a wide range of spatial indicators. These indicators were used to examine building morphology at different geographic scales, from individual buildings to the site (neighborhood) to zonal aggregations (global indicators) [19]. In addition to the Intersection over Union (IoU), widely used in the literature [14], the indicators considered in this study also included: the total number of buildings, the covered area ratio (CAR, i.e., ratio between built-up area and open area), mean deviation between neighboring structures, building orientation, number of neighbors per building within a fixed radius, and building area. This approach was based on previous studies of informal settlement morphology worldwide [5, 6, 20].

The building footprint maps of each site were used to obtain the spatial indicators to test the performance of the algorithms. The analysis was divided into two distinct parts. Firstly, there were spatial analyses conducted at both the global and individual scales [5]. To calculate these morphological indicators, we used the packages Momepy and Geopandas. Secondly, there were descriptive analyses aimed at evaluating the performance of the algorithms employed by Microsoft, Google, and Ecopia. All these data and analyses are summarized in Figure 2.

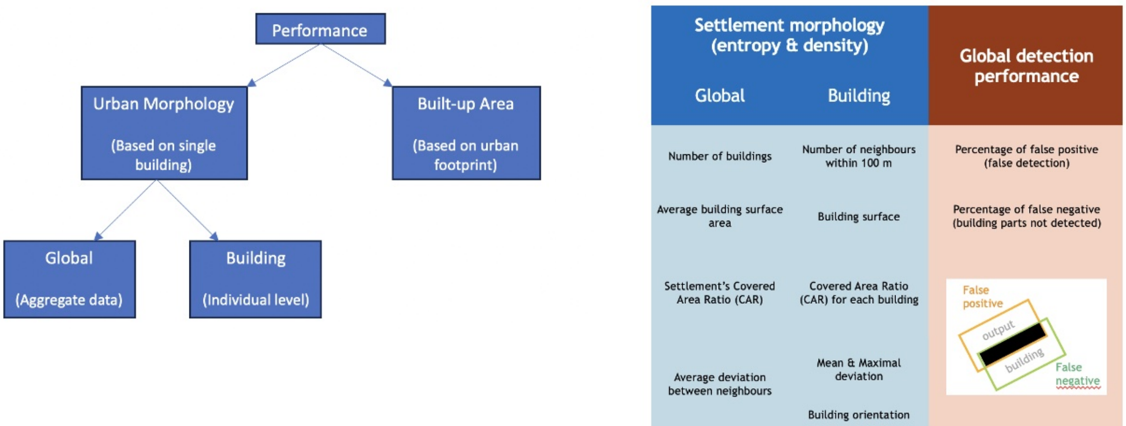

Fig. 3: Spatial indicators to test the performance of the algorithms

3 Results and Discussion

To have a global understanding of the four settlements' spatial configurations we generated thematic maps for each indicator, such as the buildings' orientations and number of neighbours (figure 3,4 & 5).

Fig. 4: Orientation variations in studied informal settlements

We can observe that uniformity in colors corresponds to similar orientations. Conversely, there are significant variations in orientations in multicolored areas.

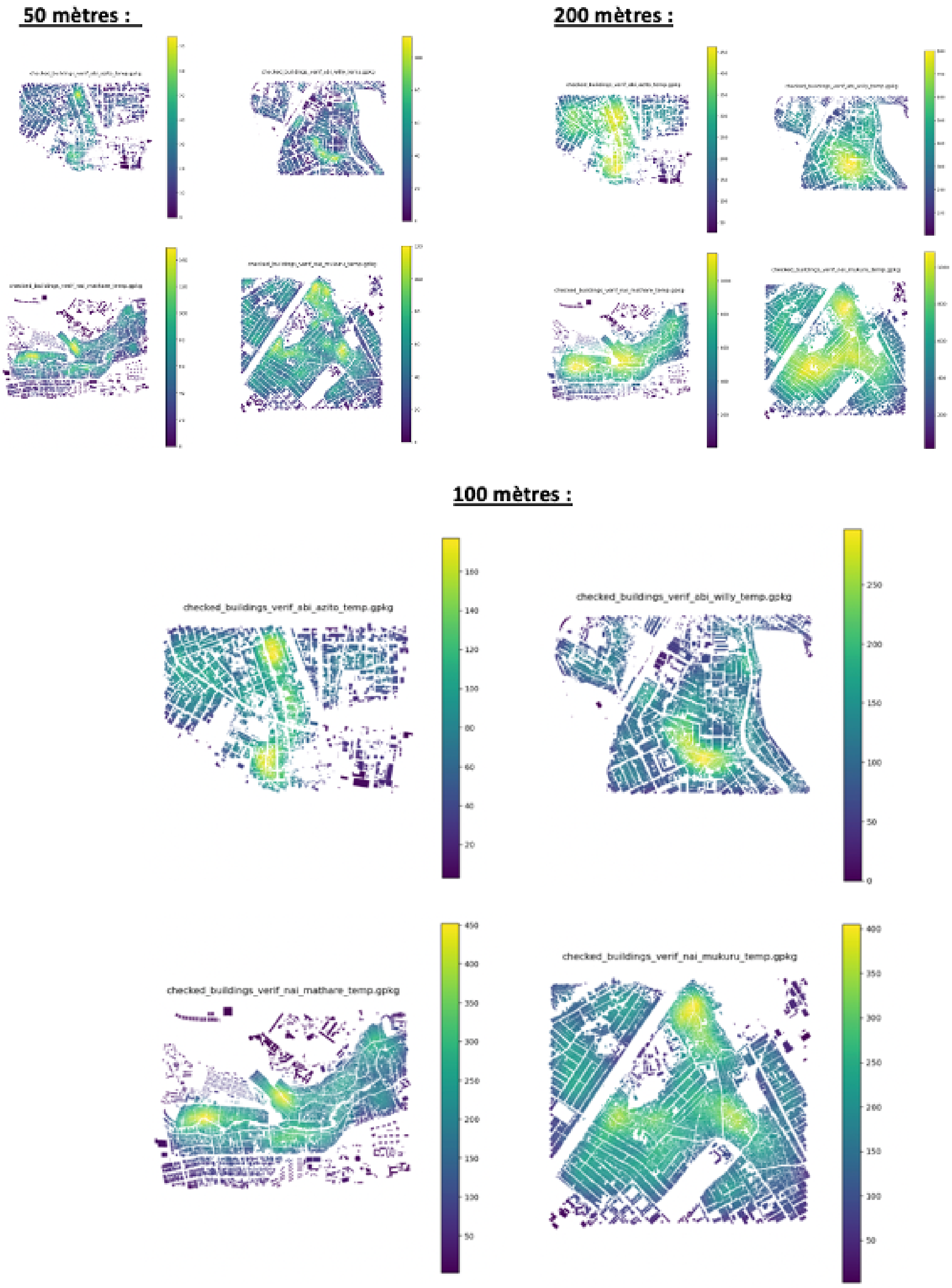

Fig. 5: Neighborhoods proximity in studied informal settlements

In these maps, we see the number of neighbors for three different radii (50, 100, and 200 meters). Thus, we can observe a higher density of buildings in the yellow-colored areas.

For 100 meters, which is subsequently used because it is the most relevant concerning the changes in the number of neighbors related to the radius, we can observe a gradual change following a normal curve. In contrast, for the other radii, the number of neighbors remains constant.

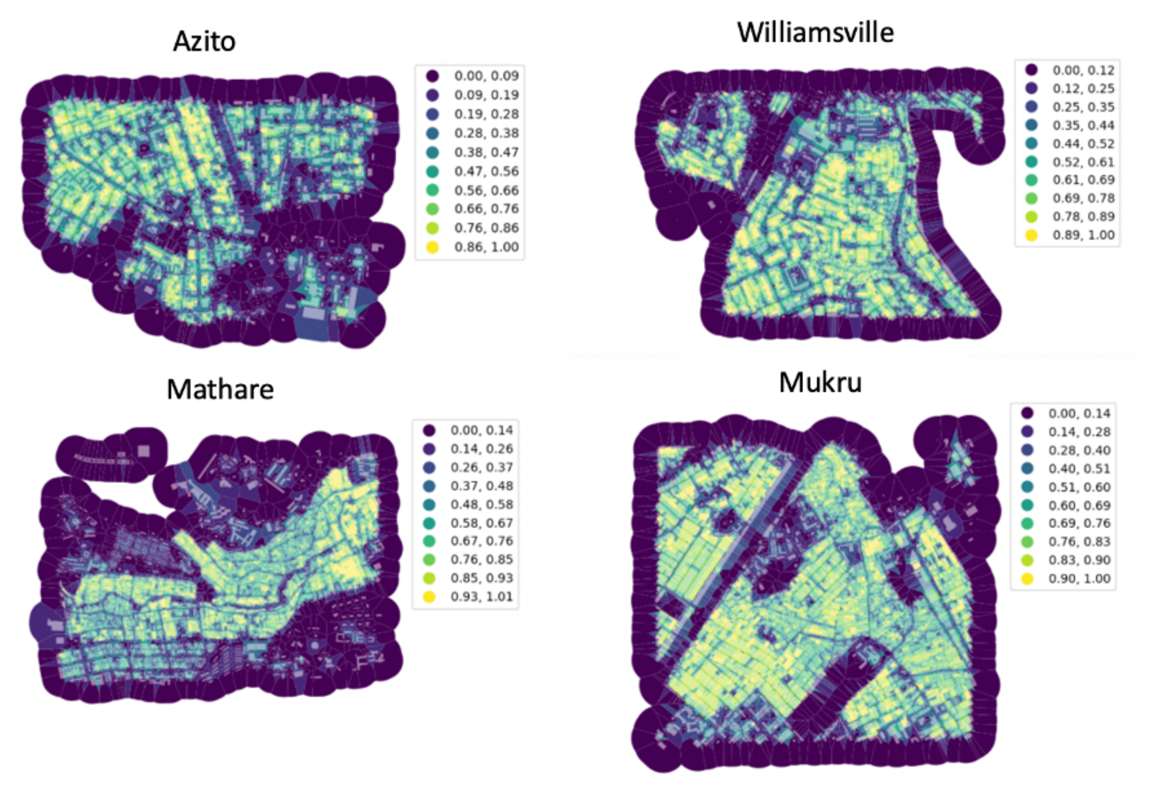

Fig. 6: Covered Area Ratio (CAR) in studied informal settlements

This density measure is used to assess the relation between built-up areas and open spaces. It is different than the Floor Area Ratio (FAR), or Ground Coverage Ratio, which are typically calculated by dividing the total floor area of a building by the total land area on which the building is located. These ratios help understanding the density and intensity of development in a specific area. In the maps, we can observe that the areas colored in yellow have a ground coverage ratio close to 1 (very dense), meaning that the building uses nearly the entire land parcel.

The results of our data analyses allow us to evaluate the remote sensing performance of each algorithm we examined. By examining the table presenting the overall results (Annex Figure 13) and the corresponding graphs for each site (Figures 6), we can confirm the hypothesis that the algorithms tend to simplify the built environment. This trend is particularly evident when we compare the number of detected buildings, which is generally lower than reality, to the average building area, which is often larger than reality. The algorithms tend to group several neighboring buildings into one.

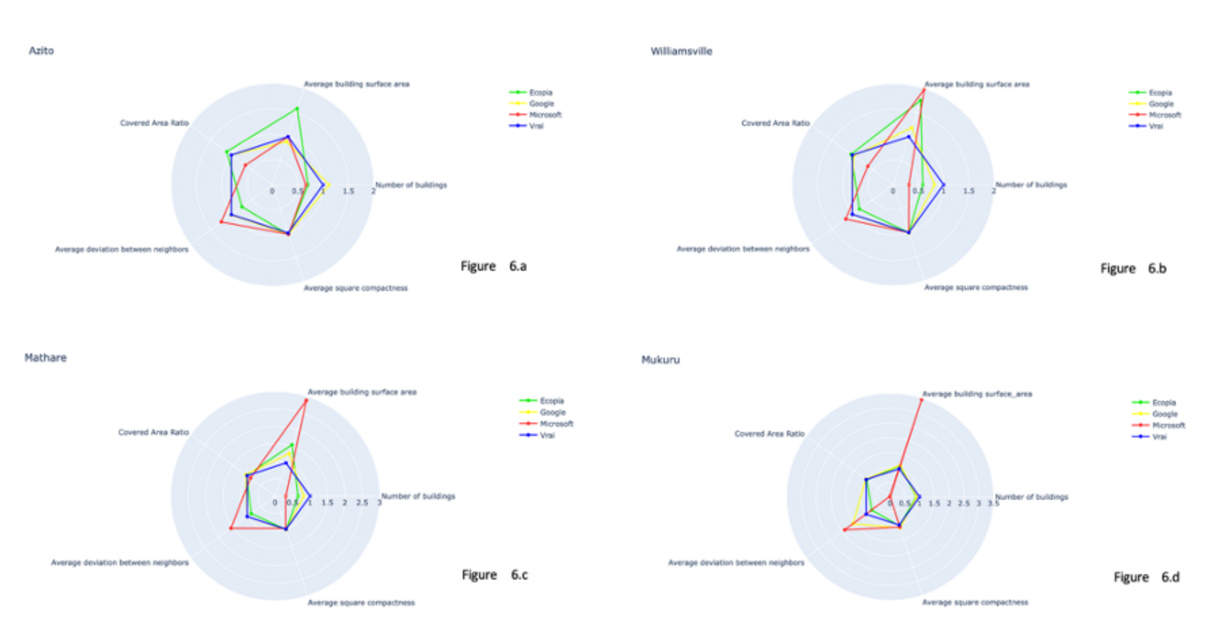

Fig. 7: Polar graphics of global statistical analysis

Examining Figure 6.a, which represents the polar chart for Azito (Abidjan), we observe that the number of detected buildings tends to remain lower than reality, confirming the simplification of shapes by the algorithms. However, the average building area often approaches or exceeds reality, indicating a strong tendency to group multiple distinct buildings into one. This trend is repeated for the Williamsville and Mathare sites, as shown in Figures 6.b and 6.c, with a significantly lower number of buildings and a significantly higher average building area, regardless of the algorithm considered. For the Mukuru site (Figure 6.d), Ecopia's algorithm closely approximates reality, as does Google, while Microsoft is entirely out of the norm due to low building detection (only 7), leading to significant variations in indicators. Overall, it is clear that Microsoft's algorithm is the furthest from reality, in addition to the general tendency of algorithms to "structure" informal settlements.

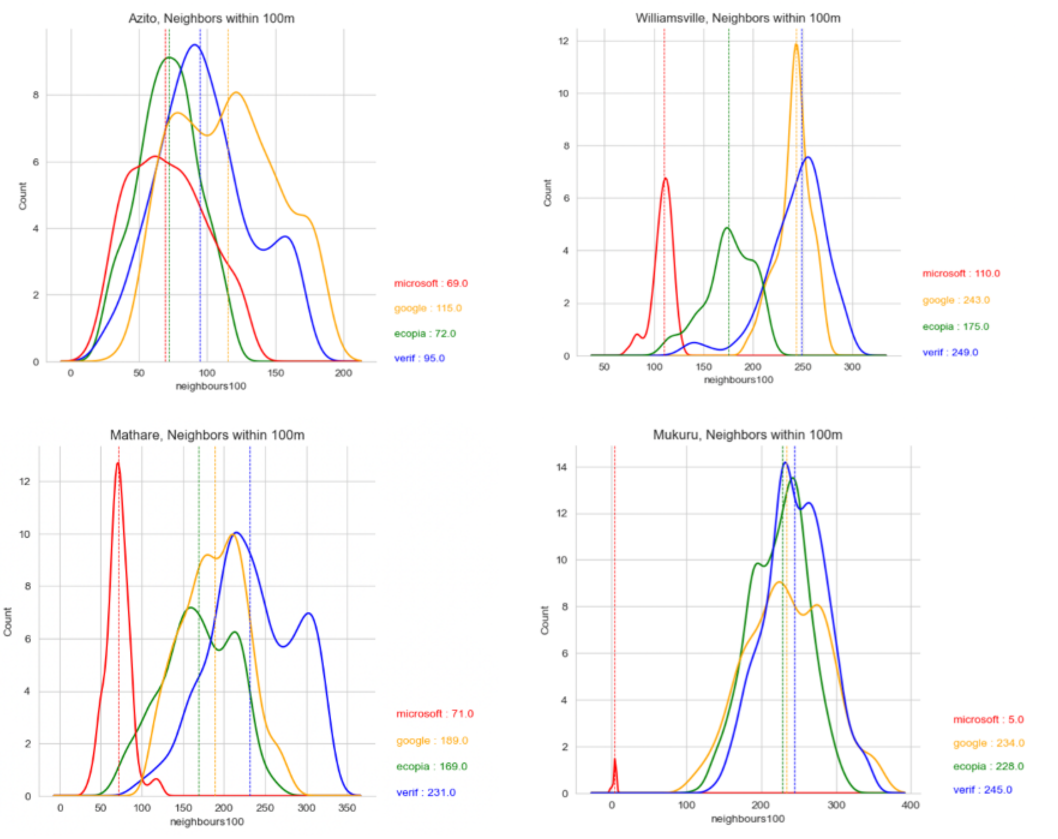

Fig. 8: Neighbors within 100 meters for each buildings

Furthermore, we conducted local analyses, represented by Figures 7. The first analysis concerns the number of neighbors within a radius of 100 meters (the most significant among 50 - 100 - 200 meters) (Figure 7.a). Our expectations were that the average number of neighbors found by the algorithms would be lower than reality due to the spatial simplification they perform (grouping multiple buildings into one). This hypothesis is confirmed by the graphs, showing that the average number of neighbors within a 100-meter radius is lower than reality for all algorithms, except Google for the Azito site. Google proves to be the algorithm closest to reality in terms of the number of neighbors, regardless of the site.

The examination of building area at a local level also confirms our hypothesis. We anticipated that algorithms would identify a higher number of larger buildings, while the actual scenario would include more smaller buildings, due to the spatial simplification tendency. This is supported by statistical analysis, indicating that the algorithms' calculated average building area is significantly larger than true values. In fact, the median area values indicate an average ranging from 30% to 250% of the real building areas.

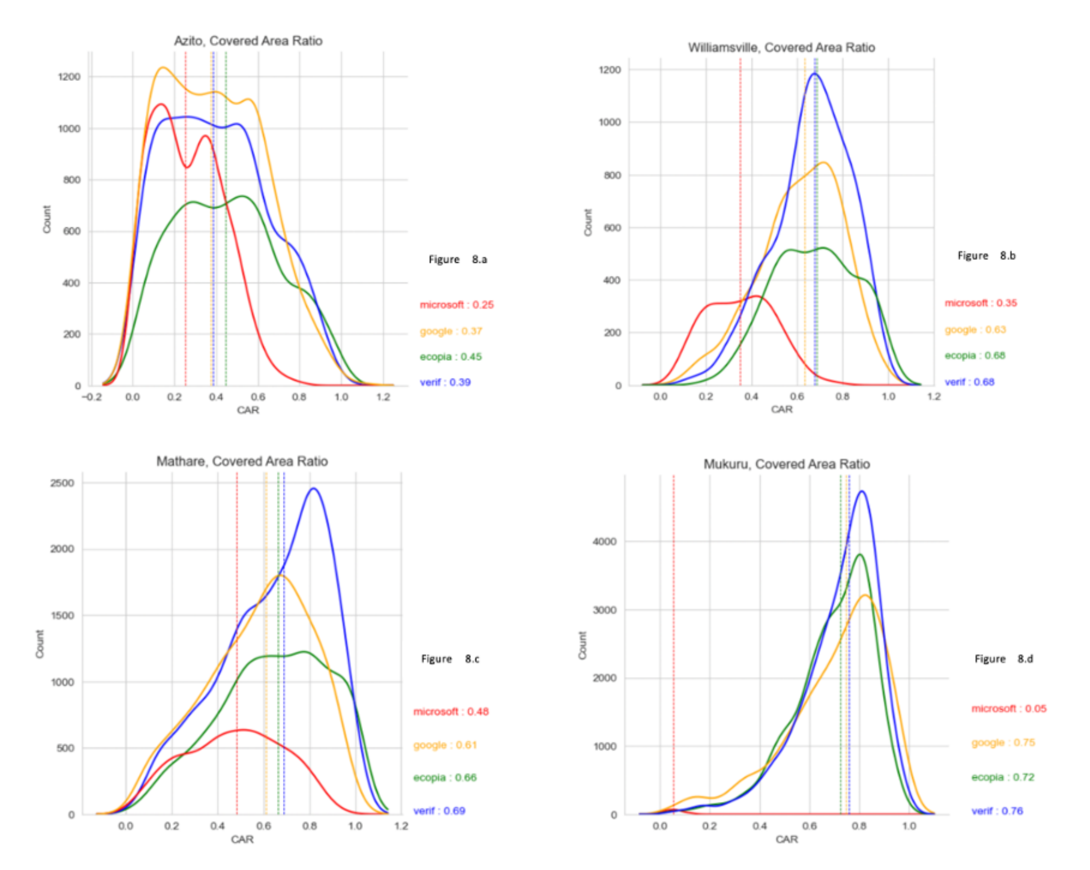

Fig. 9: Covered Area Ratio, represent the density

The Covered Area Ratio (CAR) represented in Figure 8.c characterizes building density. As before, we expected building density to be lower for the algorithms compared to reality, which is generally confirmed by the graphs. However, the difference is not significant, except for Microsoft, which shows a much lower density than reality. Ecopia's algorithm has a density close to, or slightly higher than, reality. This slight difference in density can be explained by the algorithms' ability to confuse buildings with the ground, often due to the texture of roofing materials.

Continuing our analysis of the hypothesis of geographic space simplification by algorithms, we calculated the orientation of buildings relative to the North (Figure 7.d). Algorithms, being trained in remote sensing from satellite images, tend to create a consistent orientation of buildings, thus approaching planned neighborhoods. This is reflected in the graphs, where the blue curve (reality) shows a greater variety of orientations compared to the curves representing algorithms orientations. Therefore, we can conclude that there is a greater diversity of orientations in reality compared to those detected by remote sensing.

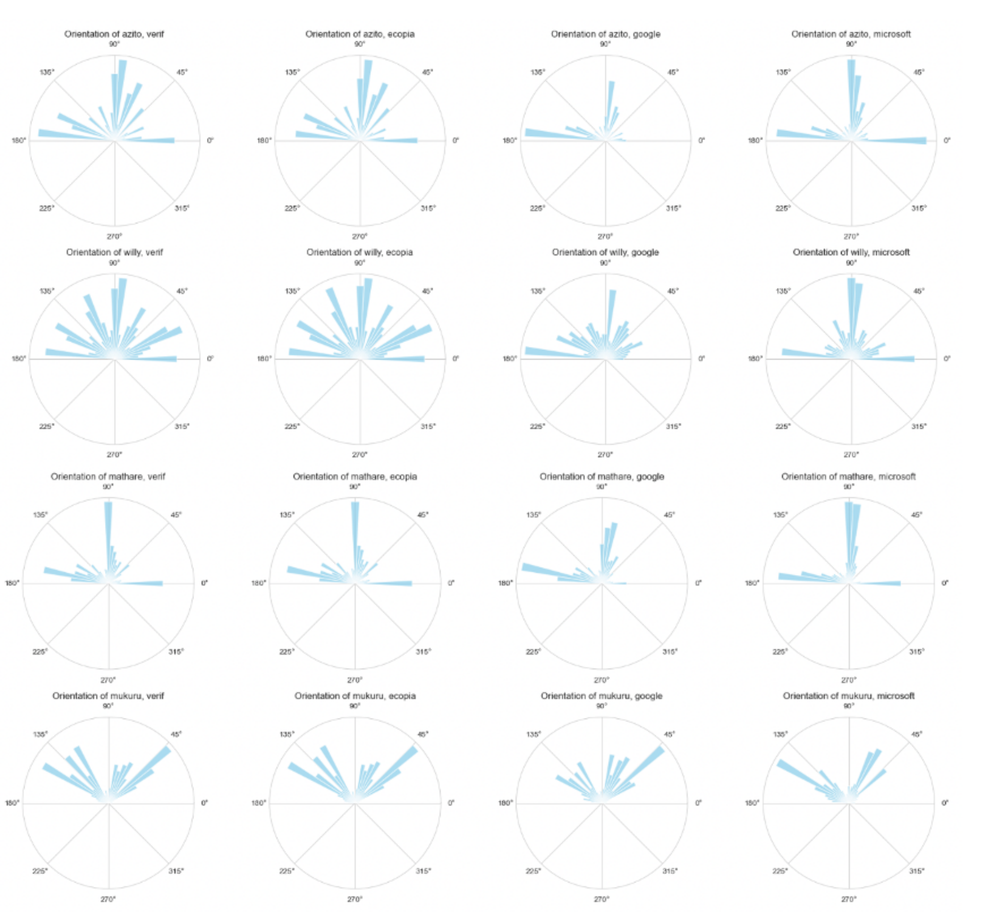

Fig. 10: Polar graphics representing the orientation diversity

However, this difference is not very visible in the curve graphs. To illustrate it better, we created polar graphs showing the quantity and diversity of orientations for each site and algorithm (Figure 9). These graphs reveal a greater variety of orientations in reality, while algorithms simplify this diversity. Microsoft's algorithm deviates the most from reality in this regard, while Google's algorithm is the closest. Moreover, at the site level, we can observe distinctions in orientation diversity. For example, in the mapping, we noted that the Williamsville site is much more heterogeneous, while in Mukuru, some neighborhoods are structured and planned around an inner courtyard (orange), while others are more random (red).

Fig. 11: Comparison of the arrangement in space between Williams & Mukuru

In addition to calculating orientation relative to the North, we calculated the average and maximum deviation from the four nearest neighbors (Annex figure 16 & 17). We expected the average and maximum deviations to be greater in reality than in the algorithms. However, this assertion has limits, as the average of these deviations is not relevant due to the proximity of values between Google and reality, Ecopia being lower, and Microsoft being higher than it. This statistic is not suitable for confirming the general hypothesis because it does not take into account the number of buildings detected by the algorithms. Thus, Microsoft, which detects the fewest buildings and low density (CAR), displays higher deviations.

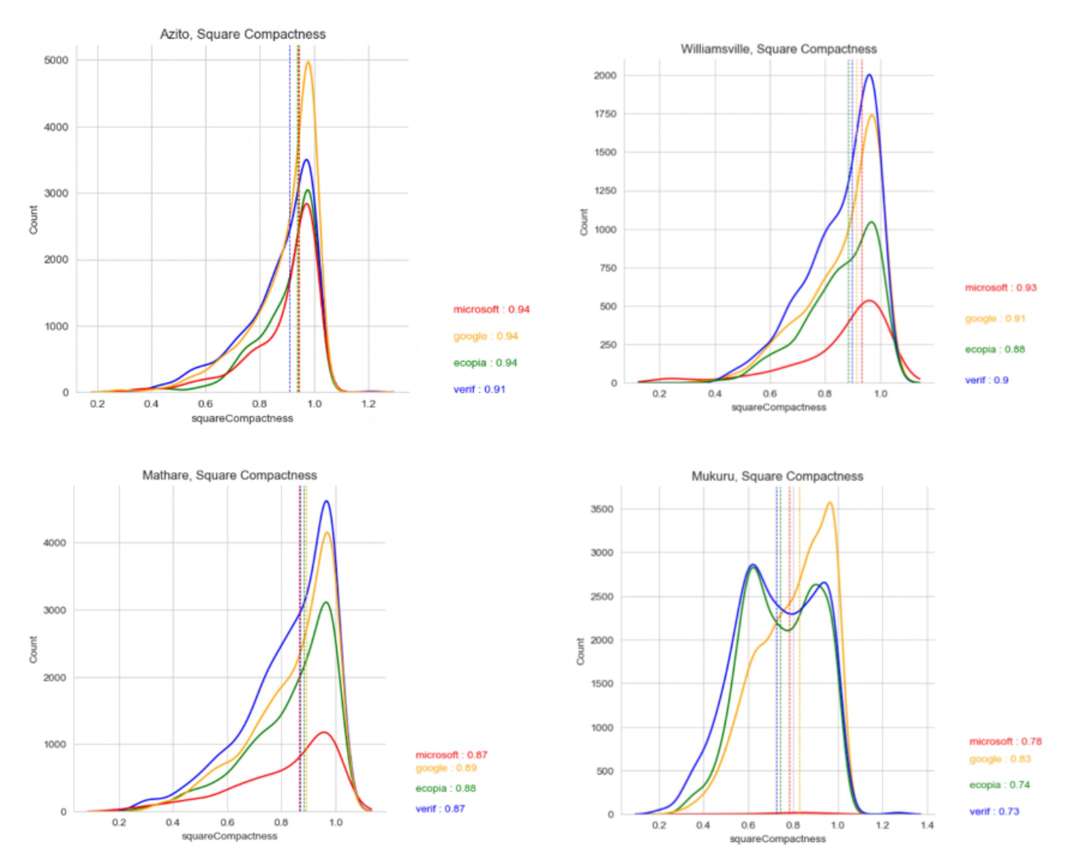

Fig. 12: Square compactness, show the buildings morphology simplification

Algorithms exhibit a greater rectangular compactness than reality, thus confirming the phenomenon of polygon (building) simplification at the local scale. The blue curve (true values) is generally more spread out than the curves representing algorithmic values. Therefore, we observe a lower morphological diversity of buildings detected by the algorithms compared to reality, which is reflected in a tendency for rectangular compactness values to approach 1.

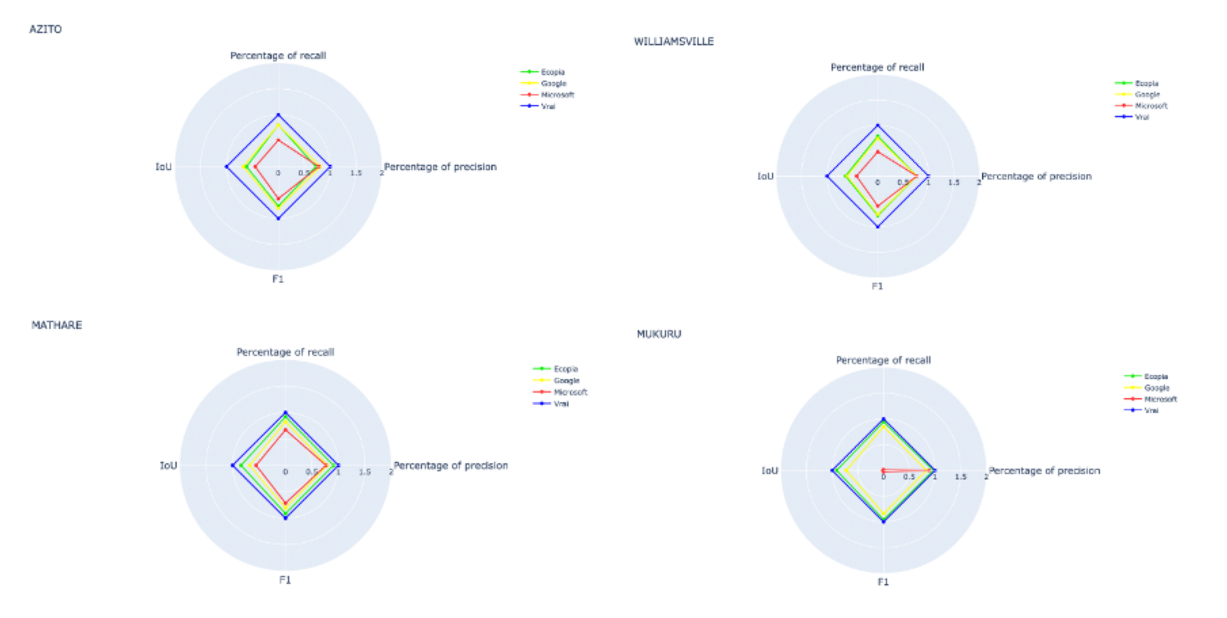

Fig. 13: Polar graphics showing precision and accuracy performance

General performances in accuracy and detection of algorithms are summarized in these polar graphs. Overall, Google is the algorithm that comes closest to reality in terms of the number of buildings, average area, deviation from neighbors, and land usage coefficient. Ecopia follows, and Microsoft is the farthest from reality. However, Ecopia is the algorithm that comes closest to reality in terms of precision and correct detected buildings. Google follows, and Microsoft is the farthest from reality. Moreover, in terms of morphological accuracy, Ecopia is the algorithm closest to reality, with an accuracy of 80 to 95%, while Google has an average accuracy of around 75%, and Microsoft only 60%, which is relatively low. Therefore, although Google offers a better overall morphological analysis, its inaccuracy is more pronounced at the building level (local).

Study Limitations: The sample size (study conducted on 4 sites in only 2 cities) limits the generalization of the results. Ground truth data was generated manually, and therefore is not as precise as an actual site survey conducted by specialists.

Unexpected Results: Google's performance, which proved to be close to Ecopia, contrary to Microsoft, which is significantly less accurate.

4 Conclusion

As we saw, it is essential to note that scale is a critical element in these analysis. Indeed, we observe that at a global scale, algorithms like Google and Ecopia provide almost adequate precision for assessing aspects such as the global built-up area. However, at a local scale, their imprecision is crucial. Our research highlights the significant inaccuracy and imprecision of these algorithms by realizing local spatial analysis. Indeed, we notices that these 3 remote sensing algorithms tend to simplify the morphology of buildings in informal neighborhoods. In addition, the layout to detecting buildings where there are none and vice versa, was confirmed by the results obtained as we have seen. There is therefore a real lack of precision in the maps representing the buildings in these areas. Any use of these data must be made with caution as regards the lacks precision at the local scale, which can have important economic and social impact and consequences for the planning and modernization of these areas.

This project allows us to raise awareness among users of remote sensing data that it lacks precision especially at the local scale, which can have important social and economic impacts as well as consequences for the planning and renovation in informal settlements. Finally, there is also the possibility to improve the spatial detection of these algorithms by machine learning thus, training them on informal settlements in Africa. (Williamsille, Azito, Mathare and Mukuru)

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6 Annex

	Site	Indicators	True	Ecopia	Google	Microsoft
0	Azito	Building_numbers	782.000000	550.000000	873.000000	517.000000
1	Azito	Average_building_surface_area	101.909597	161.485199	91.100107	101.630842
2	Azito	Covered_Area_Ratio	0.346773	0.386472	0.346064	0.228633
3	Azito	Average_deviation_between_neighbors	3.900108	2.892221	3.948051	4.865073
4	Azito	Average_square_compactness	0.867873	0.895929	0.890982	0.891099
5	Azito	Average_circular_compactness	0.508446	0.542443	0.539486	0.535003
6	Azito	Percentage_of_precision	1.000000	0.721900	0.808800	0.779700
7	Azito	Percentage_of_recall	1.000000	0.804500	0.802000	0.510800
8	Azito	IoU	1.000000	0.614160	0.674180	0.446377
9	Azito	F1	1.000000	0.760965	0.805386	0.617235
10	Willy	Building_numbers	493.000000	289.000000	403.000000	154.000000
11	Willy	Average_building_surface_area	57.894709	101.660576	68.742191	115.192669
12	Willy	Covered_Area_Ratio	0.795210	0.818552	0.771835	0.494244
13	Willy	Average_deviation_between_neighbors	6.061582	5.010060	6.101179	7.048066
14	Willy	Average_square_compactness	0.858155	0.858320	0.867403	0.857665
15	Willy	Average_circular_compactness	0.483802	0.498055	0.518277	0.529767
16	Willy	Percentage_of_precision	1.000000	0.766400	0.764900	0.770000
17	Willy	Percentage_of_recall	1.000000	0.788900	0.742900	0.478900
18	Willy	IoU	1.000000	0.635975	0.604801	0.418968
19	Willy	F1	1.000000	0.777487	0.753740	0.590524
20	Mathare	Building_numbers	1309.000000	858.000000	1067.000000	398.000000
21	Mathare	Average_building_surface_area	70.207063	108.744382	90.131917	202.849191
22	Mathare	Covered_Area_Ratio	0.591212	0.600229	0.618679	0.519372
23	Mathare	Average_deviation_between_neighbors	4.045241	3.454838	4.043891	6.352541
24	Mathare	Average_square_compactness	0.826299	0.835140	0.841829	0.809987
25	Mathare	Average_circular_compactness	0.465776	0.480178	0.495786	0.490369
26	Mathare	Percentage_of_precision	1.000000	0.906300	0.789000	0.764700
27	Mathare	Percentage_of_recall	1.000000	0.920100	0.825100	0.671400
28	Mathare	IoU	1.000000	0.840177	0.675949	0.556444
29	Mathare	F1	1.000000	0.913148	0.806646	0.715019
30	Mukuru	Building_numbers	1473.000000	1298.000000	1327.000000	7.000000
31	Mukuru	Average_building_surface_area	82.985466	91.960129	93.809911	287.251808
32	Mukuru	Covered_Area_Ratio	0.746003	0.728468	0.759724	0.012271
33	Mukuru	Average_deviation_between_neighbors	2.752283	2.101047	4.264611	5.235605
34	Mukuru	Average_square_compactness	0.724907	0.746990	0.798932	0.779257
35	Mukuru	Average_circular_compactness	0.400962	0.402157	0.452216	0.426273
36	Mukuru	Percentage_of_precision	1.000000	0.966500	0.832200	0.883000
37	Mukuru	Percentage_of_recall	1.000000	0.943700	0.851100	0.014600
38	Mukuru	IoU	1.000000	0.913810	0.726436	0.014572
39	Mukuru	F1	1.000000	0.954964	0.841544	0.028725

Fig. 14: Statistical analysis of each settlements for every algorithms

B. Evaluation Metric

Generally, evaluation metric methodologies can be divided into two categories: pixel-level metrics and instance-level metrics. The pixel-level method counts the correctly classified and misclassified pixels pixel-wise. In the instance-level method, a building is correctly extracted only when the IoU between the prediction and ground truth is larger than a specific threshold. Semantic segmentation-based building footprint extraction aims to classify every pixel, whether or not it belongs to a building, for a specific input image. Therefore, we apply a pixel-level metric including precision, recall, F1-score and IoU to evaluate the performance of MAP-Net and other different methods.

There are four classifying conditions: true prediction on a positive sample (TP), false prediction on a positive sample (FP), true prediction on a negative sample (TN) and false prediction on a negative sample (FN). Precision represents the percentage of TP in total positive prediction, recall indicates the percentage of TP over the total positive samples, the F1-score is the weighted average of precision and recall, which considers both FP and FN, and IoU is the average value of the intersection of the prediction and ground truth over their union of the whole image set. Equations are given as follows:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{5}$$

$$IoU = \frac{Precision * Recall}{Precision + Recall - Precision * Recall} \tag{6}$$

Fig. 15: Statistical calculus of precision and accuracy performance for remote sensing algorithms. Reference 14 : MAP-Net, Multiple Attending Path Neutral Network for Building Footprint Extraction from Remote Sensed Imagery, 2019.

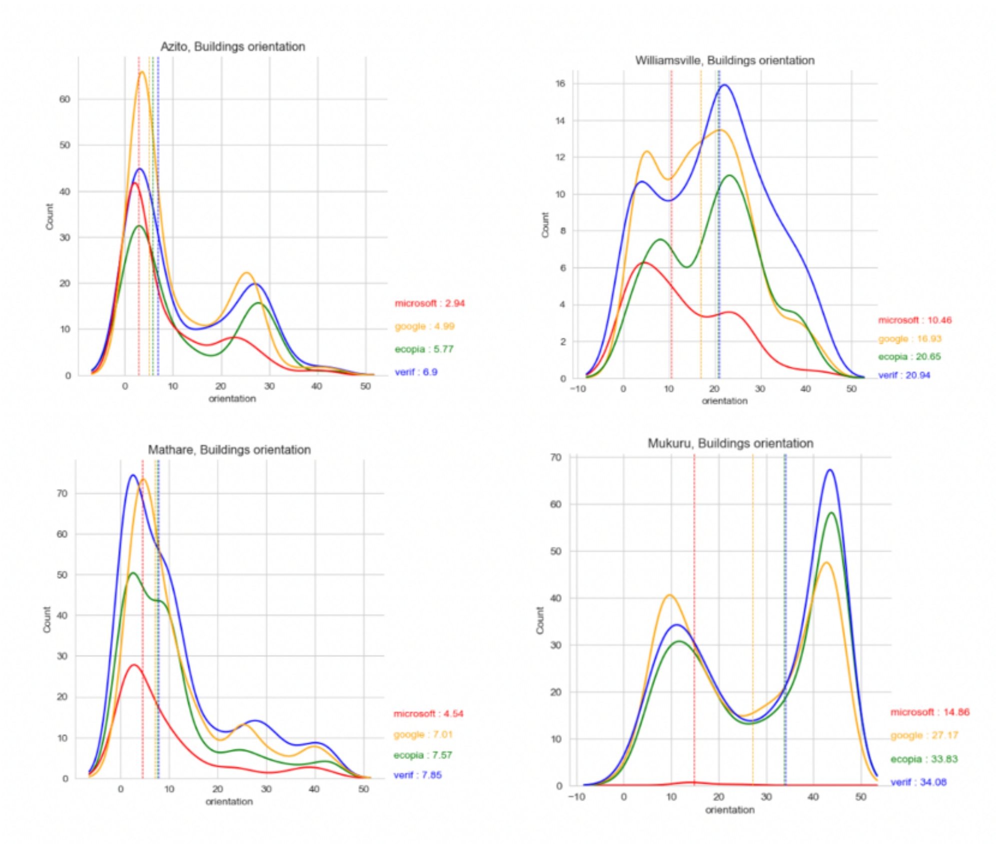

Fig. 16: Buildings orientation diversity regarding the North direction

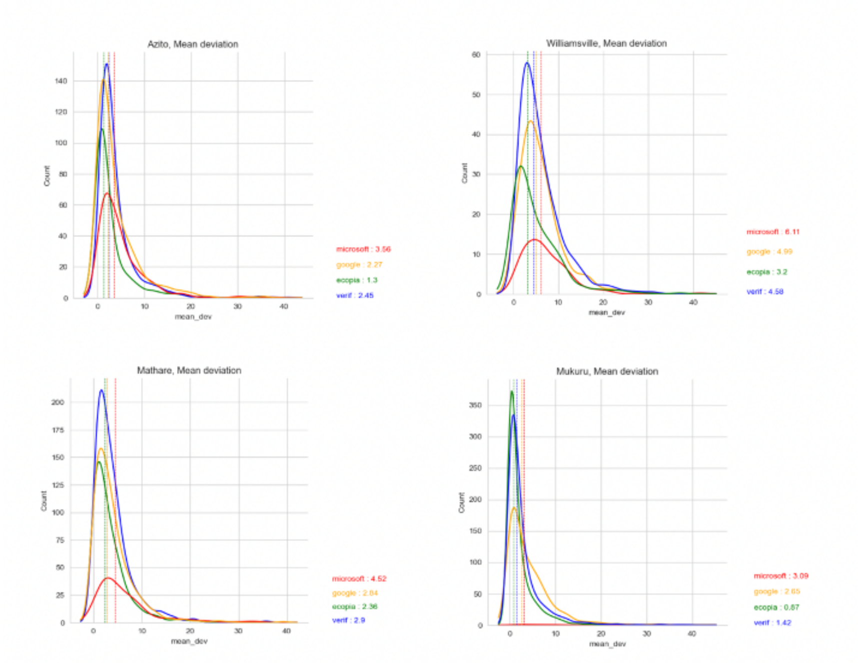

Fig. 17: Mean deviation for the four nearest neighbours according to Queen

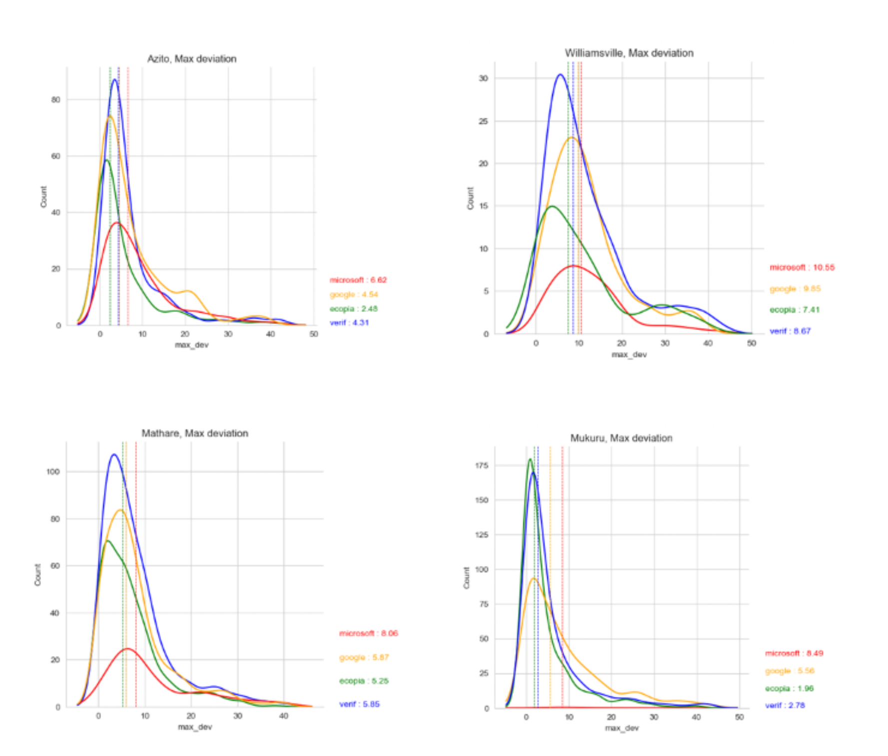

Fig. 18: Maximum deviation for the four nearest neighbours according to Queen