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The role of global open geospatial data in measuring SDG indicator 11.7.1: Public open spaces

Julia Cramwinckel

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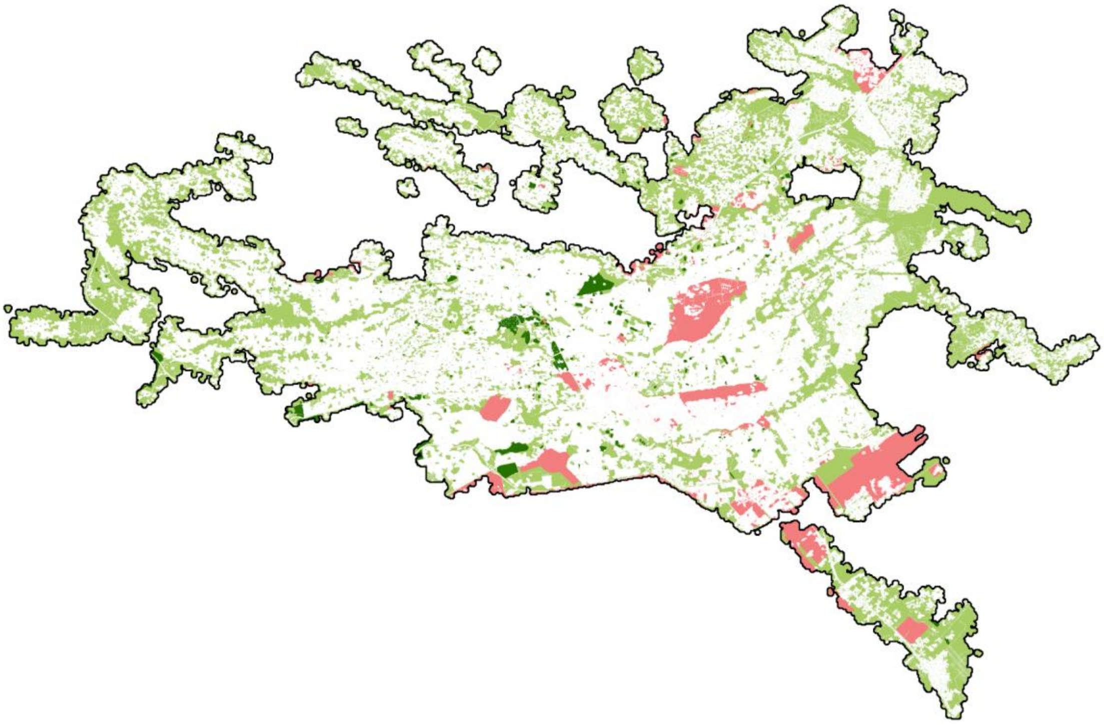

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THE ROLE OF GLOBAL OPEN GEOSPATIAL DATA IN MEASURING SDG INDICATOR 11.7.1: PUBLIC OPEN SPACES

Julia Cramwinckel

Registration number 95 10 03 164 020

Supervisors:

Dr. Sarah Carter
Dr. Nandika Tsendbazar

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ABSTRACT

Global open geospatial products originating from Earth Observation (EO) and Volunteered Geographic Information (VGI) could potentially be used to measure the sustainable development goals (SDGs), in particular indicator 11.7.1: Average share of the built-up area of cities that is open space for public use. No research has yet focused on analysing the potential of these products for measuring this indicator, while they could provide a solution for data-poor countries. The objective of this thesis was therefore to investigate the role of open global geospatial data products in measuring SDG indicator 11.7.1. In order to do so, potential useful geospatial products were identified. These were used to measure the elements (the urban extent, the street space, and the public open spaces) of the indicator for the city Nairobi, following and building upon the official proposed methodology of the indicator. The results of the different products were compared against each other and against reference data originating from a public open space assessment performed by UN-Habitat and Nairobi County. Additional reference data for the street space was created using high resolution satellite imagery. The results showed that global open geospatial products can play a role. They can provide reflection upon the UN-proposed methodology, assist in the delimiting of public open spaces if EO and VGI products are combined, and outperform local datasets.

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LIST OF ABBREVIATIONS

AFRICOVER	Multipurpose Land cover Database for Africa
BU	Built-up
CCILC	Climate Change Initiative Land Cover maps
CCILC20	S2 prototype land cover 20m map of Africa
GlobCov	Glob Cover project
C-CLOPS	Copernicus Global Land Service
EO	Earth Observation
ESA	European Space Agency
FROMGLC10	Finer Resolution Observation and Monitoring of Global Land Cover
GHS	Global Human Settlement built-up grid from Landsat
GHS-S1	Global Human Settlement built-up grid from Sentinel-1
GRIP	Global Roads Inventory Project
GRUMP	Global Rural-Urban Mapping Project
GUF04	Global Urban Footprint 0.4 arc seconds
HBASE	Global Human Built-up and Settlement Extent
HRSL	High Resolution Settlement Layer
LAPOS	Land allocated to open public spaces
LAS	Land allocated to streets
LAS samples	Land allocated to streets in sample areas
MDGs	Millennium Development Goals
MODIS500	MODIS 500 meter map of global urban extent
NAIROBI LU	Nairobi Kenya Land Use Map
NAIROBI roads	Nairobi major roads dataset
NBU	Non-built-up
OSM	Open Street Map
SDGs	Sustainable Development Goals
SDI	Spatial Data Infrastructure
UN	United Nations
USDGs	Urban Sustainable Development Goals
VGI	Volunteered Geographic Information

1. INTRODUCTION

1.1. CONTEXT AND BACKGROUND

In 2015 the Millennium Development Goals (MDGs), a guiding framework developed by the United Nations (UN) meant to foster international development, had ended. It became clear that while progress had been made, it had been unevenly distributed across countries (United Nations, 2015a). A post 2015 development agenda was required to continue the work. Therefore, the UN identified a new set of goals in 'Transforming our world: The 2030 Agenda For Sustainable Development' (United Nations, 2015b). These goals are known as the Sustainable Development Goals (SDGs).

A central issue of the MDGs was the lack of monitoring mechanisms, caused by the absence of appropriate data and methods (Klopp & Petretta, 2017; United Nations, 2015b). There has been a call for a 'data revolution' (IEAG, 2014) and as a consequence the SDGs are more focussed on the role of data in monitoring the progress. Especially geospatial data, as it is seen as "the basis for evidence-based decision-making, monitoring, and accountability" (United Nations, 2015b). The Earth Observation Group brought out a report in which they emphasise the role Earth Observation (EO) data could play in monitoring the SDGs (Paganini et al., 2018). The UN also established a working group on geospatial information. Geospatial information obtained by EO and other sources have the capacity to monitor spatial changes on a global scale which is essential for monitoring.

Another criticism on the MDGs was the lack of attention for the role cities played in development (Klopp & Petretta, 2017). Cities are more and more seen as important locales for sustainable development in every pillar of sustainability: environmental, social, and economic (Fitzgerald, 2010; Haughton & Hunter, 2004; Parnell, 2016). It is expected that by 2050 68% of the world's population will live in cities (UN DESA, 2018). The UN acknowledges the central role of the city as it sees urbanization as "a powerful tool for sustainable development for both developing and developed countries" (United Nations, 2016, p. IV). Therefore, the new development agenda incorporated goal 11 dedicated to development in cities. This goal calls to "make cities and human settlements inclusive, safe, resilient, and sustainable".

One way to make cities inclusive, safe, resilient, and sustainable is by providing public open spaces. They provide amongst others space for social interaction, relaxation, nature, political development, and business opportunities (Carr et al., 1992). However, increasing and overlapping demands of land put pressure on availability and accessibility of open space. In order to maintain and create sustainable cities, it is necessary to reverse this trend. This is why the UN has included target 11.7: "Providing universal access to safe, inclusive, and accessible green and public spaces, in particular for women and children, older persons, and persons with disabilities".

To achieve this target, it is important to know if, how and why open spaces are changing. A way to answer these questions is to monitor changes in public open spaces over time. This is the function of indicator 11.7.1: "Average share of the built-up area of cities that is open space for public use for all, by sex, age, and persons with disabilities". This indicator consists of two elements: a geophysical part (average share of the built-up area of cities that is open space) and a social part (for public use for all, by sex, age, and persons with disabilities). Geospatial information could particularly be useful to measure and monitor the first element. By doing so it could contribute to the data revolution within the SDGs.

1.2. PROBLEM DEFINITION

In order to monitor the indicator, suitable data is needed, in terms of thematic, temporal, and spatial extent. Klopp and Petretta (2017, p. 93) identified several challenges of the indicators of goal 11 and one of the main issues is the lack of "standardised, open and comparable data". While some countries have an abundance of highly detailed datasets, other countries lack data altogether, resulting in a 'digital divide' (Scott & Rajabifard, 2017). This digital divide may lead to misconceptions about the progress that has been made on sustainable development goals between different countries. It also may mean that some countries are able to act while others are not, because when monitoring can't be done it is harder to plan interventions to address the goals. Not only a lack of data but also a lack of good quality data may increase the digital divide. Boyer et al. (2015) argue that city data obtained through national and local surveys are often sparse and not always of high quality. Therefore, they stress the need to use global EO data.

EO data has often been used to monitor land cover changes on a global and national scale. Several global data products have been developed such as GlobeLand30, Global Land Cover Characterization, and MODIS land cover. They are used to analyse topics such as resource management, climate change, and urban development (J. Chen et al., 2017). However, for inner-urban land change analysis the use of data is often limited to local analysis on satellite data or aerial photographs, rather than existing EO data products. This is due to the fact that urban analysis requires a spatial resolution of 40 m or lower (Tran et al., 2011). Until recently, no global open products with such a spatial resolution existed. Another issue with urban analysis is the need for land use data rather than only land cover data, to provide information on the function of urban space rather than only its physical structure. Moreover, most traditional EO products did not have urban as their main topic, as they were focussed on generic land cover classes.

For measuring the urban SDGs (USDGs) innovative EO-derived measures that bring more spatial and thematic detail are needed (Boyer et al., 2015). Over the past few years, more and more global EO-derived products have been developed to provide higher spatial detail and more focussed information on the urban space, these include land-cover products, built-up products, land-use products and road datasets. Examples are the Global Human Settlement Layer and the Global Urban Footprint products. Other novel open-source products such as Volunteered Geographic Information (VGI) products could provide more thematic detail and land use information. These include amongst others Open Street Map (OSM). Lu et al. (2015) and Boyer et al. (2015) acknowledge the potential role of these novel open-source data products for monitoring the USDGs. While these products might not have been directly developed to help monitor the USDG and indicator 11.7.1 in particular, they could be useful in deriving information about urban open spaces. For example, work by Liu and Long (2016) has shown that OSM road data can be used to generate individual parcels required for urban land use mapping. This re-purposing of available open data is also seen by the United Nations (2015b) as a solution for the digital divide. Some exploratory research into the role EO data and other global open geospatial products can play in monitoring the SDGs show their potential (Copernicus, 2018; Noort, 2017). However, no research has focussed yet on discovering the capabilities of these existing geospatial data for measuring indicator 11.7.1 in particular, while this data could potentially provide a solution for data-poor countries.

Indicator 11.7.1 is classified as a Tier II, which means that the indicator is conceptually clear and has an internationally established methodology and standard, but data is not collected yet (United Nations, 2017). There are several reasons why data might not have been collected yet. Firstly, the geospatial data to be acquired requires quite some resources in time, expertise, and finances. This is because it either requires a manual classification of remote sensed satellite imagery or already available highly detailed datasets. This is especially problematic for countries with less developed spatial data infrastructures (SDIs) (Sarvajayakesavalu, 2015), which accounts for most countries in Africa and Asia (Klopp & Petretta, 2017). Secondly the method to distinguish the urban open spaces is not complete, as it describes how to make an on-the-ground assessment of public open spaces, but not how to identify these spaces. It does mention a role for geospatial data, but it does not specify which data, nor does it provide a clear method on how to use this data. Furthermore, it is stated that different data products can be used, but there is no clear indication what the effect will be when different products are used to measure the same indicator. This poses questions about the quality of the data, not just in terms of accuracy, but also if the data used actually measures what you want to measure. This is known as the suitability or 'fitness for use' (Devillers, Jeansoulin, & Goodchild, 2006; Zaveri et al., 2016).

In sum, there are two elements that are missing which need to be researched. Firstly, it is not yet clear if, how, and which open geospatial data products can be used to measure this indicator. Secondly, it is also not clear if using different data products and accompanying methods will yield similar results. The problem is thus a lack of knowledge about the role open geospatial data can play in measuring indicator 11.7.1.

1.3. OBJECTIVES

The main objective of this thesis is to *investigate the role of open global geospatial data products in measuring the sustainable development goal indicator 11.7.1: Average share of the built-up area of cities that is open space for public use.* The focus lies on using geospatial data, which means that only the geophysical part of the indicator will be measured. Thus data will be analysed to measure the built-up area of cities that is (public) open space, not whether this space is usable for all by sex, age, and persons with disabilities.

In order to reach the main objective, three sub-objectives are formulated:

(1) Identify open global geospatial data products that could potentially be used to measure at least one of the three elements of SDG indicator 11.7.1 (urban extent, street space, and public open space).

(2) Develop and execute methods to assist in measuring SDG indicator 11.7.1 using the different identified data products.

(3) Analyse the effect of using the different data products and methods on the measuring outcome of SDG indicator 11.7.1.

The first sub-objective helps to narrow down the open geospatial products to those that have the suitability or 'fitness for use' to measure the indicator. The next sub objective then focusses on the question how these potential products can be used to me SDG 11.7.1. The last sub objective looks at the importance or validity of the role of these geospatial products in relation to the products that are used in the recommended methodology.

2. METHODOLOGY

2.1. THE INDICATOR

The core outcome for indicator 11.7.1 is the share of built-up area of the city that is open space in public use. To obtain this, several elements were required. The first element was the urban extent. The urban extent encompasses both the built-up area and the urbanized open space (UN-Habitat, 2018a). The built-up area is defined as "a contiguous area occupied by buildings and other impervious surfaces" (UN-Habitat, 2018a, p. 1). However, as the denominator of the indicator ("built-up area of the city"), the built-up area equals the urban extent.

The open space in public use consists of two elements: public open spaces and street space. Public open space is defined as "undeveloped land or land with no buildings (or other built structures) that is accessible to the public" (UN-Habitat, 2019, p. 10). The types of these spaces can vary per city but the general types are: parks, recreational areas (playgrounds, riverfronts, etc.), civic parks, and squares and plazas. This means that there are green, non-green, and water public open spaces. For assessing the public open space, UN-habitat has developed a sub-indicator. This is the land allocated to public open spaces (LAPOS), which was calculated using Formula 1.

$$\mathbf{LAPOS} = \frac{Total\ surface\ of\ f\ public\ open\ space}{Total\ surface\ of\ the\ urban\ extent} * 100 \tag{1}$$

Streets and accompanying spaces are also seen as spaces for public use. Streets are publicly owned and accessible and they include avenues and boulevards, pavements, passages and galleries, bicycle paths, sidewalks, traffic islands, tramways, and roundabouts (UN-Habitat, 2018a). For assessing the street space, UN-habitat has developed a sub-indicator. This sub-indicator is the land allocated to streets (LAS) and was calculated by Formula 2.

$$\boldsymbol{LAS} = \frac{Total\ surface\ of\ street\ space}{Total\ surface\ of\ the\ urban\ extent} * 100 \tag{2}$$

For the core outcome of the indicator, the surfaces of the urban extent, the public open spaces, and the street space were required. To obtain the outcome Formula 3 was used:

$$\boldsymbol{Share\ of\ the\ built-up\ area\ of\ the\ city\ that\ is\ open\ space\ in\ public\ use}\ (\%) = \frac{Total\ surface\ of\ public\ open\ space + Total\ surface\ of\ street\ space}{Total\ surface\ of\ the\ urban\ extent} * 100 \tag{3}$$

2.2. WORKFLOW

The methodology consisted of three parts (Figure 1). First, useful geospatial products were identified (part 1), consisting of built-up, land-cover, land-use, and street products. They were then used to measure the three elements (urban extent, street space, and public open space) of the indicator (part 2). In part 3, the outcomes of part 2 were compared against each other and against the reference data.

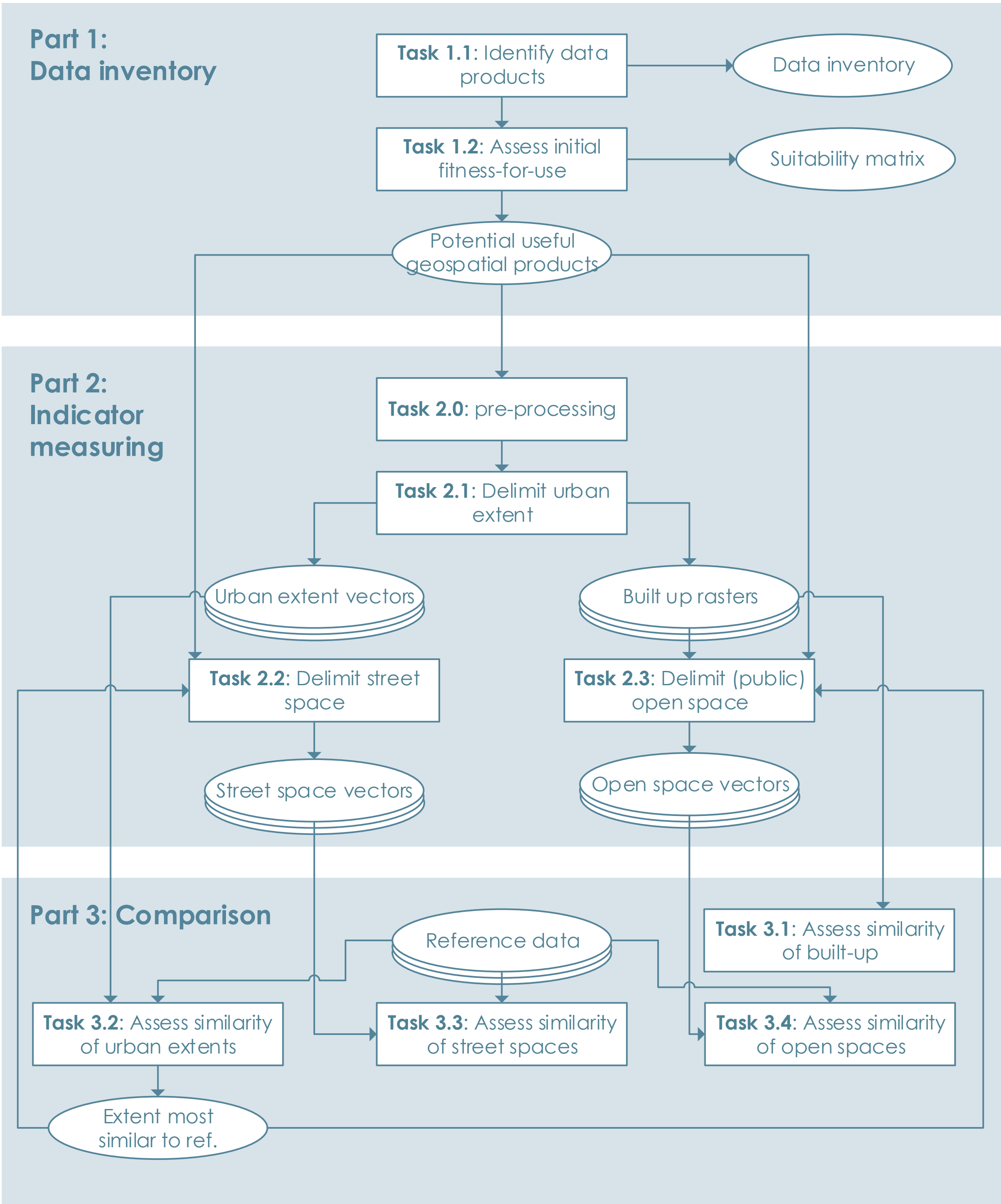

Figure 1. *Methodological framework of this thesis showing the three parts and accompanying tasks.*

2.3. SOFTWARE

The spatial processing software used in this thesis is ArcGIS Pro (version 2.2.4). In ArcGIS pro the model builder was used to be able to repeat the processing steps for every product. The main tools used in this thesis were spatial analysis, data management, and conversion. The output maps were also produced in ArcGIS Pro. The OSM data has been downloaded using Overpass turbo, a web based data mining tool for OSM data. Google Earth Pro imagery has been used to measure street widths. Excel was used for the calculation of the indicator elements (LAS, LAPOS, etc.) and for the creation of tables and graphs. Supporting figures were created with Adobe Photoshop.

2.4. STUDY AREA

The city of Nairobi in Kenya was selected as the research area to measure the indicator (Figure 2). Nairobi is the capital of Kenya and was founded by the British colonial authorities. It is located in the southern part of Kenya sits along the Nairobi River. It is bordered by the Nairobi National park and several forests. In 2009, the population of the city was 3.1 million (KNBS, 2010). The city has a mixture of high-end residential neighbourhoods, middle-income neighbourhoods, and slums. Nairobi was selected for several reasons. Firstly, Nairobi was designed as a garden city in the colonial period, meaning it has a history of planned open public spaces. However, due to urban sprawl a lot of these public spaces have been lost and they are now trying to bring them back (Makworo & Mireri, 2011). Secondly, while there was some local data available, the quality and temporal coverage is not sufficient for regular monitoring. The outcomes of this research in terms of the usability of open data products are therefore also useful for other countries with insufficient local data. Lastly, UN-Habitat and the Nairobi County collaborated to perform an 'Open Public Spaces Inventory and Assessment' in the city (UN Habitat, 2016). The results of this assessment could be used as a reference to compare the other products against.

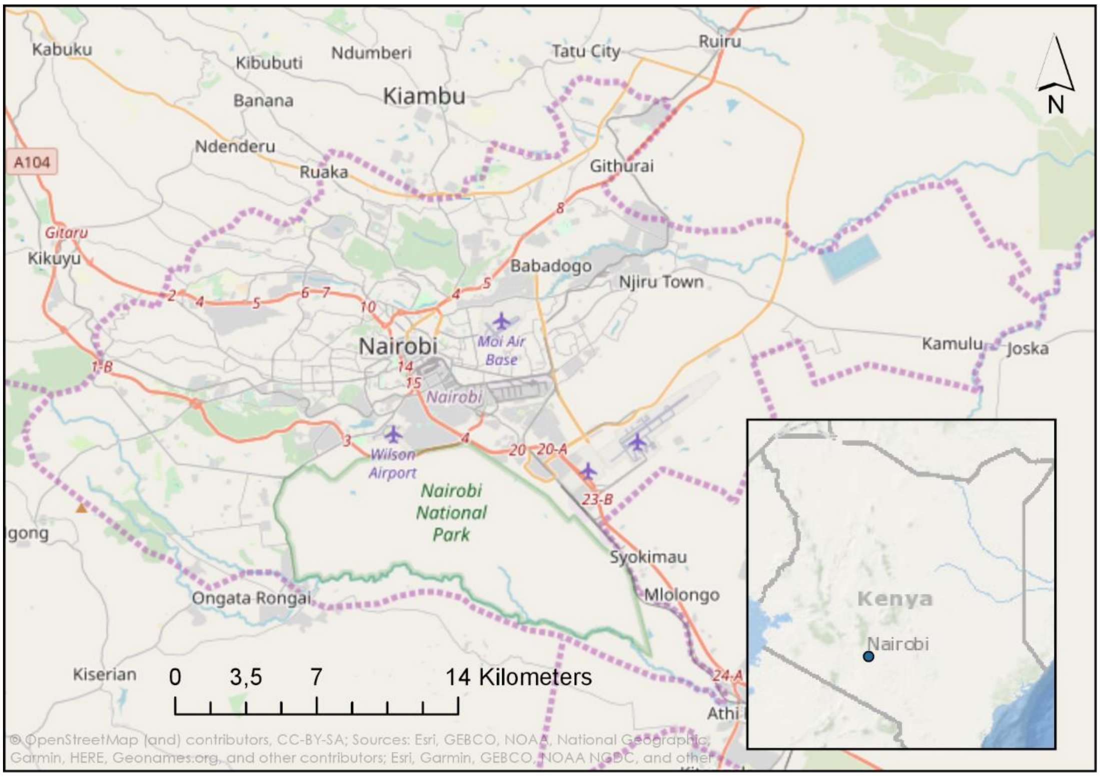

Figure 2. *Study area Nairobi, Kenya. The purple line is the administrative extent.*

2.5. PART 1: IDENTIFY POTENTIAL USEFUL PRODUCTS

2.5.1. Task 1.1: Identify data products and characteristics

The first task was to search for open geospatial data products. The thematic contents had to correspond to either one of the elements (urban extent, land allocated to streets, or open space).

2.5.2. Task 1.2: Assess initial fitness for use

To assess the initial fitness of use of the identified products, a suitability assessment was made. Three main criteria were selected: the spatial extent, the temporal extent, and the thematic content. **Table 1** summarizes the suitability scores per criteria and per indicator element. Each criteria consists of maximum four different classes, each having its own score. These scores range from not suitable ('-' sign and red colour) to most suitable ('++' sign and dark green colour).

Spatial resolution

For urban analysis, the higher the spatial resolution the more suitable a product is (Welch, 1982). For the suitability classification the spatial resolution requirements are based on the recommendations for urban analysis by Tran et al. (2011). The same classification was used for assessing the suitability of products to delimit open spaces.

- A spatial resolution of 30 m or less was considered as most suitable, as even individual buildings could be distinguished.
- Between 31 - 40 m was labelled as suitable, since it allows for detection of small residential blocks (Tran et al., 2011).
- Between 41 - 60 m was labelled as less suitable, since it allows for detection of only larger building blocks (Tran et al., 2011).
- Any spatial resolution above 60 m was marked as not suitable, because at such a resolution building blocks are hard to identify.

The spatial resolution criterion has not been taken into account for delimiting the street space. This was due to the fact that all the potential street data products were in vector format, which means their 'spatial resolution' could not be directly compared. Because there were only a limited amount of datasets found it was more important to make a selection based upon thematic content.

Temporal resolution

For the temporal resolution data acquired close to the year 2015 was required. This year was chosen because the reference data from the open space assessment was acquired that year and it marks the start of the monitoring period for the SDGs. Ideally, the data acquisition should not have taken place more than five years before or after 2015, to make sure the urban space has not changed too much.

- Any product that dates from before 2010 was labelled as not suitable.
- A low suitability was given to products around 2015, but with no expected future updates.
- If the data product is likely to be produced for multiple years (including one close to 2015) it was labelled as having a higher suitability, as it allows for monitoring over time.
- If the product will be produced within a 5-yearly basis it was marked as most suitable, as the indicator is monitored on a 3 to 5-year interval (UN-Habitat, 2018a).

Thematic content

The suitability of the thematic content of the data products differs per element. It is based on the definitions of the elements described in section 2.1. For delimiting the urban extent, the scoring was as follows:

- Data products that use a built-up class definition that contains both buildings and impervious surfaces were labelled as most suitable.
- If the definition of built-up was only to contain (a part of a) building, it was given a lower suitability score, as you would not be able to identify 'other impervious surfaces'.
- If there was no aggregation possible, the product was labelled as not suitable. This was the case when the built-up was based on other factors such as light intensity.

The thematic content score for delimiting the street space was:

- Highest suitability if the street product contained separate classes for streets, avenues and boulevards, pavements, passages and galleries, and bicycle paths. Ideally, the exact width of every street would be known, however none of the datasets contained this information. Therefore, the dataset with the most detailed classification was deemed to be most suitable.
- If the product only contained a broad classification of streets, it was scored as moderate suitable.
- If the product only contained one single class, it was scored as not suitable.

The scoring for identifying public open spaces was:

- Data products that contained classes such as parks, recreational areas, civic parks, and squares and plazas received the most suitable score.
- If they contained only broad open space classes (e.g. green and non-green open spaces) they got a slightly lower suitability score, as the calculation of the indicator itself does not require this detail. Data products that had a class that contained only buildings also got the same suitability score, as they could be used to identify the open spaces by excluding the buildings from the built-up area.
- If there was no aggregation possible, the products were scored as not suitable.

Overall suitability ranking

Once the scores per suitability criteria were known, the overall suitability per product per element was distinguished. The general rule was that as soon as a product scored a 'not suitable' on either one of the criteria, its overall suitability was labelled as not suitable. Out of the remaining products a final selection was made by comparing the scores per criterion and ranking them from 1 (most suitable) to six (least suitable). For delimiting the urban extent and the open spaces six products were selected. For delimiting street space, one product was selected. The thematic content was given the highest importance, followed by the spatial and the temporal resolution. The reason for this is that quality outweighs quantity. If a single year product turns out to be most useful, it could serve as a baseline or its methods could be used to measure multiple years. The selected products can be found in section 3.1.

***Table 1**. Suitability criteria and scores per element to assess the usability of the products.*

Spatial resolution Pixel size in meters	**Temporal resolution** Year(s) of (expected) data acquisition	**Thematic content** Definition of classes used	**Score** per criteria
For delimiting urban extent			
≤ 30 m	Multiple years with interval of ≤ 5 years, including any year between 2010 and 2019	Built-up class equals UN habitat definition	++
30 m > ≤ 40 m	Multiple years with interval of > 5 years, including any year between 2010 and 2019	Built-up class contains only buildings	+
40 m > ≤ 60 m	Single year between 2010 and 2019		-
> 60 m	Single year < 2010	No aggregation possible	-
For delimiting street space			
	Multiple years with interval of ≤ 5 years, including any year between 2010 and 2019	Street classes equal UN habitat definition	++
	Multiple years with interval of > 5 years, including any year between 2010 and 2019	Only broad street classes	+
	Single year between 2010 and 2019		-
	Single year < 2010	Only single street class	-
For delimiting public open space			
≤ 30 m	Multiple years with interval of ≤ 5 years, including any year between 2010 and 2019	Open space classes equal UN habitat definition	++
30 m > ≤ 40 m	Multiple years with interval of > 5 years, including any year between 2010 and 2019	Only broad open space classes / building class	+
40 m > ≤ 60 m	Single year between 2010 and 2019		-
> 60 m	Single year < 2010	No aggregation possible	-

2.6. PART 2: USE PRODUCTS TO MEASURE INDICATOR 11.7.1

The identified products were used to measure indicator 11.7.1 in Nairobi, for the elements: (1) the urban extent, (2) the street space, and (3) the public open space. Using these elements, the sub- and final indicator(s) were calculated.

2.6.1. Task 2.0: Pre-processing

The pre-processing phase consisted out of several steps. When the individual tiles did not fully cover the city, raster tiles of the same product were merged to create full coverage. In addition, the products were projected to the local coordinate system used in the reference data (WGS 1984 UTM Zone 37S). The products were then clipped to the product with the smallest extent to reduce processing time. This was particularly important for products that only provided raster tiles containing the whole continent.

2.6.2. Task 2.1: Delimiting the urban extent

For delimiting the urban extent, the UN-habitat proposed methodology was followed. The method has been developed in the Atlas of Urban Expansion project (Angel et al., 2016). The steps including the tools and settings to be used in ArcGIS are described in training module 3: Land Use efficiency (UN-Habitat, 2018b). However, some parts of the methodology were missing they had to be developed as part of this research (Table 2).

***Table 2**. Tasks and steps in methodology already existing and developed for this thesis.*

Steps in methodology	Developed by
Task 2.1 Step 1 – 3 up to identifying fringe open spaces	UN-Habitat (2018) and Angel et al. (2016)
Task 2.1 Step 3 identifying captured open spaces	This thesis
Task 2.1 Step 5 up to calculating buffer distance	UN-Habitat (2018) and Angel et al. (2016)
Task 2.1 Step 5 from calculating buffer distance till end of step	This thesis
Other tasks	This thesis

To obtain the urban extents, four main steps were performed for each selected geospatial product. These steps consisted of: defining the built-up (step 1), defining the urban built-up, which consists of the contiguous and suburban built-up without the rural built-up pixels (step 2), defining the urban areas, which is the urban built-up plus the surrounding open space (step 3), and finally delimiting the urban extent, which contains the urban areas in close proximity of the city core (step 4). Figure 3 shows the different elements that play a role in these steps.

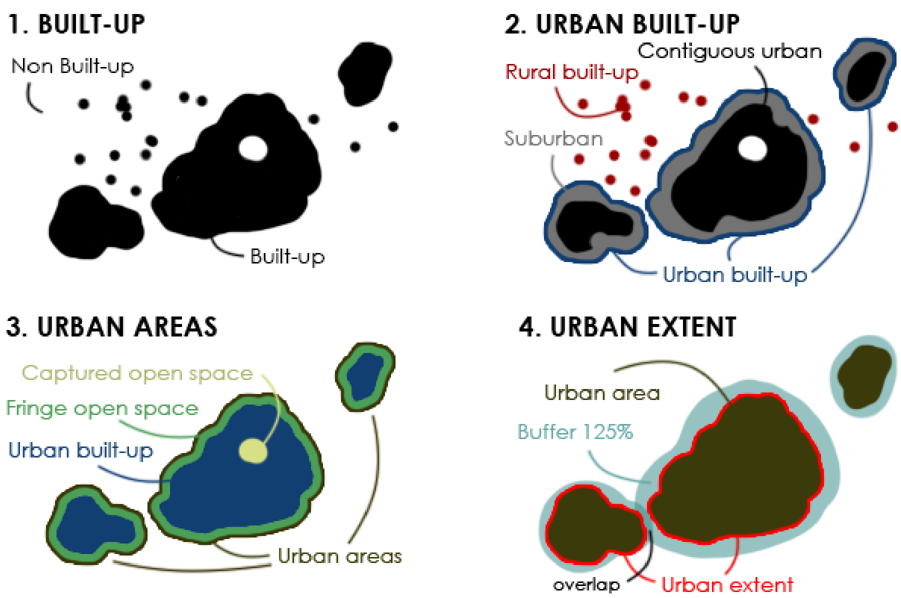

***Figure 3**. The elements that play a role in delimiting the urban extent:*
1. Built-up pixels, 2. Urban built-up pixels, 3. Urban areas and, 4. Urban extent.

Step 1: Define built-up

The first step of this task was to reclassify the products into a binary classification of built-up (BU) pixels and non-built-up (NBU) pixels (Figure 3.1). For most products the existing classes could be reclassified into these binary classes. For GHS however the confidence map was used to set a new threshold (10) for BU, as the original threshold (127, on a scale from 0 to 255) was under-estimating the built-up pixels. This threshold was chosen visually by overlaying the confidence map on high resolution satellite imagery of 2015, available in ArcGIS Online.

Step 2: Define urban built-up

For obtaining the urban extent, only the urban BU pixels and not the rural BU pixels are required. UN-Habitat (2018b) therefore proposes to make a distinction between rural, sub-urban, and contiguous urban pixels (Figure 3.2). This classification depends on the urban density of the surrounding pixels within a circle with an area of one km^2 (Angel et al., 2016). Using the percentage of BU in this walking distance circle, each BU pixels was classified into one of these types (Table 3). The rural pixels were excluded to obtain only the urban BU (suburban + contiguous BU pixels).

***Table 3**. Built-up pixel classification according to UN-Habitat (2018) and Angel et al. (2016).*

BU pixel density within walking distance circle (1 km) of a given pixel	Type
Less than 25%	Rural built-up
25% - 50%	Suburban built-up
50% or more	Contiguous urban built-up

Step 3: Define urban areas

The next step was to define the urban areas, which are the clusters of urban BU pixels and the surrounding open space. This space consists of fringe and captured open space (Figure 3.3). Fringe open space is the open space within 100 m of the urban BU pixels (UN-Habitat, 2018b). To obtain these, a buffer was placed around the urban BU pixels.

Captured open space is any space smaller than two hectares and fully surrounded by either the urban BU or the fringe open space (UN-Habitat, 2018b). They were identified by selecting all the open space areas surrounded by the urban BU and fringe open space and excluding the areas that were larger than two hectares. I choose to work with polygons as it allows for easy detection of NBU areas and it directly gives you the size of those areas. The polygons were not simplified (their boundaries exactly match the original pixels) to make sure that they could be converted back to raster in a later stage. Once the fringe and captured open spaces were identified they were merged with the urban BU to form the urban areas.

Step 4: Delimit urban extent

Once the urban areas were identified, the urban extent could be delimited (Figure 3.4). Often there are multiple urban areas, such as towns. Therefore, to obtain the city under investigation, only urban areas in close proximity of the city core were taken into account. Angel et al. (2016) have determined that an urban area is seen as part of the urban extent if it overlaps with the main urban area when they both are buffered by 125%. Since buffering can only be done with a given distance, this distance was calculated first. Therefore, the function 'buffer by percentage' originally created for QGIS by Dugge (2018) and adjusted to ArcGIS by fatih_dur (2018) was used. This function iteratively increases the buffer distance until the area of the buffer resembles the desired area (125% of the original area), to obtain the required buffer distance. Once the urban areas were increased by this distance, the ones whose buffers overlapped with the main buffer were selected to obtain the urban extent.

Selection of urban extent for delimiting the other elements of the indicator

One single extent needed to be selected to serve as extent for delimiting the other two elements of the indicator, to be able to compare the results in part 3. The extent which resembled the reference extent the most was selected. For information on this assessment see task 3.2. In this case it was the extent derived from the GHS.

2.6.3. Task 2.2: Delimiting street space

For delimiting street space, Open Street Map (OSM) was used. The streets were projected and clipped to the GHS extent. The resulting OSM road dataset contained attributes such as the type of street but not the widths required for calculating street space. In order to obtain the widths, manual measurements were required. The street types were aggregated into eight classes (Table 4) and for each class 20 points were randomly selected (Appendix A. Figure 1). Using Google Earth Pro high resolution satellite imagery, the widths of the streets on these points were measured. For measuring the width, not only the streets itself, but also the surrounding street-space (adjacent open space, sidewalks, and central reservations) was included. To reduce the influence of outliers, the median value per class was taken. These values were then used to buffer the polylines per class to obtain the total street space. Once the street space was delimited, the LAS was calculated (Formula 2).

Table 4. *Aggregated OSM street classes.*

Aggregated OSM street classes	Original street types
Path	Footway, Path, Steps, Cycleway
Pedestrian (e.g. shopping streets)	Pedestrian
Motorway	Motorway, Motorway_link, Trunk, Trunk_link
Primary road	Primary, Primary_link
Secondary	Secondary, Secondary_link
Tertiary	Tertiary, Tertiary_link
Residential	Residential
Unclassified	Unclassified

2.6.4. Task 2.3: Delimit public open space

To obtain the public open spaces per product, two steps have been performed. First, the open spaces were identified from the products themselves. Next, OSM data was used to identify which open spaces were public and which were not.

Step 1: Identifying open spaces using built-up and land cover products

The products that have been used in task 2.1 were also used in this task, but now they were 'inverted'. These are the binary built-up classification products, also including the rural pixels. Instead of using the built-up pixels, the non-built-up pixels were used. First, the products were clipped to the GHS extent. To avoid issues related to different spatial resolutions than the GHS resolution, the other geospatial products were converted to polygons. The next step was to take out the street space identified earlier, to avoid counting this space twice (once as street space and once as open space), and to divide the open space in smaller identified areas.

Step 2: Classifying open public and non-public spaces using OSM

OSM contains polygons that are tagged with a land-use function. These function tags were used to identify which space was likely to be public and non-public. Table 5 shows the open space categories present in the reference dataset and the corresponding OSM key-tag pairs, which have been downloaded. Table 6 shows the key-tag pairs that represent spaces that are unlikely to be public.

The OSM data was downloaded and pre-processed in a similar way as described in task 2.2. Two additional pre-processing steps were required: converting the roundabout polylines into polygons and removing overlaps between polygons.

By combining both the data retrieved from the land cover and built-up products and the OSM data, a classification in the publicness of open spaces could be made. The OSM public open and non-public open space datasets were clipped to the open spaces identified from the products. If the open space of the product overlapped with the OSM public open space dataset, that particular space was classified as ‘public open space’. If it overlapped with the OSM non-public open space dataset, it was classified as ‘non-public open space’. The remaining spaces were classified as ‘possible public’. Once the classifications were known, the LAPOS (Formula 1) were calculated for the public open spaces, and for the public and possible public open spaces combined.

Table 5. *Public open space classes in reference data and corresponding OSM key-tags.*

Reference class	OSM key	OSM tag
Community centre	n/a	n/a
Forest	Landuse	forest
Roundabout	Junction	roundabout
Sidewalk	n/a	n/a
Cemetery	Landuse	cemetery
Community park	n/a	n/a
Community yard	Natural	scrub
Garden	Leisure	Garden
Open market	n/a	n/a
Park	Leisure	Park
Parking lot	Amenity	parking
Playground	Leisure	playground
Road, power, railway reserve	n/a	n/a
Sports fields	Leisure	Pitch
Square	Place	Square
Street*	n/a	n/a
Vacant space	n/a	n/a
Water body front	Natural | water	Water | all

* Belongs to street space, thus removed from the reference

Table 6. *OSM key-tags of spaces that are likely to be non-public.*

OSM key	OSM tag
Leisure	Golf course
	Swimming pool
	Resort
	Track
	Nature reserve
Tourism	Campsite
Landuse	military
	Industrial
	Construction
	Landfill (waste disposal)
	Farmland
	Quarry
	Farmyard
	Meadow
	Orchard
	Plant nursery
	Railway
Military	All
Aero way	aerodrome

2.7. PART 3: COMPARE RESULTS

2.7.1. Task 3.1: Assessing similarity of built-up classifications

Since the BU classification of the different products forms the basis for delimiting the urban extent and the open spaces, it is relevant to compare the BU classifications, even though they are not a required outcome for the indicator. There was however no reference data available for the built-up classification, so they had to be compared against each other. To give an indication of the overall agreement spatially, the built-up pixels of the products were overlaid. This required a resampling of every product to match the pixel size of the product with the largest pixel size. In this case this was GHS with a spatial resolution of about 38 m. A nearest neighbour resampling method was chosen as it concerned categorical data (Baboo & Devi, 2010). After this, every built-up pixel contained information about how many products agreed it was BU, ranging from one to six.

2.7.2. Task 3.2: Assessing similarity of urban extents

The assessment of the urban extents is object- rather than pixel-based as it concerns vector data. In this case reference data was available, so the extents of the individual products were compared against the reference extent. The reference extent (Figure 4) originates from the Open Public Spaces Inventory and Assessment made around 2015. It is created according to the UN proposed methodology, using a supervised classifications of 30 m Landsat imagery. The product extents were assessed by looking at the similarity in size (area in km^2) and overlap with the reference extent.

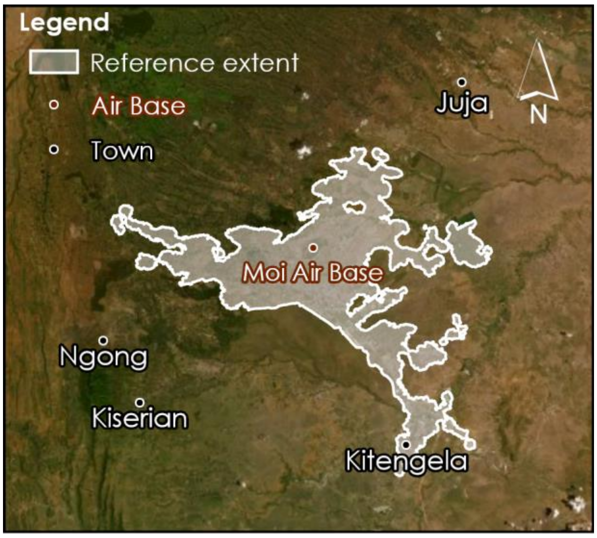

Figure 4. *Reference urban extent created for the Nairobi Open Public Spaces Inventory and Assessment by UN-Habitat (2016).*

2.7.3. Task 3.3: Assessing similarity of street spaces

The street space identified by OSM was assessed by comparing it against both a local dataset and digitized reference data. The Open Public Spaces Inventory and Assessment used a local authoritative street dataset of the Nairobi government to calculate the LAS. This dataset only covers the administrative area, and its quality is unknown. Therefore, reference street data was created, following the UN-habitat proposed methodology. Streets were digitized using high resolution spatial imagery from 2015 available through ArcGIS Online. This was done in 100 circle samples of ten hectares each, which were randomly sampled in the study area (Figure 5). In this case, the study area was the area where both the GHS urban extent and the administrative extent overlapped, to avoid selecting samples where the local dataset roads were not present.

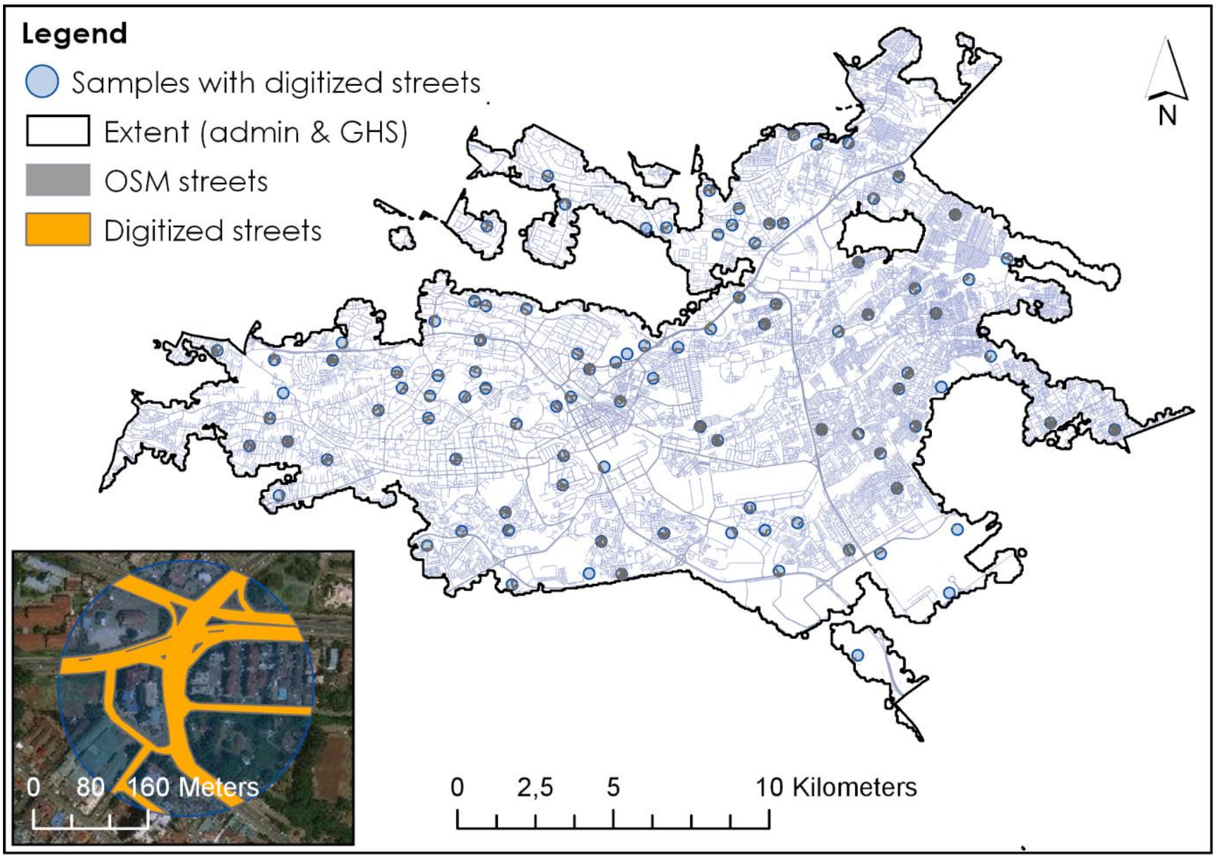

Figure 5*. Sample locations used to digitize street space as reference. Cut-out shows example of digitized street space in a sample.*

The average LAS in these samples ($LAS_{samples}$) was calculated for OSM, the local dataset, and the digitized streets. The $LAS_{samples}$ were calculated using Formula 4, which is the sample-based alternative of Formula 1. By comparing both the OSM $LAS_{samples}$ and the local dataset $LAS_{samples}$ against the reference $LAS_{samples}$, their similarity with the reference was assessed.

$$\text{LASsamples} = \frac{Total\ surface\ of\ street\ space\ in\ all\ locales}{Total\ surface\ of\ all\ locales} * 100\% \tag{4}$$

2.7.4. Task 3.4: Assessing similarity of public open spaces

The identification of the public open spaces by the different products was assessed by comparing the ability of the products to capture the public open spaces of the reference dataset of the Open Public Spaces Inventory and Assessment (Figure 6). The reference consists of manually digitized public open spaces that were validated on the ground. The spaces are also classified by surface texture: either soft-textured (green), hard-textured (non-green), or water.

The similarity between the product-derived open spaces and the reference open spaces was assessed by analysing both the number of and the area of reference open space(s) identified by the products. A reference open space was labelled as 'identified' if the overlap with the product open space was more than 50%. This threshold was chosen following Zhan et al. (2005). The percentage of reference open spaces identified by the products was calculated for the total reference spaces and per surface texture. For assessing the similarity in terms of area, the total area of the product open space overlapping with the reference was calculated. This was expressed as a percentage of the total reference area.

To analyse the effect of the spatial resolution of the products, the relationship between the sizes of the open space on the ability of products to identify them was analysed. The reference open spaces were divided into size classes with more or less equal observations, and the percentage of reference open spaces identified in each size class for the different products was calculated. This was done separately for each surface texture to reduce the effect of this variable.

Next, the ability of the products and OSM to correctly classify the reference public open spaces was assessed. This was done by calculating the number of the reference public open spaces that were correctly identified and those that were wrongly identified. This was based on the object-based accuracy assessment method by Zhan et al. (2005). To determine what classification was given to the open spaces, the majority rule was used to label the identified reference space as one of the product open space classes (public, possible public, or non-public). This meant that the class of the dominant class inside each polygon was used (Radoux & Bogaert, 2017). If the reference public open space was identified as either public or possible public, it was labelled as correctly identified. If the space was identified as non-public, it was labelled as wrongly identified.

To calculate the percentage of area of the reference public open spaces that were correctly identified, the area of all the (possible) public open space that overlapped with the reference open spaces was used. For the wrongly identified, the non-public space that overlapped with the reference was used.

The last element that was important to assess was whether products identified more public space than was present in the reference. This meant that they either identified too many non-public open spaces, or over-identified the open spaces in general. Therefore, the area of (possible) public open spaces that did not overlap with the reference was calculated. It was expressed in percentage of the area of the reference spaces.

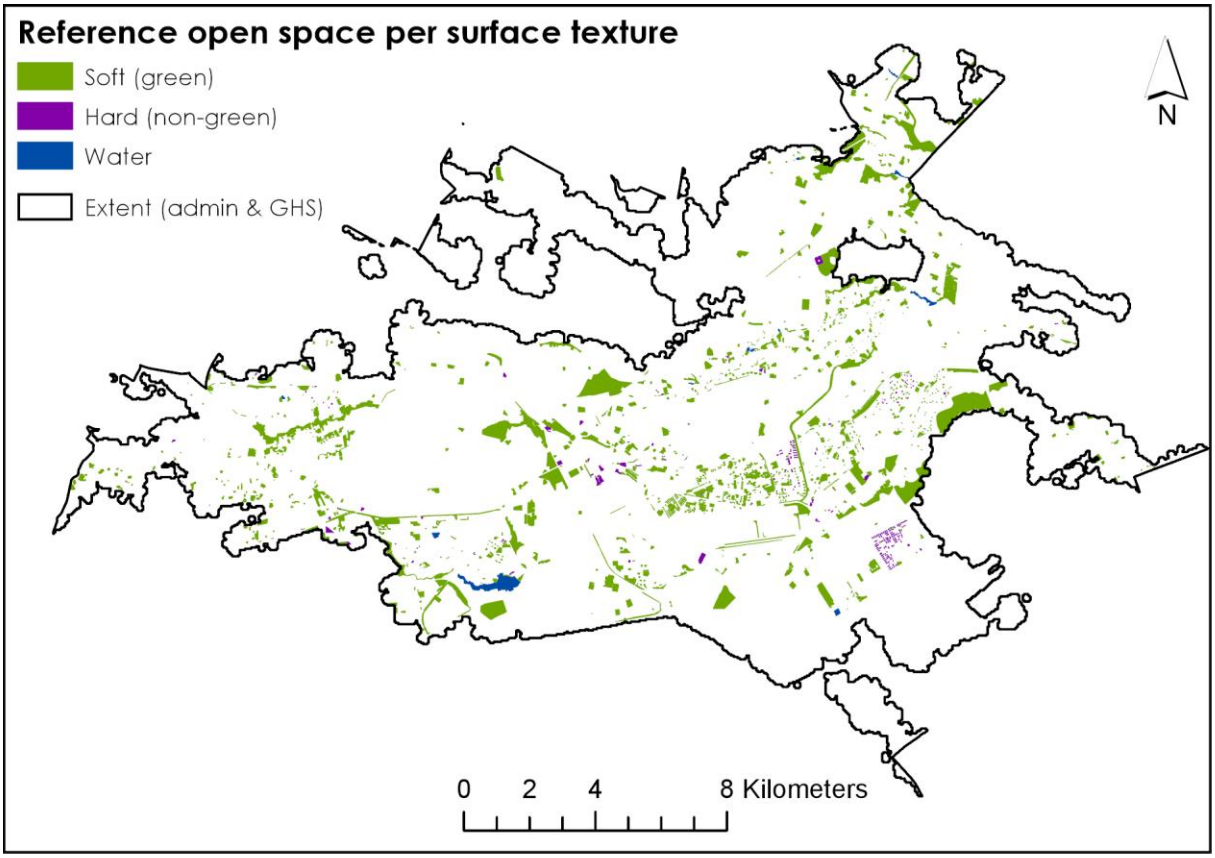

Figure 6*. Reference open spaces per surface texture from UN-Habitat (2018).*

3. RESULTS

3.1. SELECTION OF GEOSPATIAL PRODUCTS

3.1.1. Identified geospatial products

A total of 17 geospatial products were identified that could potentially be used to measure indicator 11.7.1. These consist of six built-up products, six land-cover products, two land-use products, and three road datasets. They are shown in Tables 7 - 10.

Table 7. *Identified global built-up products and their characteristics*

Data product code	Product name	Author(s) / institution	Spatial resolution Pixel size (m)	Temporal resolution	Thematic content Definition of built-up	Source data	Other
GHS	Global Human Settlement Built-up Grid	European Commission Joint Research Centre (Pesaresi et al., 2015)	38	MY: 1975, 1990, 2000, 2014	Containing a building or part of it	Optical Landsat	New version (GHS-S1) is being developed based on Sentinel-1 (Radar)
GUF04	Global Urban Footprint	German Areospace Centre (DLR) (2016)	12	SY: 2011 but updates expected	Contains buildings (features with a vertical component)	Radar TerraSAR-X/TanDEM-X	12 m only available for science, 84 m available for non-profit
GRUMP	Urban Extents Grid	CIESIN, IPFRI, The World Bank & CIAT (2011)	1000	SY: 1995	Frequency with which lights were observed	Population counts, settlement points, & night-time lights	
HBASE	Global Human Built-up And Settlement Extent	Socioeconomic Data and Applications Centre (Wang et al., 2017)	30	SY:2010	Impervious surfaces	Optical Landsat	
HRSL	High Resolution Settlement Layer	Facebook Connectivity Lab & CIESIN (2016)	30	SY: 2015	Contains buildings	Optical DigitalGlobe (0.5 m)	
MODIS 500	MODIS 500-m map of global urban extent	Schneider, Friedl, and Potere (2009)	500	SY: 2002	Impervious surfaces	Optical MODIS	

MY = Multiple years; SY = single year; CIESIN = Centre for International Earth Science Information Network, Colombia University; IPFRI = International Food Policy Research Inst.; CIAT = Centro Internacional de Agricultura Tropical

Table 8. *Identified global land-cover products and their characteristics.*

Data product code	**Product name**	**Author(s) / institution**	**Spatial resolution** Pixel size in meters (m)	**Temporal resolution** Year(s) of data acquisition	**Thematic content** Definition of built-up class	**Source data**
AFRICOVER	Multipurpose Land cover Database for Africa	Food and Agriculture Organisation (2002)	n/a (vector)	SY: 1995	Impervious surfaces	Optical Landsat
CCILC	Climate Change Initiative Land Cover	ESA Climate Change Initiative - Land Cover led by UCLouvain (2017)	300	MY: Yearly between 1992 – 2015, expected updates	Same as GHS and GUF	GHS/ GUF04
CCILC20	Climate Change Initiative Land Cover - S2 Prototype Land Cover 20m Map of Africa 2016	ESA Climate Change Initiative - Land Cover led by UCLouvain (2017)	20	SY: 2016 but targeted to cover multiple years	Same as GHS and GUF	GHS/ GUF04
C-CLOPS	Copernicus Global Land Service land cover map	ESA Copernicus (2019)	100	SY: 2015 but targeted to be yearly	Impervious surfaces	GUF04
GlobCov	GlobCover2009	ESA and UCLouvain (2010)	300	SY: 2009	Impervious surfaces	Optical MERIS
FROMGLC10	Finer Resolution Observation and Monitoring of Global Land Cover	Gong et al. (2019)	10	SY: 2015 (sample) / 2017 (source imagery)	Impervious surfaces	Optical Landsat sample transferred to optical Sentinel-2

MY = Multiple years; SY = single year; ESA = European Space Agency

Table 9. *Identified global land-use products and their characteristics.*

Data product abbreviation	**Product name**	**Author(s) / institution**	**Temporal resolution** Year(s) of data acquisition	**Thematic content** (Non) public open space classes	**Source data**	**Other**
NAIROBI LU	Nairobi, Kenya Land Use map 2010	Columbia University's Center for Sustainable Urban Development (2010)	SY: 2010	No public open space classes, only generic open space	Unknown	Limited to administrative extent
OSM	OpenStreetMap	OpenStreetMap contributors (n.d.)	MY: continuously updated	Wide variety: see Table 5	Collected by community (VGI)	

MY = Multiple years; SY = single year

Table 10. *Identified global street datasets and their characteristics.*

Data product abbreviation	**Product name**	**Author(s) / institution**	**Temporal resolution** Year(s) of data acquisition	**Thematic content** Street classes	**Source data**
GRIP	Global Roads Inventory Project - 2018	Meijer et al. (2018)	SY: Between 2000 - 2009	Highways, primary, secondary, tertiary, local roads	Different sources, including Google Mapmaker, Intergovernmental Authority on Development, and the UN World Food Programme Vulnerability Analysis and Mapping
OSM road	OSM road	OpenStreetMap contributors (n.d.)	MY: 2004 - now	motorway, trunk, primary, secondary, tertiary, unclassified, residential, pedestrian, path, cycleway, footway	Collected by community (VGI)
NAIROBI roads	Nairobi major roads	Columbia University Earth Institute (2010)	SY: 2010	no classes	Topographic maps

MY = Multiple years; SY = single year

3.1.2. Assessment of initial fitness for use and selection

Suitability for delimiting the urban extent

The six land cover and six built-up products contain a built-up or urban class, and are thus potentially suitable for delimiting the urban extent. Table 11 shows the suitability of these products, based upon their spatial resolution, temporal resolution, and thematic content. Products with a score of one have are deemed most suitable.

Table 11. *Suitability score of land-cover and built-up products for delimiting urban extent, based on spatial resolution, temporal resolution, and thematic content.*

Data product	**Spatial resolution** Pixel size in meters (m)	**Temporal resolution** Year(s) of data acquisition	**Thematic content** Definition of built-up / urban class	**Suitability ranking** 1 = highest
Land-cover products				
AFRICOVER	n/a	--	++	Not suitable
CCILC	--	++	+	Not suitable
CCILC20	++	+	+	**4**
C-CLOPS	--	++	++	Not suitable
GlobCover2009	--	--	++	Not Suitable
FROMGLC10	++	-	++	**1**
Built-up products				
GHS	+	-	+	**6**
HBASE	++	-	++	**2**
HRSL	++	-	+	**5**
GRUMP	--	--	--	Not suitable
GUF04	++	+	+	**3**
MODIS500	--	--	++	Not Suitable

AFRICOVER, CCILC, C-CLOPS, GlobCover2009, GRUMP, and MODIS were deemed not suitable, either because of a spatial resolution above 50 m, a single year coverage before 2010, or a not usable definition of the built-up class. CCILC20, FROMGLC10, GHS, HBASE, HRSL, and GUF04 were assessed as suitable. On paper, FROMGLC10 and HBASE had the highest suitability, because their building class definition covers both buildings and artificial surfaces. They were followed by GUF04, CCILC20, and HRSL due to their detailed spatial resolutions. Their built-up definition however covers just buildings, and they are (yet) only produced for a single year. GHS has the lowest spatial resolution. Its built-up definition only contains buildings. These six data products were thus selected to delimit the urban extent.

Suitability for delimiting street space

Table 12. *Suitability score of road datasets for delimiting street space, based on temporal resolution, and thematic content.*

Data product	**Temporal resolution** Year(s) of data acquisition	**Thematic content** Detail in street types	**Suitability ranking** 1 = highest
GRIP	--	+	Not suitable
OSM roads	++	++	**1**
NAIROBI roads	-	--	Not suitable

For delimiting street space, three products were identified (Table 12). Only two products had enough detail in their street types to be useful. The national road data product does not contain any distinction in types of streets and was therefore omitted. The OSM road data product has both a very good temporal resolution and a detailed classification. The GRIP data product has less detail in the classification and its temporal resolution (2000 – 2009) is not recent enough.

Suitability for delimiting open space

Table 13. *Suitability score of land-cover and built-up products and datasets for delimiting open space, based on spatial resolution, temporal resolution, and thematic content.*

Data product	**Spatial resolution** Pixel size in meters (m)	**Temporal resolution** Year(s) of data acquisition	**Thematic content** Definition of classes used	**Suitability ranking** 1 = highest
Land-cover products				
AFRICOVER	n/a	--	+	Not suitable
CCILC	--	++	++	Not suitable
CCILC20	++	-	++	**2**
C-CLOPS	--	++	+	Not suitable
GlobCover2009	--	--	+	Not Suitable
FROMGLC10	++	-	+	**5**
Built-up products				
GHS	+	+	++	**4**
HBASE	++	-	+	**6**
HRSL	++	-	++	**3**
GRUMP	--	--	--	Not suitable
GUF04	++	+	++	**1**
MODIS500	--	--	+	Not Suitable

The land-cover and built-up products could not only potentially be used to delimit the built-up, but also the open spaces, by 'inverting' them. As Table 13 shows, the same land-cover and built-up products were suitable for delimiting open space as for delimiting built-up (Table 11). However, their ranking was reversed. GUF04, CCILC20, HRSL, and GHS had the highest scores while FROMGLC10 and HBASE had the lowest. This was because FROMGLC10 and HBASE have a built-up class which contained more than only buildings. This meant that the identification of open spaces that consist of impervious surfaces might be difficult.

***Table 14**. Suitability score of land-use products and datasets for delimiting public open space, based on spatial resolution, temporal resolution, and thematic content.*

Data product	**Spatial resolution** Pixel size in meters (m)	**Temporal resolution** Year(s) of data acquisition	**Thematic content** Definition of classes used	**Overall suitability** 1 = highest
		Land-use products		
OSM	**n/a**	++	++	**1**
NAIROBI LU	n/a	-	+	2

Next to the land-cover and built-up products, also the land use products were assessed on their suitability for delimiting open space, in particular public open space (Table 14). OSM seemed highly suitable as it has many detail in its land use classes and because it is continuously updated. NAIROBI LU has less thematic detail and only covers a single year. Given the high temporal resolution and the detailed thematic content, OSM was selected.

3.2. MEASURING AND COMPARING ELEMENTS OF INDICATOR 11.7.1

3.2.1. Built-up pixels

Built-up agreement between all products

The BU agreement between the products was assessed by analysing for each pixel how many products classified it as BU or NBU, ranging from zero to maximum six. The highest agreement about the BU classification, where five to six products agree the pixels are BU, are found in the centre of the city and in the centres of the surrounding urban clusters (Figure 7a). This covers 13% of all the pixels that are classified as BU. The most disagreement was found near the edges of the urban clusters and in areas with scattered buildings (Figure 7b). Also, clusters of disagreement pixels can be found that seem to form road-like structures (Figure 7d). Here two to four products classified a pixel as BU and two to four as Non-BU, which made up 37% of the total BU pixels. The remaining 50% of the built-up pixels was only classified as BU by a single product. The majority of the BU pixels that were classified once, were located outside the urban areas. However, there were some clusters of single-classified pixels at the edge of the urban areas and within the centre (Figure 7c). This also means that most of the products agreed that those pixels were NBU. Of the total pixels in the area, 79% was agreed to be NBU by all products.

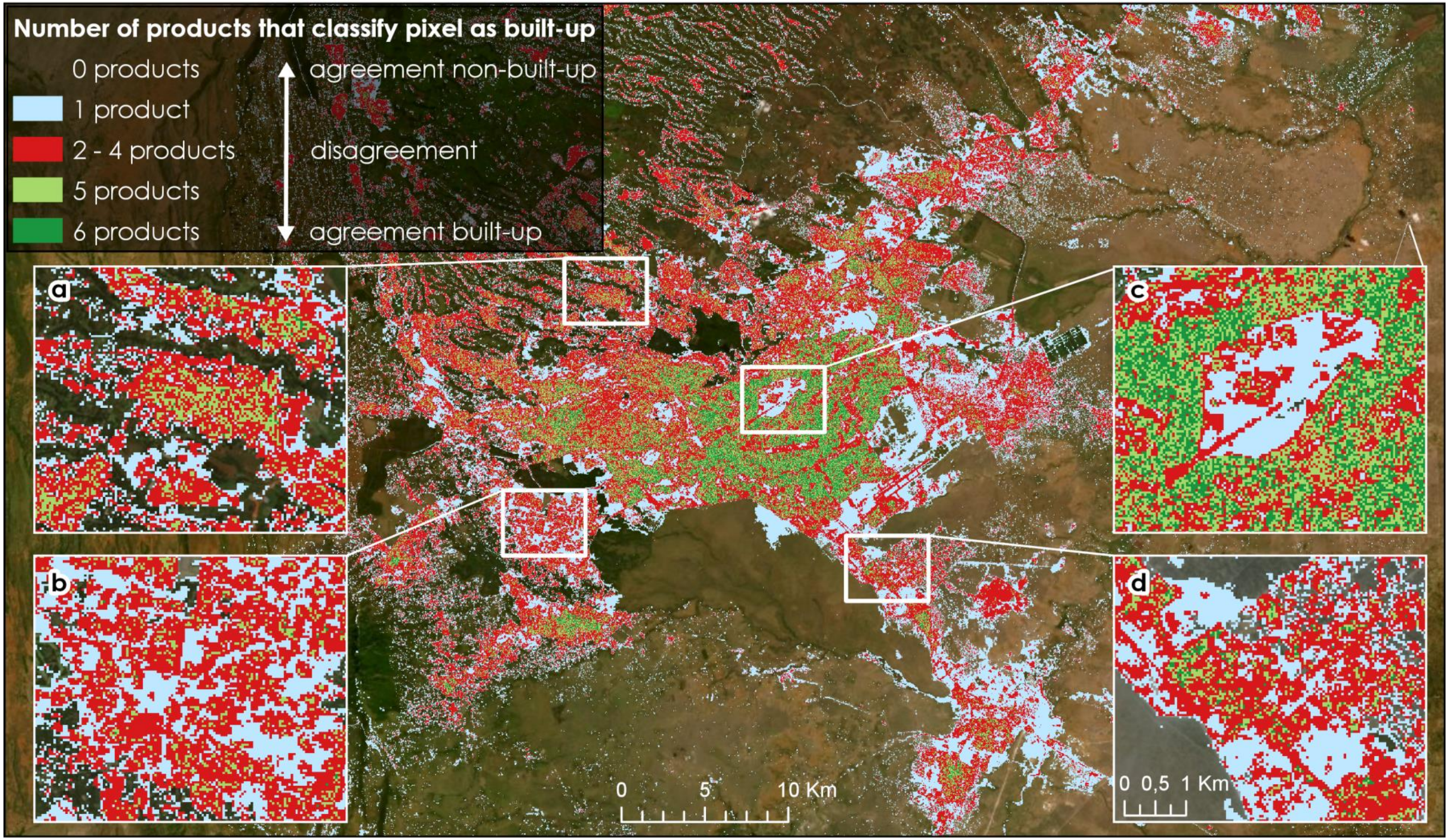

Figure 7. *Built-up classification (dis)agreement per pixel between all products. Examples show: (a) small BU agreement clusters in the north; (b) an area of high disagreement; (c) an area of high Non-BU agreement; and (d) small disagreement corridors that seem to correspond to roads.*

3.2.2. Urban extents

Urban extents identified by products

The selected built-up and land-cover products were used to delimit the urban extent. In Appendix 1 the individual maps of the urban extent can be found (Appendix B. Figure 1a – f).

GHS identified an extent with an area of 362 km^2. It found one 'gap', a NBU area larger than two hectares, in the North-East (Figure 8e). It however did not identify Moi Airbase (Figure 8f) as a gap, while some other products did.

HBASE identified a large extent of 740 km^2. It covers most of the surrounding towns of Nairobi, also including Juja in the North-East (Figure 8b), Kitengela in the South-East (Figure 8c), and Ngong and Kiserian in the South-West (Figure 8d). HBASE did not identify the gap in North-East nor Moi Airbase.

The urban extent identified by GUF04 covers an area of 364 km^2. It is more similar to the GHS extent, but it excludes the towns in the South-East (Figure 8c) and includes the area below Ngong forest in the South-West (Figure 8d). The extent contains the gap to the North-East, but in addition GUF04 also identified the Moi Air Base as a NBU area larger than two hectares (Figure 8f).

The extent of CCILC20 covers 351 km^2. It is almost equal to the one identified by GUF04. The main difference is the small isolated urban area in the North-West (Figure 8g). This is not identified as part of the urban extent by CCILC20.

FROMGLC10 identified a small extent of 128 km^2. It only includes the city core and a small part of the area in the South-East (Figure 8c). There were no gaps identified.

The last product, HRSL, identified an urban extent of 365 km^2. It is similar to the GHS extent but it does not cover the area in the South-East (Figure 8c) and it reaches much further in the North-East (Figure 8b). HRSL identified gaps, including the airbase (Figure 8f) and the area in the North-East (Figure 8e).

Urban extents of products versus reference

In terms of size, the urban extents identified by GHS and GUF04 are most comparable to the reference extent (Figure 8 and Table 15). However, looking at the overlap of each of the products with the reference extent, the GHS extent shows more overlap than the one identified by GUF04. The urban extent of HRSL has more overlap with the reference than the GUF04 extent, but in terms of size it is smaller. CCILC20 shows the same percentage of overlap as GUF04, but the extent itself is smaller. The extents from FROMGLC10 and HBASE deviate the most from the reference when looking at the size. The extent identified by FROMGLC10 is a third of the reference. On the contrary, HBASE delimited an extent which is almost twice the size of the reference extent. The reference extent is however almost completely overlapped by the HBASE extent.

Table 15*. The size of the urban extents delimited by the products and their overlap with the reference extent. Both expressed in area (km^2) and percentage of the reference area.*

	Size of product extent		Overlap of product with reference	
▼ Products	Km^2	% of ref (374 km^2)	Km^2	% of ref (374 km^2)
GHS	362	**97%**	276	**74%**
HBASE	740	**198%**	343	**92%**
GUF04	364	**97%**	232	**62%**
CCILC20	351	**94%**	231	**62%**
FROMGLC10	128	**34%**	128	**34%**
HRSL	356	**95%**	243	**65%**

Almost all products defined an extent which covers more area in the north-west (Figure 8a). CCILC20, GUF04, HBASE, and HRSL also included more area in the north-east than the reference (Figure 8b). In the south-east most of the products, except for HBASE, included less area than the reference extent (Figure 8c). CCILC20, GUF04, and HBASE also included an area in the south-west that is not part of the reference (Figure 8d). In the reference extent only one gap was identified (Figure 8e). Almost all products, except for HBASE and FROMGLC10, also identified this gap. However, one more gap was identified by most products that was not by the reference, which was the Moi Air Base (Figure 8f).

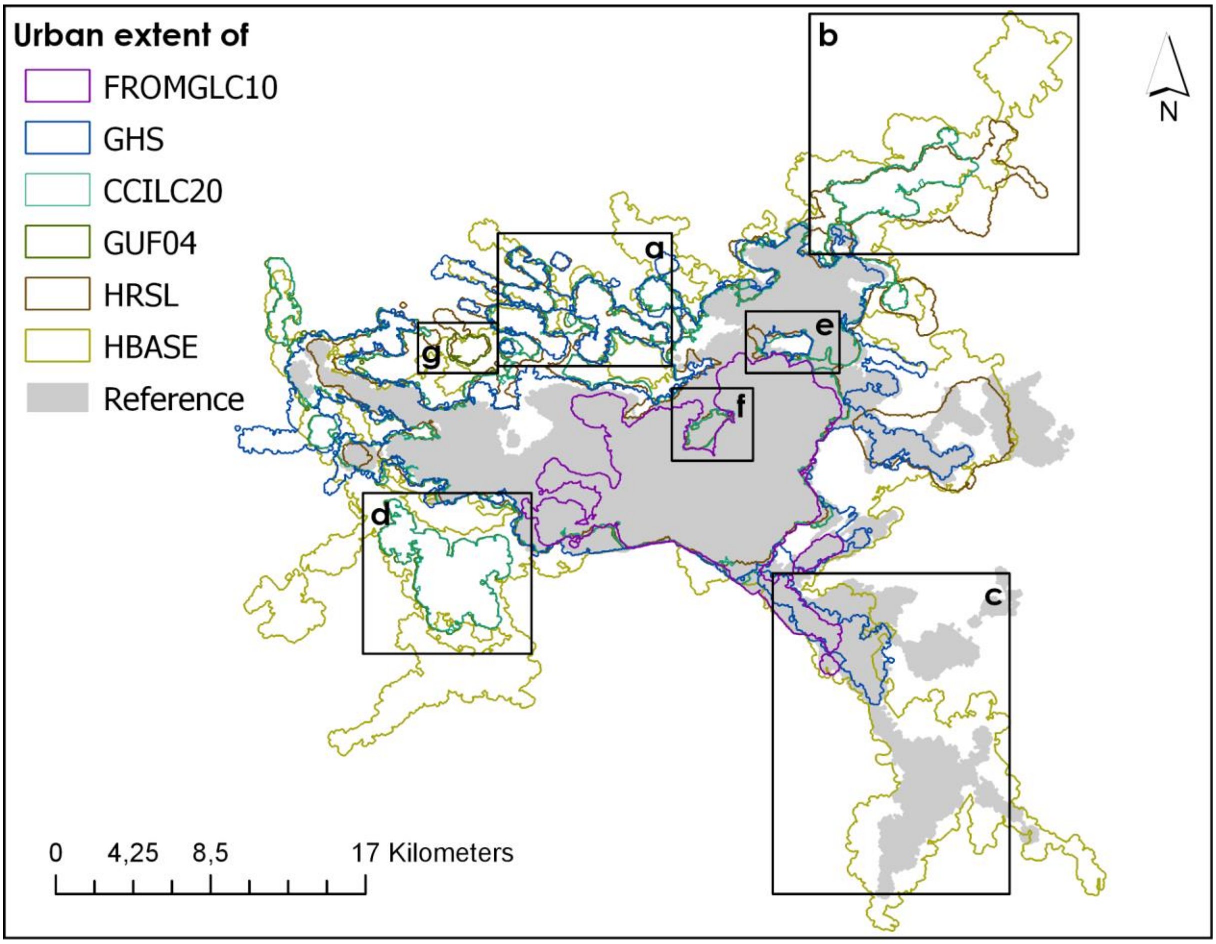

Figure 8*. Urban extents of the products and the reference.*

3.2.3. Street space

Street widths

For delimiting the street space using the OSM road dataset, the widths per street type were measured. The measurements per type were analysed and presented by boxplots shown in Figure 9. Outliers where detected using the Tukey fences method (Tukey, 1977).

The width decreases with the importance of the road type. This decrease is however not so evident when going from the motorway to the primary and the secondary road type. Their median widths are very close. For the motorway road type one extreme outlier of 36 m was measured, while for the primary and secondary road type two less extreme outliers were measured. The overall variability of these types is high, with about ten meter difference between the lowest and the highest width measurement (outliers excluded). However, most of the measurements are within three meter of the median width. The highest variability is shown for the tertiary road type, with a maximum difference of 12 m. But again, most measurements do not differ more than three meter from the median. The residential and unclassified road types also show a relatively high variability. The unclassified road type has two outliers that are both larger than the median. The pedestrian and path types have the lowest median width and also the lowest variability.

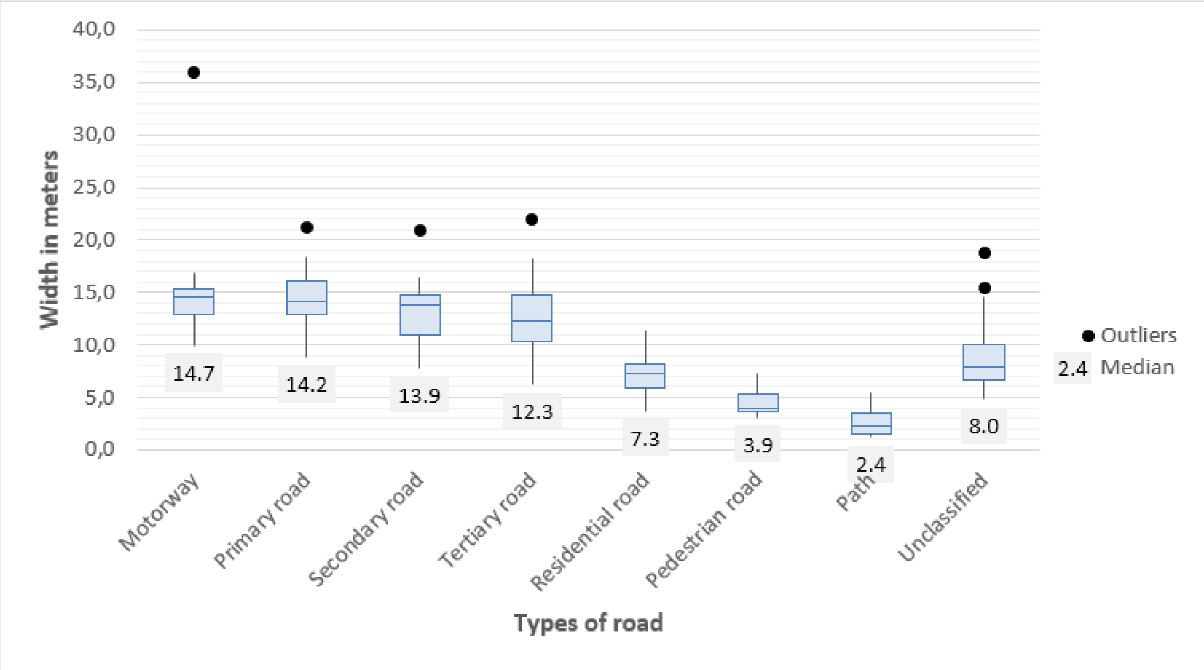

Figure 9*. Boxplots of width measurements per OSM road type, showing the median, the quartiles, whiskers, and outliers.*

Street space identified by OSM and local authoritative dataset

The street space identified by OSM, using the mean widths per road type, covers an area of 33.9 km^2 (Figure 10). This results in a LAS of 9.4%. The LAS differs per area, as can be seen in Figure 10a, b, and c. Figure 10a shows street space in the affluent suburb Spring Valley, where the roads are quite sparse but those that are present mostly secondary roads, which are relatively wide. Here the LAS is 14.3%. Figure 10b shows the street space in the slum Kibera with mainly paths, with an LAS of 4.4%. Figure 10c shows the street space in the middle-income residential neighbourhood Parklands, were residential roads are most common. For this area, the LAS is 9.5%.

The local dataset, originating from the Nairobi open space assessment by UN-Habitat, has identified 14.3 km^2 of street space. The LAS is therefore 4.0% of the GHS identified urban extent. This dataset does not cover the full extent (Figure 11). It has no road data beyond the administrative boundaries of the city. Furthermore, it also does not cover certain areas inside the administrative boundary, such as the slum Kibera (Figure 11b). The LAS for the affluent suburb is 9.3% (Figure 11a). For the residential neighbourhood, the LAS from the local dataset is 6.0% (Figure 11c).

Street space of products versus reference

The reference data has a LAS locales of 12.0%. This means that for every sampled locale of 10 hectares, on average around 1.2 hectare is covered by street space. OSM has a lower LAS locales of 9.2%, corresponding to an average street space of 0.9 hectares per locale. The local dataset has an even lower LAS locales of 5.0%. Here, street space covers on average 0.5 hectare per locale.

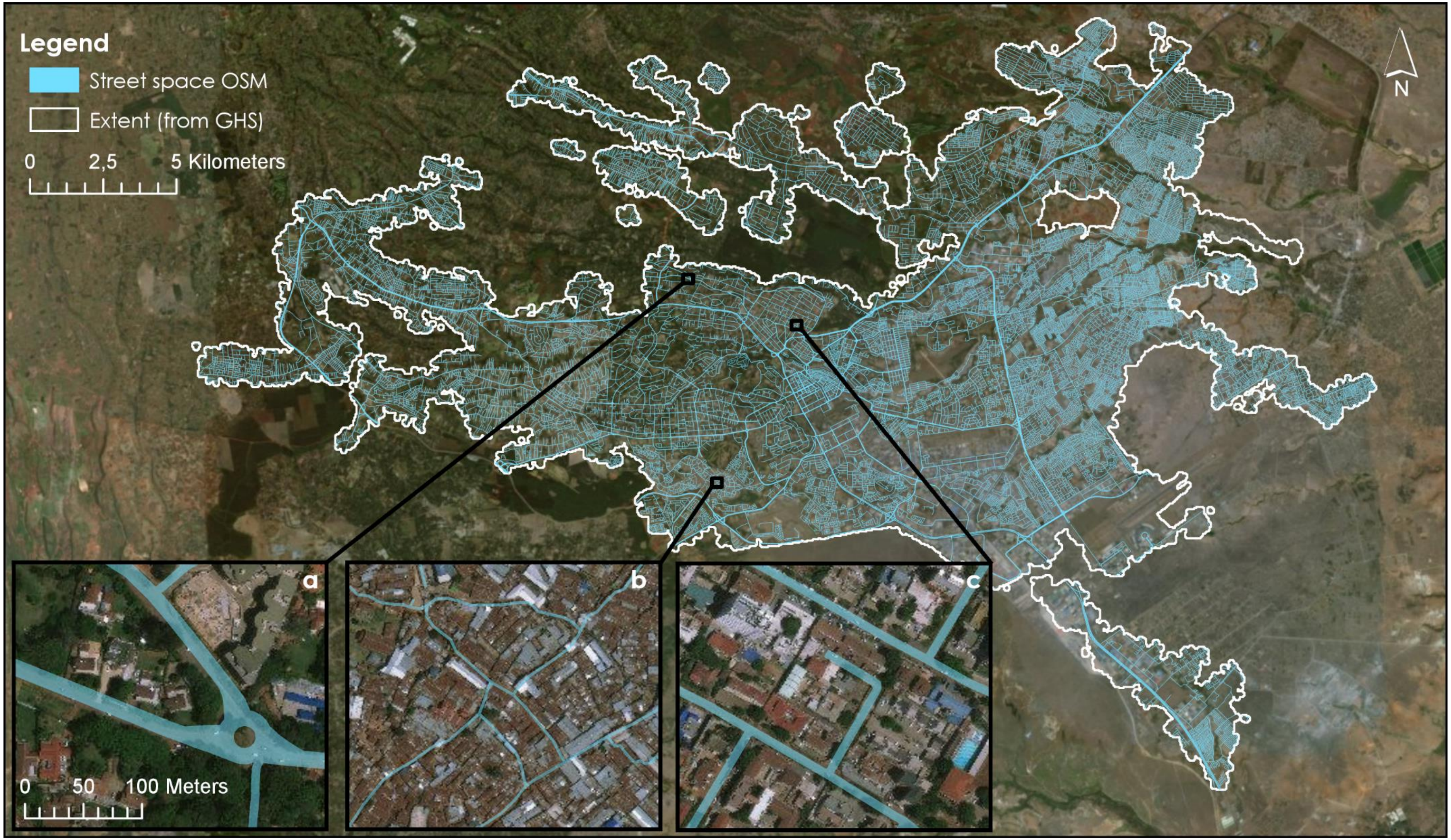

Figure 10. *Street space identified by OSM. Examples shown: (a) affluent suburb Spring Valley; (b) slum area Kibera; and (c) residential neighbourhood Parklands.*

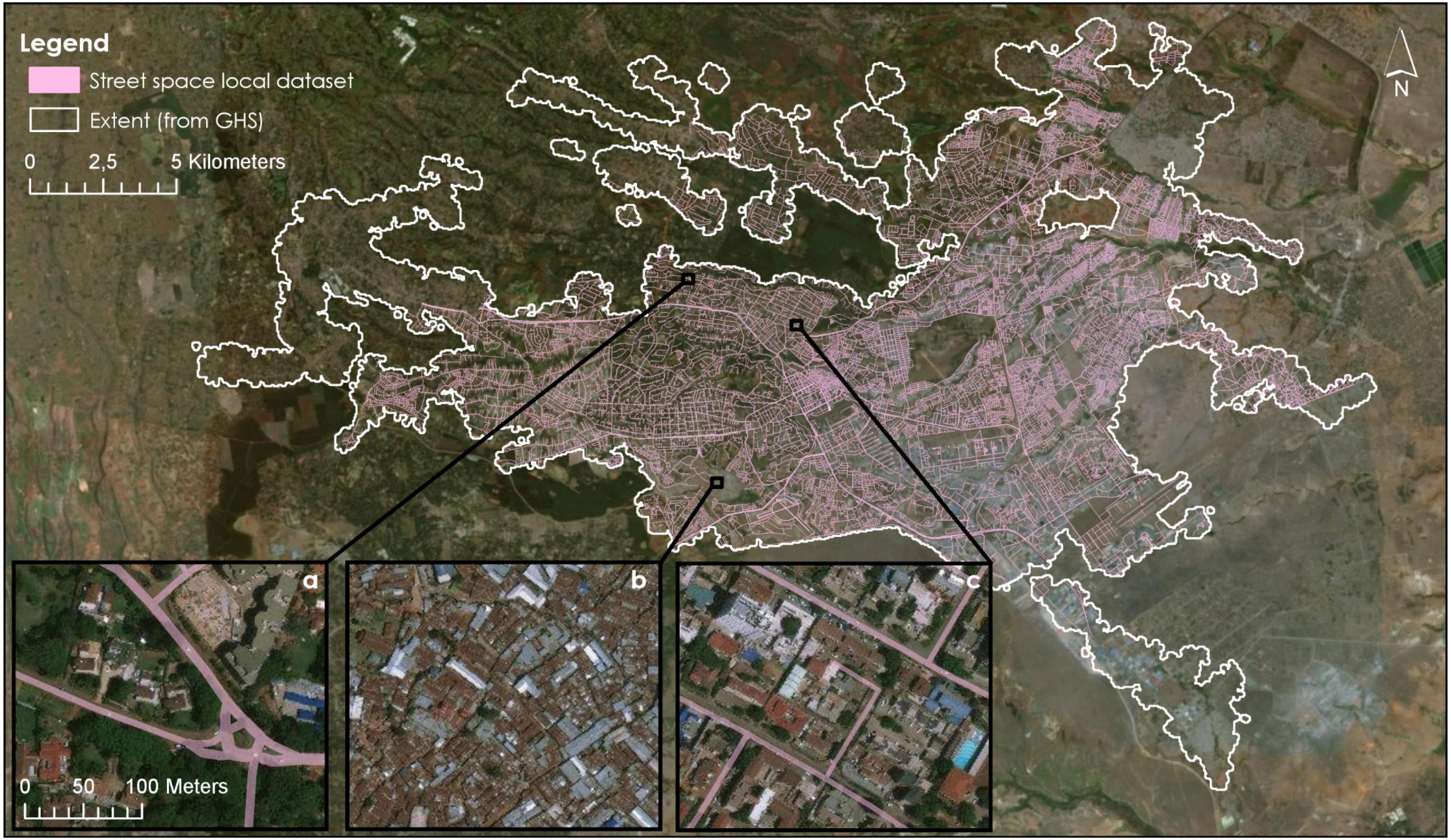

Figure 11. *Street space identified by local dataset. Examples shown: (a) affluent suburb Spring Valley; (b) slum area Kibera; and (c) residential neighbourhood Parklands.*

3.2.4. Public open spaces

Open space agreement between all products

The open space agreement between all products was determined by counting the number of products that classified a specific area as open space (Figure 12). Since the open spaces were identified based on the inverted BU classifications, the resulting map is the opposite image of the BU agreement map (Figure 7). The areas, inside the GHS urban extent, where the most BU disagreement could be found are the same areas where the most open space agreement occurred. Figure 12 shows that most products agree about the open spaces at the edges of the urban extent. Also some large areas with high open space agreement can be found in the centre, such as the Nairobi Arboretum and the Central and Uhuru Park (Figure 12 cut out).

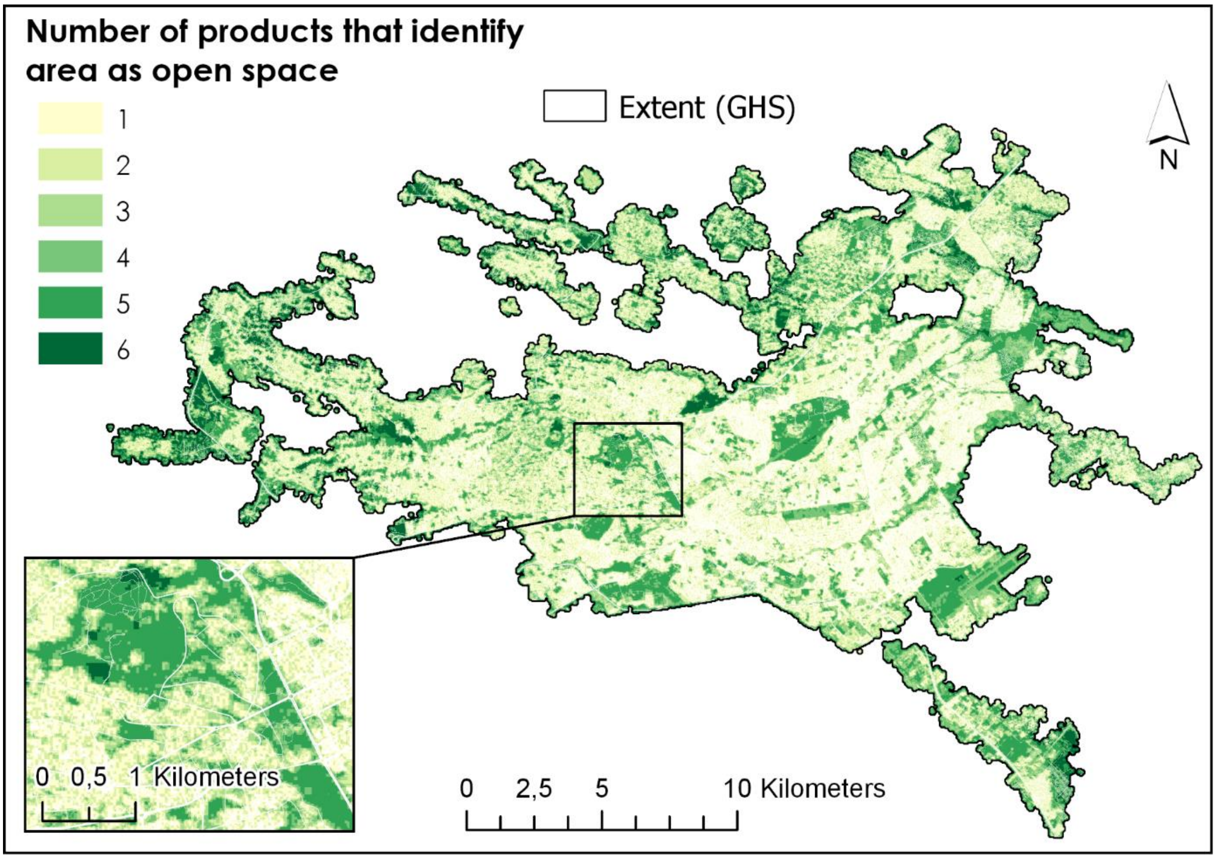

***Figure 12**. Open space agreement between all products. Cut out shows the Nairobi Arboretum, and the Central and Uhuru Park in the south-east corner.*

Public open spaces identified by products and OSM

Figures 13 - 18 show the open spaces identified by the products and classified by their publicness using OSM. Table 16 shows the area of the different types of open spaces in km2 per product.

Of the total open space, only a small part is classified as public open space. The area of public open space does not vary much between the products, except for HBASE where the area of public open space is very small (Figure 14). The area of non-public open space is higher than the area of public open space for almost all the products, but still only a minor share of the total open spaces. Again HBASE identified almost no area of non-public open space. A large majority of the total open spaces is classified as possible public for all the products. This is particularly evident in the case of FROMGLC10 and HRSL. The difference between these products is the size of the individual open space parcels. While

FROMGLC10 shows large patches of possible public open space that increase with the distance from the centre (Figure 17), HRSL shows many small patches over the whole city (Figure 18).

In terms of total open space, HBASE identified the smallest area, and FROMGLC10 and HRSL the largest, which are roughly six times the size of HBASE. GHS (Figure 13), GUF04 (Figure 15), and CCILC20 (Figure 16) show total areas of open space which are more similar to each other.

The LAPOS, which is the share of land allocated to the public open spaces, was calculated for each product. It is expressed as a range, whereby the minimum value is the LAPOS for the public open space class, and the maximum value is the LAPOS for the public and possible public open space class combined. For GHS the LAPOS is calculated to be in the range from 1.2% to 30.4%. For HBASE this range is lower, from 0.4% to max 11.3%. Again, GUF04 and CCILC20 show similar but slightly higher ranges to GHS, from 1.4% to 35.7% and from 1.3% to 34.8% respectively. The minimum LAPOS for FROMGLC10 and HRSL does not differ much from the other products with 1.6% and 1.5% respectively. Their maximums are however higher, with 66.0% and 48.7%.

***Table 16**. Area in km² of types of open spaces identified by the different products and OSM.*

▼ Products	Non-public open space (km²)	Possible public open space (km²)	Public open space (km²)	Total open space (km²)
GHS	14	106	4	124
HBASE	1	39	2	42
GUF04	21	124	5	150
CCILC20	21	121	5	147
FROMGLC10	26	233	6	265
HRSL	26	171	6	203

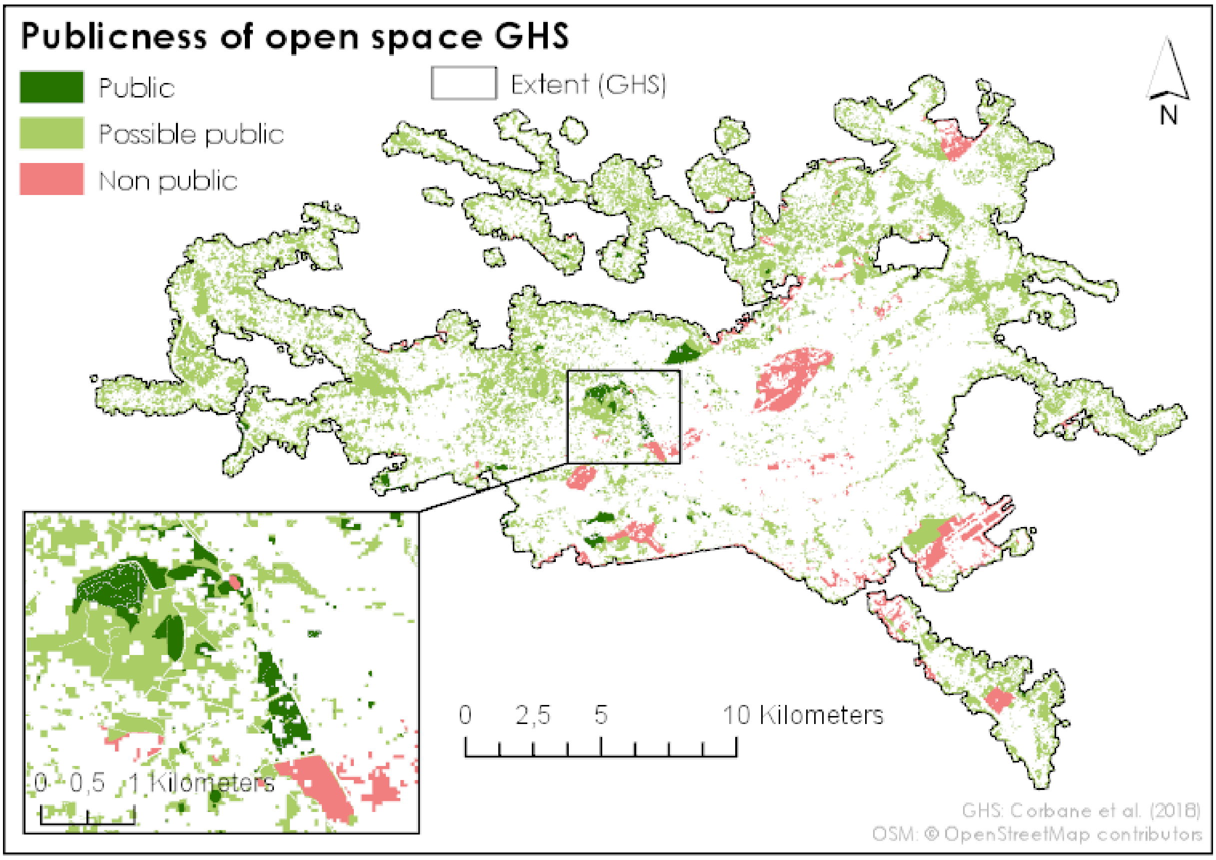

***Figure 13**. Open spaces identified from GHS and classified by publicness using OSM.*

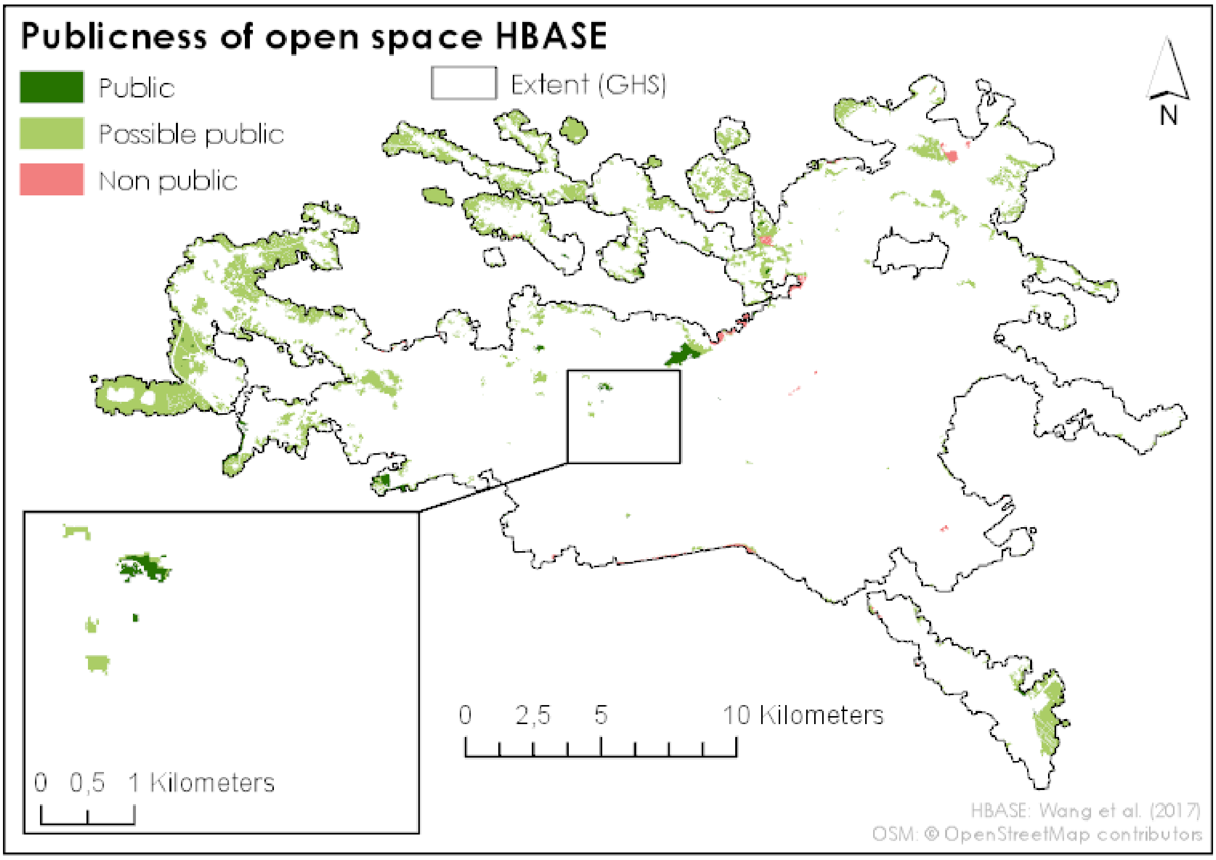

Figure 14*. Open spaces identified from HBASE and classified by publicness using OSM.*

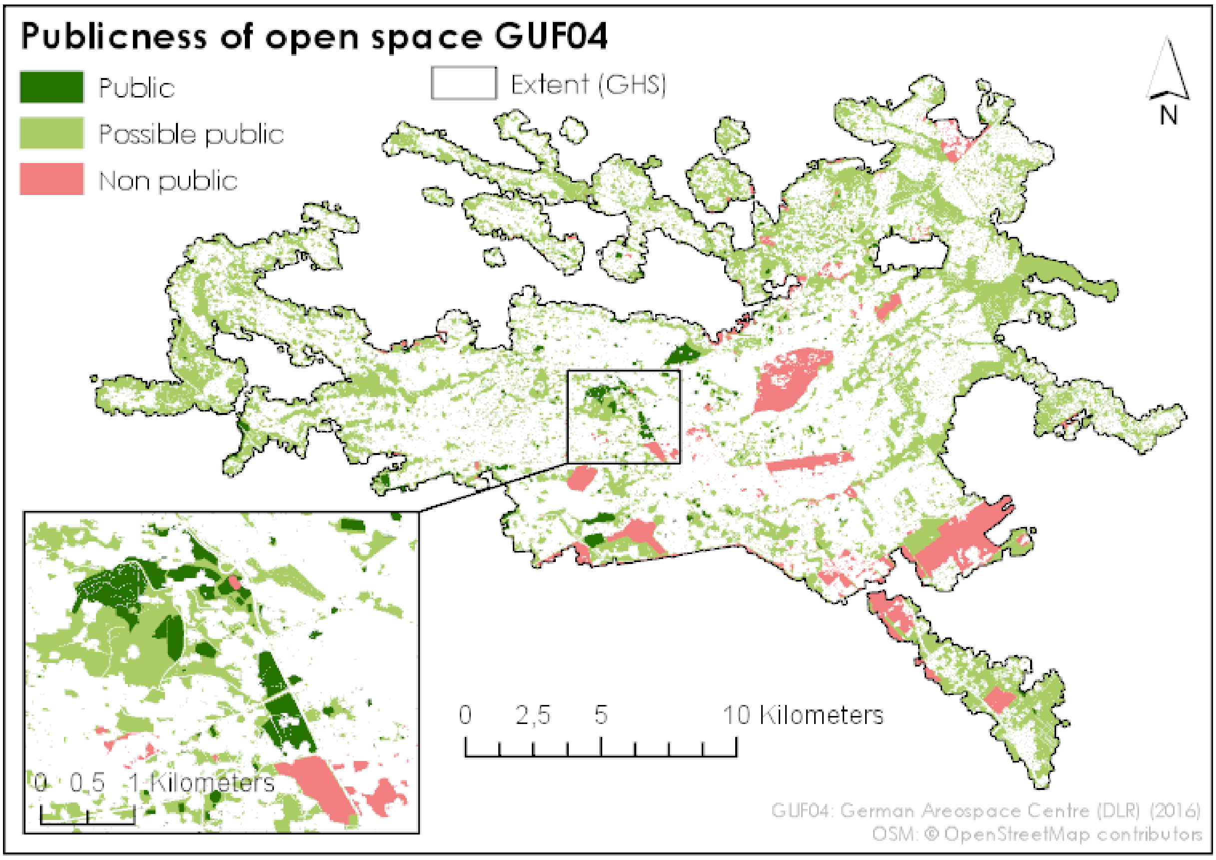

Figure 15*. Open spaces identified from GUF04 and classified by publicness using OSM.*

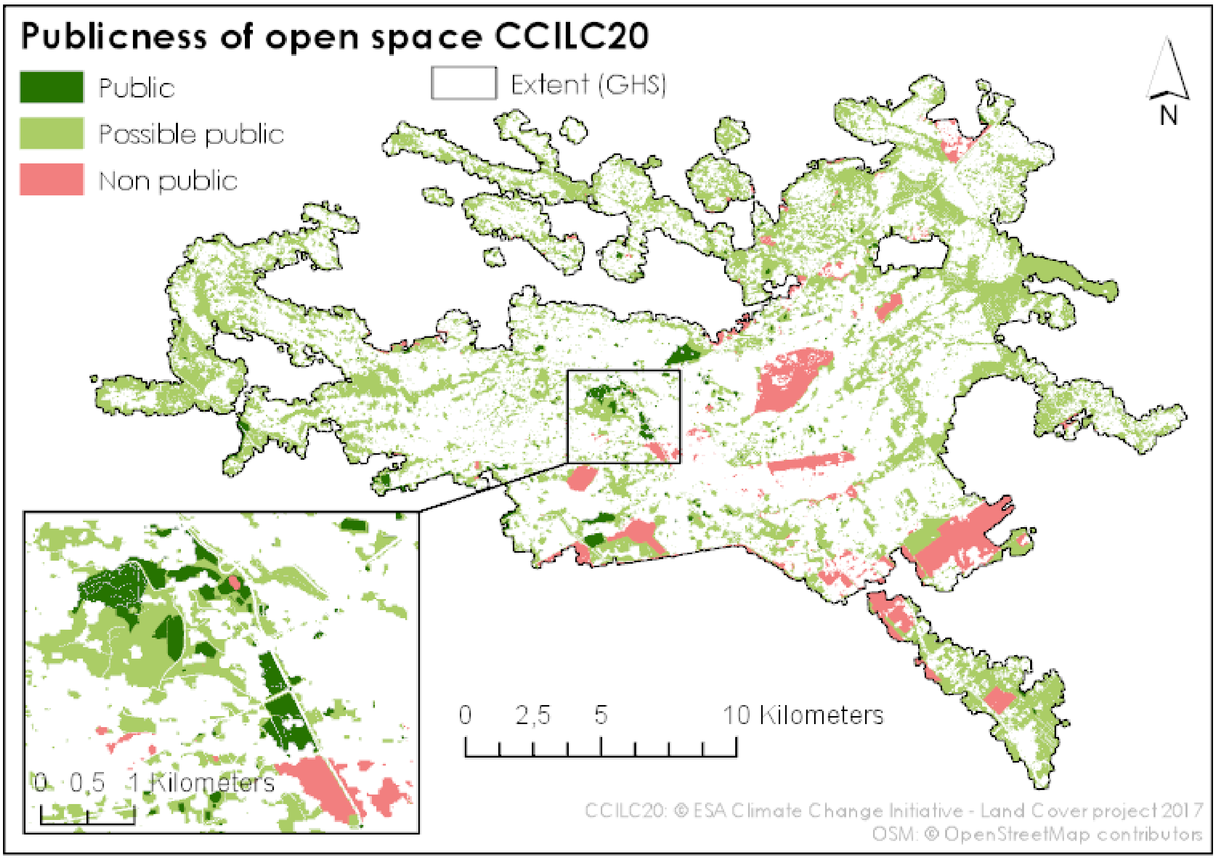

Figure 16*. Open spaces identified from CCILC20 and classified by publicness using OSM.*

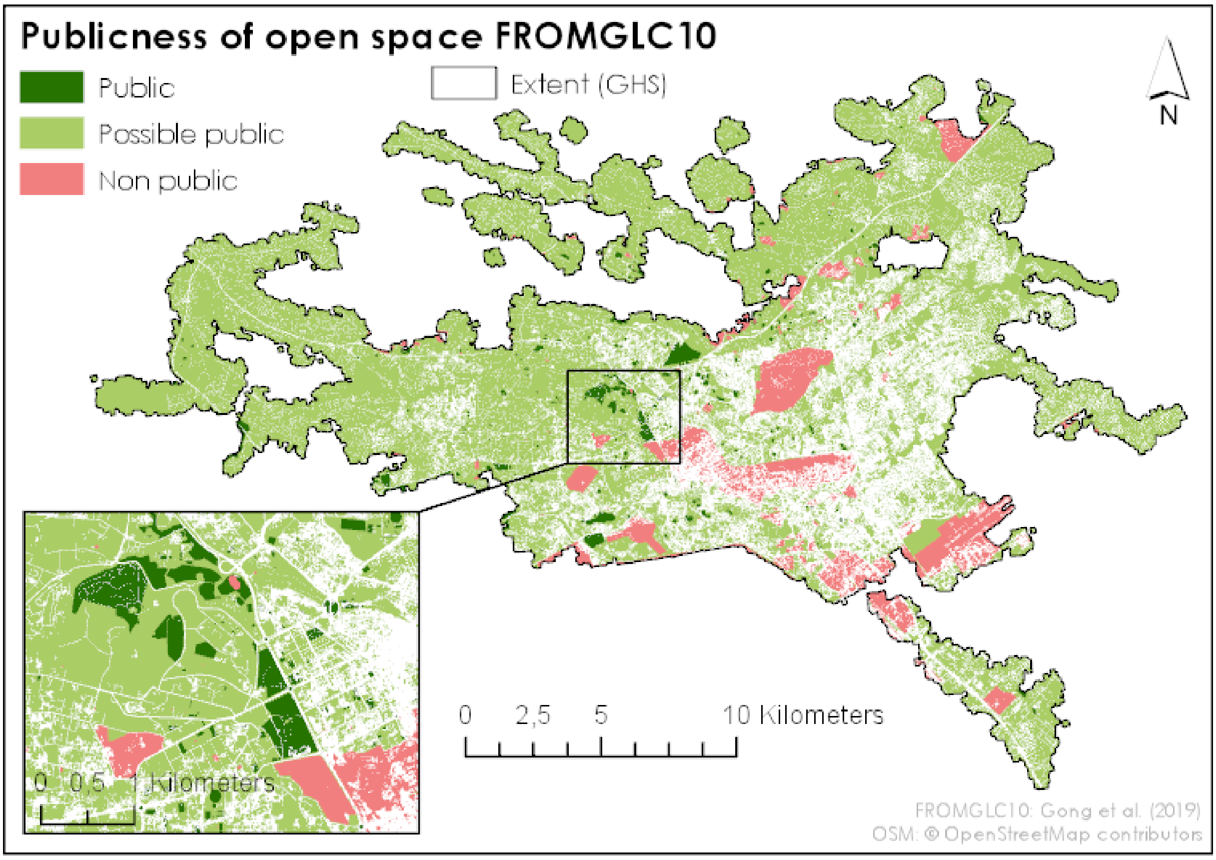

Figure 17*. Open spaces identified from FROMGLC10 and classified by publicness using OSM.*

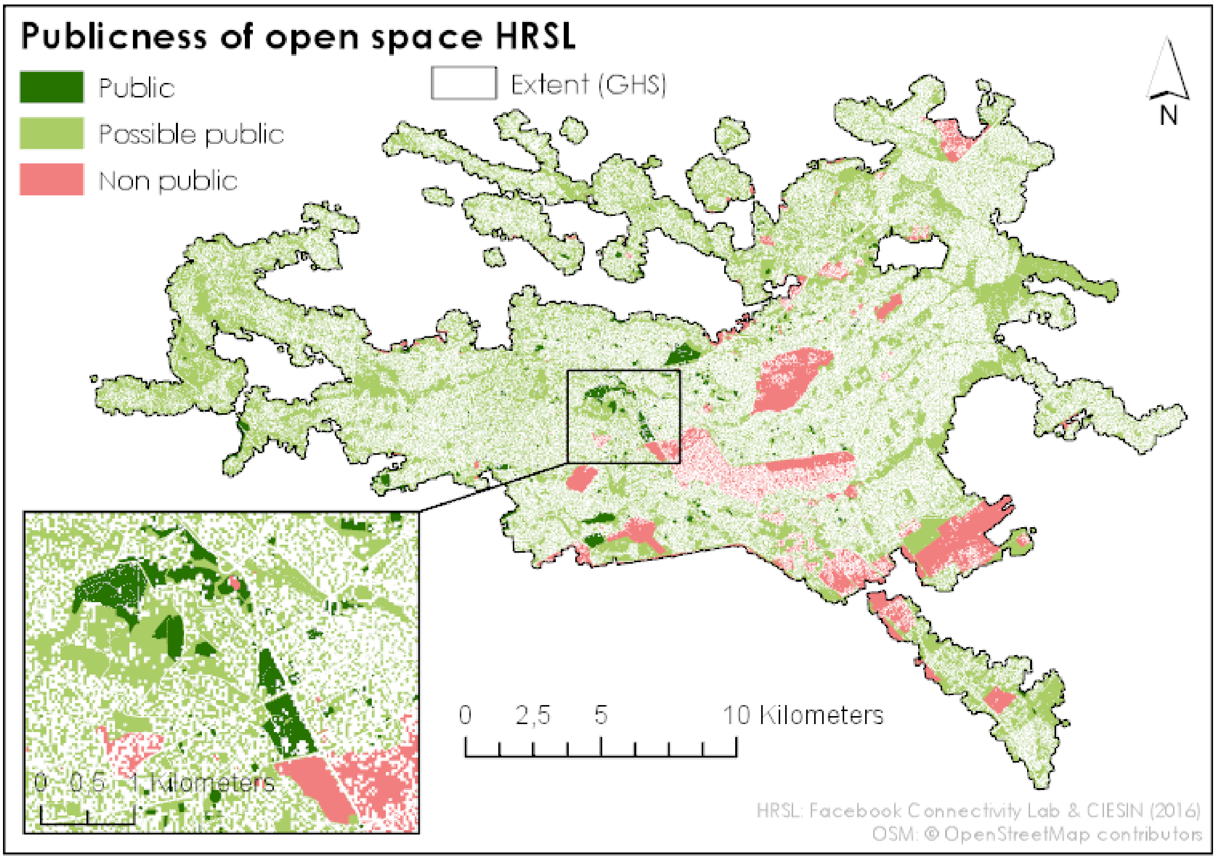

Figure 18*. Open spaces identified from HRSL and classified by publicness using OSM.*

Public open spaces of products versus reference

The (public) open spaces identified by the different products were overlaid on the public open spaces of the reference dataset. First the identification of open spaces (regardless their publicness) and the effect of surface texture and size was analysed. Figure 19 shows the percentage of open spaces in the reference that are identified by the different products in total and per surface texture. HBASE identified almost none of the reference open spaces. Out of all the products, FROMGLC10 and HRSL identified the most reference public open spaces. However, they identified no more than 59%. In terms of surface texture differences are notable. Water bodies are most identified (average of all products is 60%), followed by open spaces with soft surface texture (35%). Open spaces with hard surface textures were less identified by all products (8%). HBASE identified none of the hard textured open spaces.

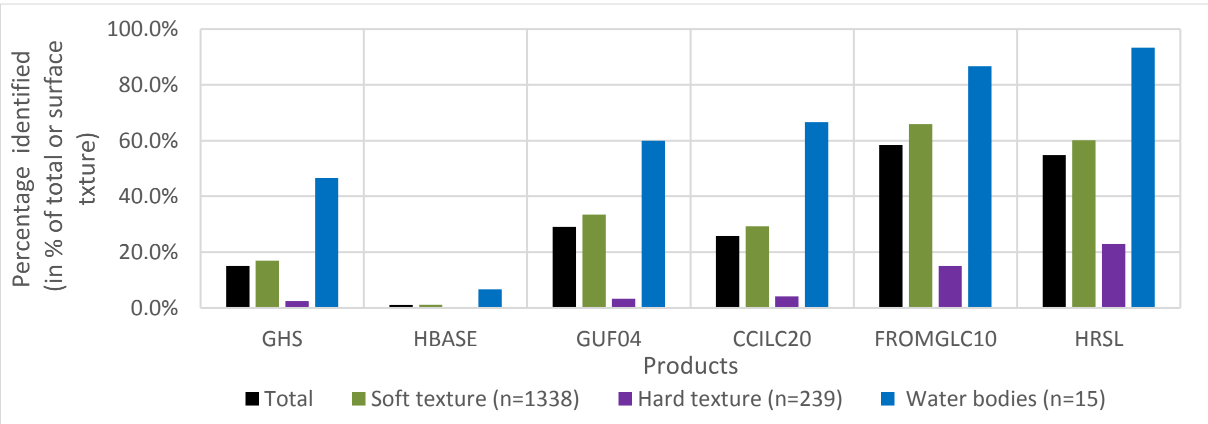

Figure 19*. Percentage of reference open spaces identified in total and per surface texture.*

The next variable that was analysed was the size of the reference open spaces. A relationship between the size and the likelihood of this reference space being identified by the products was found, at least for the soft-textured open spaces. When the size of the open space increases, it is more likely to be identified. Most products showed a clear increase in percentage of references spaces identified when the spaces were larger than 2972 m^2. For smaller spaces most products identified no more than 20%. For HBASE this relationship was not present, because this product almost identified none of the reference open spaces. For the hard-textured reference open spaces, the effect of size was less visible. For waterbodies, the relationship between size and percentage of spaces was not analysed, because there were not enough waterbodies per size class. In the appendix two figures can be found that show the percentage of reference open spaces identified per size class and product, for both the soft-textured (Appendix C. Figure 1) and hard-textured open spaces (Appendix C. Figure 2).

Not only the identification of the reference open space in number, but also in percentage of the reference area was assessed. All products identified more when comparing the area against the number of reference open spaces (Table 17). All products, except for HBASE, identified between 49% and 81% of the area. Similar to the number of reference open spaces, HBASE identified the least in terms of area percentage, and FROMGLC10 and HRSL the most. GUF04 identified 68.5% of the area, CCILC20 slightly lower and GHS just below 50%.

The publicness classification was assessed as well. This was done by assessing the percentage of the reference number and area that was correctly identified (classified as either possible public, or public) and the percentage that was incorrectly identified (classified as non-public). In the appendix, maps for each product can be found that show the reference public open spaces identified and classified by the different products (Appendix D. Figure 1 - 6). GUF04 and CCILC20 correctly identified around a quarter of the reference open spaces, which covers around 65% of the reference area (Table 17). FROMGLC10 and HRSL correctly identified more than half the number of reference open spaces, and for FROMGLC10 this covers around 80% of the total reference area. GHS correctly identified half the reference area, and HBASE correctly identified only a small part. The percentage of both the reference number and area that was wrongly classified is close to zero for all products.

***Table 17**. Percentage of number and area of the reference public open spaces identified, correctly identified, and wrongly identified by the different products.*

	Total identified		Correctly identified		Wrongly identified	
Products	**% number**	**% area**	**% number**	**% area**	**% of number**	**% area**
GHS	**15.1%**	**49.4%**	14.6%	48,1%	0.4%	1,4%
HBASE	**1.1%**	**5.4%**	1.1%	4,9%	0.0%	0,5%
GUF04	**29.2%**	**68.5%**	28.5%	67,8%	0.8%	0,7%
CCILC20	**25.9%**	**62.7%**	25.1%	62,0%	0.8%	0,7%
FROMGLC10	**58.5%**	**80.9%**	57.5%	80,1%	0.9%	0,8%
HRSL	**54.8%**	**76.6%**	53.4%	75,8%	1.4%	0,7%

The last element that was analysed was whether products identified more possible public and public open spaces than are present in the reference dataset. All products delimited a much larger area of (possible) public open spaces than the reference (Table 18). HRSL and FROMGLC10 delimited the most. The area of open space delimited by these products is respectively more than six and eight times the size of the reference area.

Looking specifically at the public open spaces that have been delimited with the help of OSM, more public open spaces are delimited than are present in the reference. Of the area of all the public open spaces that were identified around 50% was not present in the reference open space.

Table 18. *Area of the identified (possible) public open spaces that are not present in the reference.*

Products	Area not in reference (in km^2)	% of reference area (18.7 km^2)
GHS	66.6	355%
HBASE	13.0	70%
GUF04	77.1	411%
CCILC20	75.4	402%
FROMGLC10	157.9	843%
HRSL	116.8	624%

3.2.5. Indicator 11.7.1

The core indicator, the share of the built-up area of the city that is open space in public use, was calculated using the GHS-derived extent, the LAS from OSM, and the LAPOS from the different products. Since the LAPOS was calculated as a range, the core indicator is also expressed in a minimum and a maximum. The results are shown in Table 19.

The minimum share of the built-up area of the city that is open space in public use is more or less equal for every product. This percentage is mainly caused by the OSM identified LAS (9.4%) and hardly affected by the LAPOS of the different products (0.4% – 1.6%). More variation is shown in the maximum share. Since HBASE had the lowest LAPOS, the core indicator maximum is also the lowest. FROMGLC10 has the highest maximum. GUF04 and CCILC20 are in the middle, with a maximum around 45%. For the maximum share the LAPOS has a stronger effect than the LAS.

Table 19. *Minimum and maximum share of the built-up area of the city that is open space in public use, per product.*

Products	Minimum	Maximum
GHS	10.5%	39.8%
HBASE	9.8%	20.7%
GUF04	10.8%	45.0%
CCILC20	10.7%	44.2%
FROMGLC10	11.0%	75.3%
HRSL	10.9%	58.0%

4. DISCUSSION

4.1. INDICATOR 11.7.1 IN NAIROBI

UN-habitat recommends that the share of built-up area of the city that is open space in public use lies between 40 - 50%, with 30 - 35% for streets and 5 - 20% for open public space (UN-Habitat, 2019). The results show that this total share for Nairobi lies between 11% and 75%, if GHS is used to delimit the extent, OSM to delimit street space and FROMGLC10 to delimit public open space. However, if most other products are used to delimit open spaces, the maximum total share does not exceed 45%. This means that only if all open spaces identified are indeed public, the recommended total share can be reached. The street space share (9.4%) lies far below the required percentage. If the public open spaces identified with the assistance of OSM are indeed the only public open spaces, the share of public open space is maximum 1.6%, leading to a total share of 11%. According to the reference data of UN-Habitat within the administrative extent, the share is 19.7%, with 11.5% for street space and 8.2% for public open spaces (UN-Habitat, 2013, 2016). This shows there will be differences when the reference or the global products are used, especially in case of public open spaces. The relative low total share of both the global and the reference data in comparison to the recommended share also shows that the set goals are still far from the actual situation. Furthermore, the differences in street space in the different neighbourhoods shown in Figure 10 and Figure 11 also indicate that even if the share will be reached, it will not be equally divided across the city.

4.2. USING GLOBAL PRODUCTS TO MEASURE INDICATOR 11.7.1

To the author's knowledge, no research has yet analysed the capability of existing global products for delimiting the urban extent, public open spaces, and street space. This thesis showed that EO-derived global open products can be used to delimit the urban extent. However, the choice on which product to use leads to differences. The GHS extent was most similar to the reference, with a size similarity of 97% and an overlap of 74% (Table 15). The extent of FROMGLC10 was much smaller (34%) and the one of HBASE much larger (198%) than the reference. For delimiting public open spaces, the products, with the assistance of OSM, did not manage to identify more than 59% of the public open spaces of the reference. However, open spaces larger than 2972 m^2 were identified better than smaller ones. Since the indicator requires the total area of public open spaces, larger spaces will have a bigger effect on the indicator. Of all the products, GUF04 was best at identifying the open spaces, with relatively many spaces and area identified and relatively little open space area identified that was not in the reference. HBASE under-identified the most, and HRSL and FROMGLC10 identified respectively 624% and 843% more open space than was present in the reference. For delimiting the street space, OSM outperformed the local dataset by 4.2% but its share was still 2.8% lower than the reference.

4.3. EFFECT OF PRODUCT CHARACTERISTICS

4.3.1. Spatial resolution

The results showed that the spatial resolution of the products affects the delimiting of the built-up and the open spaces. For delimiting built-up, spatial resolution plays a role at the edge of the urban boundaries. This was demonstrated by the difference in extent between CCILC20 and GUF04 shown in Figure 8, as CCILC20 is an up-scaled version of GUF04. Also, identification of areas larger than two hectares in the urban extent was affected by the spatial resolution. HBASE, GHS, and the reference extent have a lower resolution compared to the other products. They did not identify gaps such as Moi Airbase, while products with a higher resolution did. The only exception is HRSL, which has a spatial resolution similar to HBASE and the reference. However, HRSL is based on source data with a very high resolution which also influences the precision of the HRSL product itself.

The relationship between identification and size of open space showed that the spatial resolution is important for delimiting open spaces. In general, products with a higher spatial resolution were more able to identify public open spaces than lower resolution products (Figure 19). Despite the advantage of higher resolution products, they did not manage to identify more than 20% of the small reference open spaces. A possible explanation could be that although some of these spaces were larger than the spatial resolution of some products, due to small widths they could not be detected.

Tran et al. (2011) state that a spatial resolution of 30 – 40 m is sufficient for distinguishing settlement patterns on a district level. This seemed to be sufficient for delimiting the urban extent, since GHS with a spatial resolution of 38 m showed to represent the reference extent most accurately. However, it must be noted that the reference extent itself is based on 30 m resolution imagery and the reference extents' accuracy is unknown. Nonetheless, such a spatial resolution is not sufficient enough to identify open spaces. According to Welch (1982) a resolution of 0 – 10 m should be used for inner-urban analysis. None of the products had a resolution lower than 10 m. Furthermore, a higher resolution may not always lead to better results. This was illustrated by the under-identification of the urban extent derived from FROMGLC10 (Table 15) and the fact that this product identified much more open spaces than were present in the reference (Table 18). This indicates an under-classification of BU. This correspond with literature, as Gong et al. (2019) have shown that its BU class does not have a very high accuracy and can get mixed-up with areas that consist of grassland and bare land.

4.3.2. Thematic content

The thematic content of the different products that were used, showed to affect the delimiting of the urban extent and the open spaces. This corresponds to research by Florczyk et al. (2018) who have shown that different global products disagree on urban extents due to, amongst others, semantic differences in the built-up class. The land-cover and built-up products used in this thesis had two different BU class definitions. BU either corresponded to only buildings, or to buildings and other impervious surfaces, which means paved squares and roads. High BU disagreement patches were found in the south that correspond to roads (Figure 7). GUF04, CCILC20, and HRSL did not identify these patches as part of the urban extent because their BU definition is only limited to buildings. HBASE, FROMGLC10, and the reference did identify these areas as part of the extent because their BU class also contained impervious surfaces. GHS did identify these roads even though it defined BU as only buildings. This is because GHS, contrary to GUF04, classifies BU with optical instead of radar data. Optical data mainly reflects the impervious surface, while radar provides information on the vertical component which is only present in case of buildings and not roads (Esch, Heldens, & Hirner, 2018). Given this disagreement about the definition of built-up and its effect on the urban extent, it would be good to reconsider the definition of BU and check with local experts which definition leads to a more representative extent.

For delimiting open spaces it was expected that products that exclude impervious surfaces from the BU class would perform better, since they would be able to delimit the hard-textured (non-green) open spaces. The results of this thesis show this is partly true (Figure 19). GUF04 and CCILC20 outperformed GHS and HBASE when it comes to identifying (large) hard-textured open spaces. Yet their ability to identify them remains limited. Furthermore, GUF04 and CCILC20 also outperform GHS and HBASE in case of soft-textured open spaces, indicating that the thematic content is not the only factor affecting the identification of open spaces. Other factors could be the spatial resolution or the classification method and training data used to obtain the BU. The latter two were however not analysed in this research. Furthermore, there were only a limited amount of hard-textured open spaces present in the reference data, especially larger ones. This means that the results are much more affected if a single hard-textured open space is not identified than in the case of soft-textured open spaces.

4.3.3. Temporal resolution

For monitoring the indicator, a temporal resolution of three to five years is required (UN-Habitat, 2018a). However, most of the products assessed in this thesis were only created for a single time period. GHS has been created for multiple years, but within a 10 to 15 year interval. Also, it remains unclear whether future updates of the old product will take place, because a new product (GHS-S1) is being developed. The new product will probably be created for multiple time periods, at a currently unknown frequency. The same applies to GUF04. Future updates are expected, but no time intervals have been determined yet. Given the lack of multiple multi-temporal products, the focus of this thesis has been on analysing the products abilities to measure the indicator, not on monitoring the indicator.

4.4. GLOBAL VERSUS LOCAL PRODUCTS

The results of this thesis illustrated that global products can outperform local products. OSM was better able to identify the land allocated to streets than the local authoritative dataset. The local dataset contains gaps in its dataset, such as in the slum Kibera (Figure 11). This is in correspondence with research by Mahabir et al. (2017) who have compared OSM road data in Nairobi against another local dataset, and found that OSM outperforms the local dataset in the city. The local dataset used in this thesis does not only contain gaps, but is also limited to the city's administrative boundaries. To delimit the open spaces, no local land use maps were found that contained sufficient detail. This shows that the quality and coverage of local datasets is not always sufficient for measuring the SDGs, as Boyer et al. (2015) pointed out.

Another disadvantage of the local dataset is that it is not regularly updated, while OSM can be updated continuously. However, this depends on the mapping community of OSM, which consists of volunteer mappers. The same goes for the spatial coverage of OSM. The slum Kibera is well-mapped, because a special project called Map Kibera has taken place to digitise the area. The coverage of OSM is not equal across the world (Barrington-Leigh & Millard-Ball, 2017). This also means that the quality is not guaranteed. However, previous research has shown that cities in general, which are the focus of the indicator, mostly have a high OSM road coverage (Barrington-Leigh & Millard-Ball, 2017; Haklay, 2010; Mahabir et al., 2017).

A disadvantage of global datasets is that not all of them are fully open and accessible. For example, the GUF04 product, which is currently only available for scientific use. A version at a coarser resolution (84m) is available for non-profit use. Given the discussed effect of spatial resolution, this resolution will probably not be sufficient for measuring the indicator, thus there is a need for making these products available for this purpose. Local products do have as advantage that they are often more detailed than global products, both in terms of spatial resolution and thematic content. This is especially in countries with a highly developed SDI. However, in Nairobi this was proven to not be the case.

4.5. COMBINING EO AND VGI

This research illustrated that the information derived from EO products can be enriched if it is combined with VGI products like OSM. By using OSM derived street space, EO-derived open spaces can be better delimited. Besides, it avoids calculating the street space as open space twice. This is something that has not been considered in the UN-Habitat proposed methodology. Using OSM to delimit street space also saves computation time compared to manually digitizing the streets. But if OSM is used, more street width measurements (>20) per street type should be taken or the amount of street types should be increased, as the variations in widths per street type were high (Figure 9). These alterations may reduce some of this variation and provide better estimates of the street widths and therefore the street space.

Furthermore, OSM showed potential to provide information about the function and therefore publicness of the EO-derived open spaces. This corresponds with the research by W. Chen et al. (2018) who have shown the added value of using VGI data in combination with EO to identify the function of urban green spaces. For excluding non-public open spaces OSM proved to be useful. It helped to reduce the possible public spaces. At the same time it did not negatively affect the results, as the amount of reference open spaces that was wrongly classified as non-public was negligible. It was less successful in classifying open spaces as public, as only half the spaces that were classified as public by OSM where present in the reference. This indicates that the OSM land use functions can be used to exclude non-public spaces, but that it is more difficult to determine if a certain land use function is indeed public.

Combining EO with VGI could improve the thematic detail of EO data required for measuring the USDG. At the same time this combination could help to improve the spatial coverage that might be missing in VGI data. OSM land use mapping tends to be quite complete in city cores and less in the suburban areas (Grippa et al., 2018). Global EO data does not have this discrimination towards the suburban areas. However, since OSM has been growing over the past few years it is likely that the spatial coverage will improve.

4.6. RESEARCH RECOMMENDATIONS

The accuracy of reference data is not always known (Congalton, 1991), which should be taken into account when the results are interpreted. In case of the urban extent, most products defined a larger urban extent to the north and a smaller extent to the south, compared to the reference (Figure 8). This could indicate that the reference data contains inaccuracies. However, assessing the accuracy of the reference data has not been the task of this research. Further research could focus on assessing the accuracies of the reference and the product derived elements.

For delimiting the open spaces, the method used in this thesis only focuses on the open spaces itself, not whether they are green, non-green, or waterbodies. Incorporating more information that is contained in land-cover products might help to make this distinction. Land-cover classes such as grasslands, forest, and water could be used to delimit green spaces and waterbodies.

Furthermore, the results showed that the open spaces require additional data, beside OSM, to define their publicness. An idea could be to include distance to street as a threshold for determining the publicness, as this could exclude spaces such as private gardens that would require access through buildings and are therefore not likely to be public. However, given the uncertainty of the derived street space, it was chosen not to include this. Future research could explore this idea and focus on ways to reduce the effect of street space uncertainty.

As the results demonstrated that some products have more difficulty identifying hard-textured open spaces, additional data could be used to obtain them. A solution would be to use a digital height model to obtain pixels that contain buildings and exclude these from the impervious surface products to obtain the hard-textured non-green open spaces. Such a digital height model could be created by subtracting a digital terrain model from a digital surface model (Weidner & Förstner, 1995). However, suitable digital elevation models were not yet available since existing elevation models contain striping artefacts that cause errors. This is a well-known problem in elevation models (Falorni et al., 2005).

4.7. GLOBAL APPLICABILITY

This thesis focussed on Nairobi, while the indicator should be assessed for different cities across the globe. Not all EO-based global products have full spatial coverage. HRSL for example, only covers some countries in the Global South and none in the Global North. Furthermore, the quality of the classification of the BU area is not equal across the world, as shown by the research of Potere et al. (2009). The fact that the BU threshold of the GHS product had to be adjusted demonstrates this. Also, countries with a more developed SDI may have local products with higher accuracies that outperform global datasets. Therefore, caution must be taken into account when the results of this thesis are generalised.

Yet, the fact that global data has outperformed local data, and that the data created according to the proposed methodology showed inaccuracies compared to the global products, show the added value of these global products for countries with less developed SDIs. Using global products instead of the proposed manual classifications reduces the time and expertise needed to measure the indicator. At the same time using a product that derives built-up information for multiple years according to the same standardised method benefits the monitoring process (Latifovic et al., 2016). Even in the case of identifying the public open spaces, the global products have an added value by guiding the manual identification of open spaces, especially where other sources are lacking. This is particularly important for countries where not only data but also time, finances, and expertise are scarce. By doing so, global products can help bridge the digital divide between countries and cities in monitoring SDG indicator 11.7.1.

5. CONCLUSION & RECOMMENDATIONS

5.1. CONCLUSION

This thesis analysed the role of global open geospatial products for measuring SDG indicator 11.7.1 by using them to delimit the urban extent, the street space, and the public open spaces and comparing the results between the products and against reference data. No research has done this before, which makes this research a valuable contribution towards both the practical monitoring of the indicator and the scientific field focussing on assessing the value of global open geospatial products.

The research was performed for the city Nairobi. The results showed that the city is far from reaching the required share of built-up area of the city that is open space in public use. Both the land allocated to public open spaces and land allocated to streets is not high enough. This research also showed that Nairobi lacks good quality local data required for measuring the indicator. Global data proved to be a valuable alternative.

Given the results of this research, the following conclusions can be made regarding the role of global open geospatial products for monitoring SDG indicator 11.7.1:

- EO optical-based products like GHS can be used to delimit the urban extent, but only as a baseline since it is unlikely that future updates of this product will take place.
- EO-derived BU and land-cover products can be used to provide a reflection upon the urban extent derived according to the proposed methodology. They can help to critically reflect upon the definition used to delimit the BU, as to whether to include impervious surfaces or not. In the future, radar-based products like GUF04 and potentially GHS S1 can be used to delimit the extent, if the definition of BU changes and the products are made publicly available for multiple time periods.
- EO radar-based products like GUF04 can play an assisting role in delimiting public open spaces by helping to identify potential public open spaces and serving as a baseline in countries that lack local datasets. They can however not be used to fully replace the current method of using local experts to manually identify the public open spaces, given their too coarse spatial resolution.
- VGI-derived street products like OSM could be favoured over local products when it comes to identifying land allocated to streets, in case the accuracy of the local product is unknown.
- VGI-derived products like OSM could support the assisting role of EO-derived products for identifying public open spaces by avoiding to count street space twice and by excluding non-public spaces.

5.2. RECOMMENDATIONS

The recommendations for monitoring the indicator are:

- Evaluate the definition of built-up used to delimit the urban extent.
- Evaluate the required outcome of the indicator concerning its feasibility in a city like Nairobi.

The recommendations for global geospatial-product development are:

- Make GUF04 and new GHS multi-temporal with a frequency of at least every five years.
- Make GUF04 freely available for monitoring the SDGs.
- Develop more fine-scaled (below 10 m) global open products using radar techniques.

The recommendations for further research are:

- Assessing new Sentinel 1-based GHS product on its suitability for monitoring this indicator.
- Explore the usefulness of future global DSM and DTM products for obtaining hard-textured open spaces.
- Explore the potential of using different land-cover classes for delimiting open spaces per surface type.
- Research additional methods to assist in delimiting public open spaces, such as using distance to streets as a way for determining the publicness of an open space
- Perform the same research in a different city where there are more open spaces with impervious (hard-textured) surfaces.
- Perform a similar assessment of global products compared to local products in countries with highly developed SDIs.

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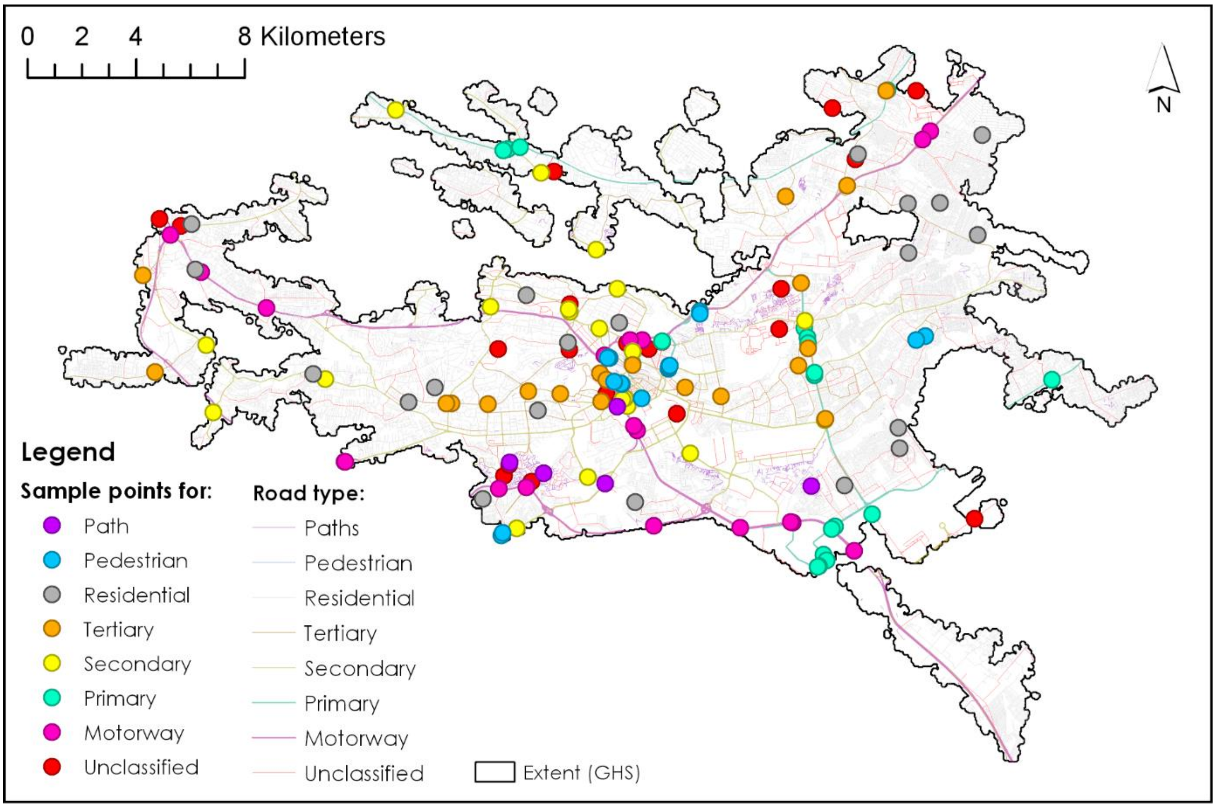
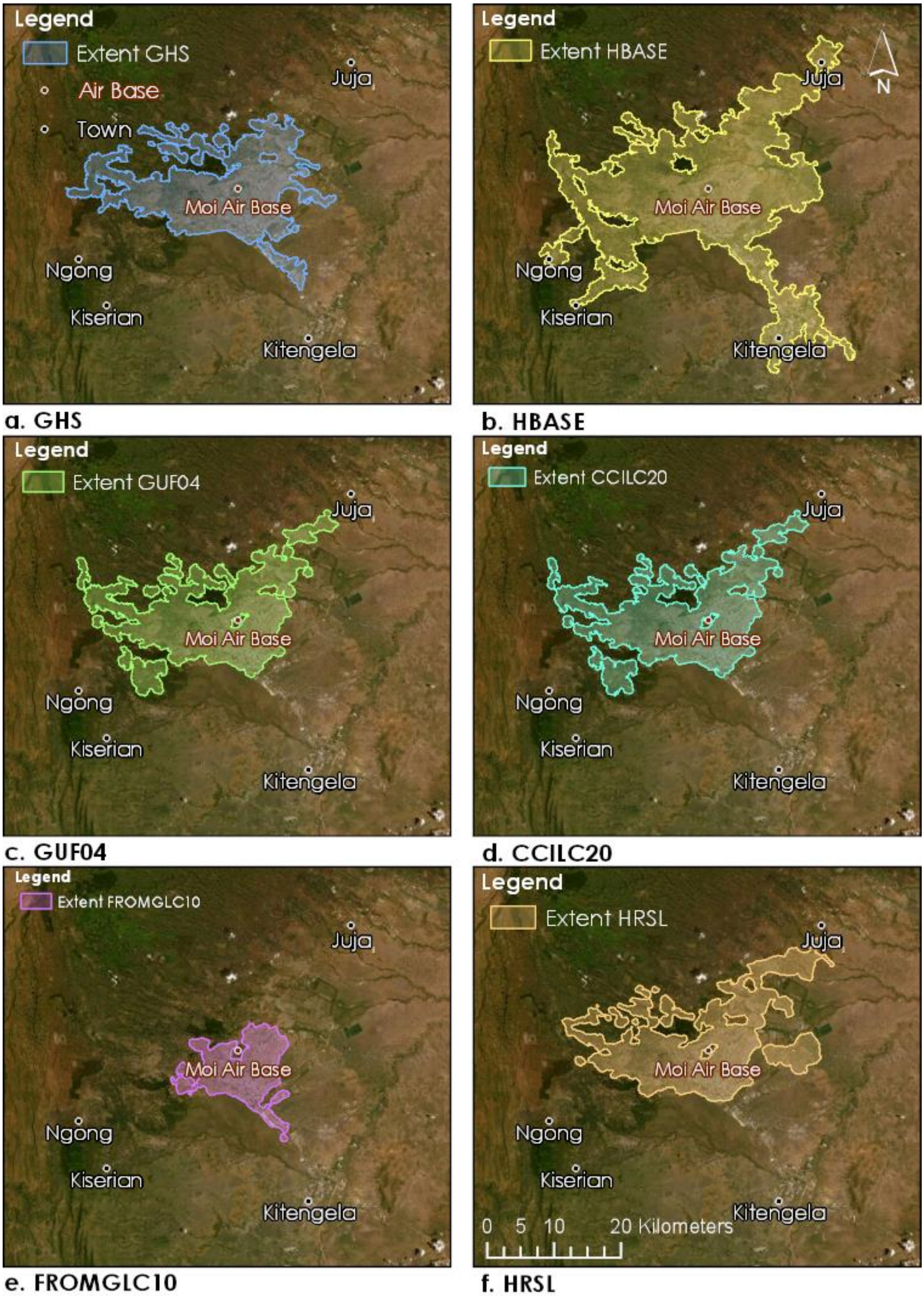
APPENDICES

APPENDIX A: MAP OF SAMPLE POINTS FOR MEASURING STREET WIDTH



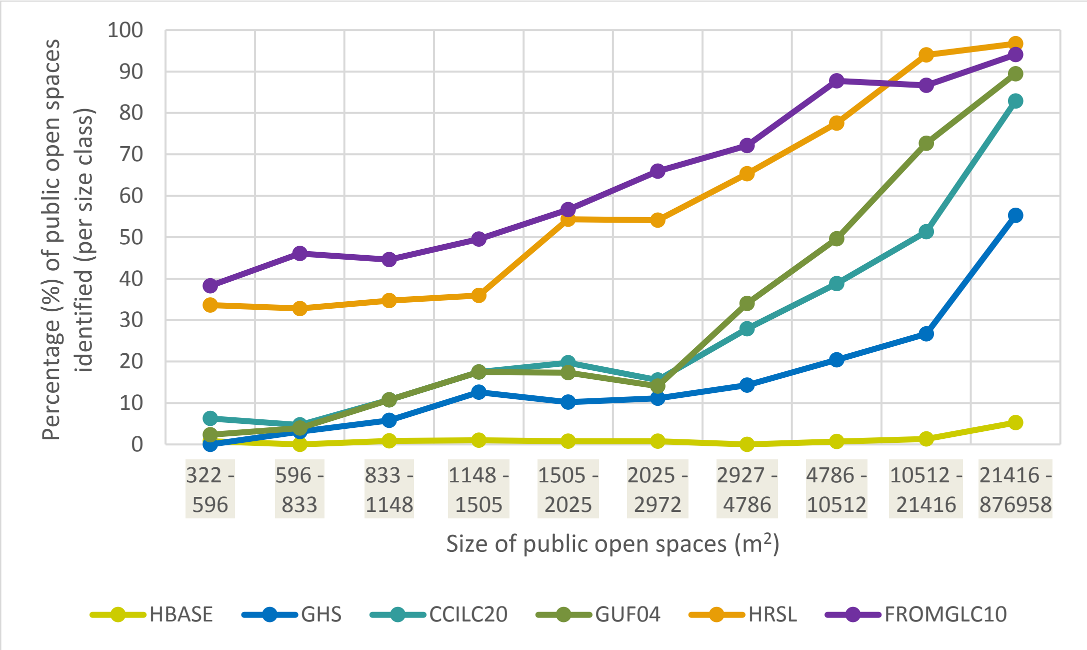
Appendix A. Figure 1. *Sample points used to measure street width per street type.*

APPENDIX B: MAPS OF URBAN EXTENTS

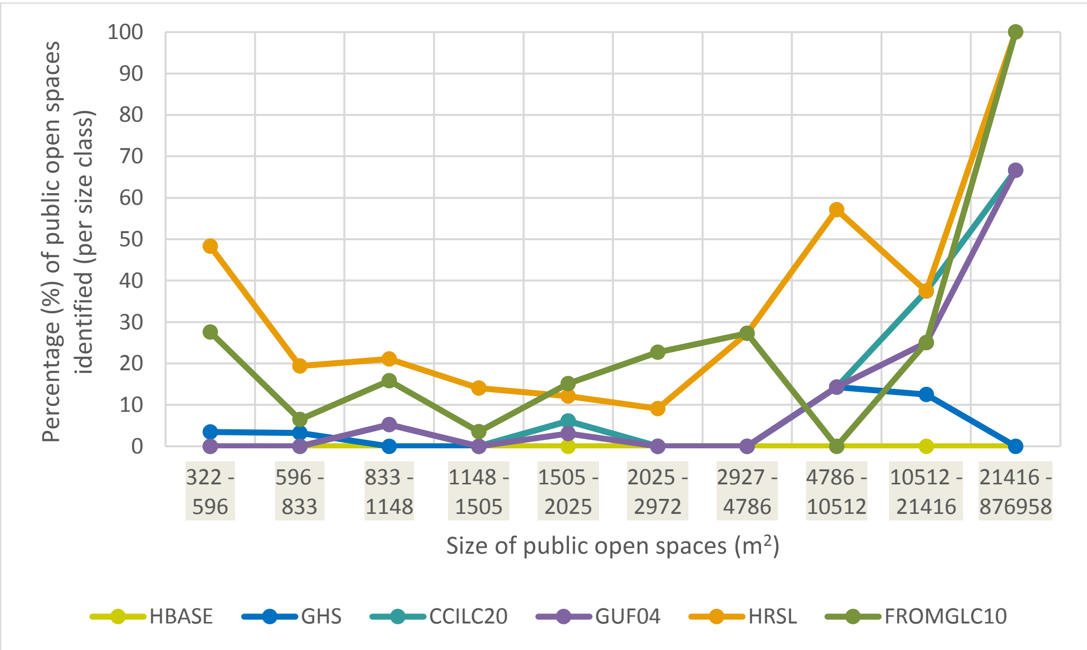


Appendix B. Figure 1. *Urban extent of Nairobi as derived from the different products.*

APPENDIX C: GRAPHS OF OPEN SPACES IDENTIFIED PER SIZE CLASS

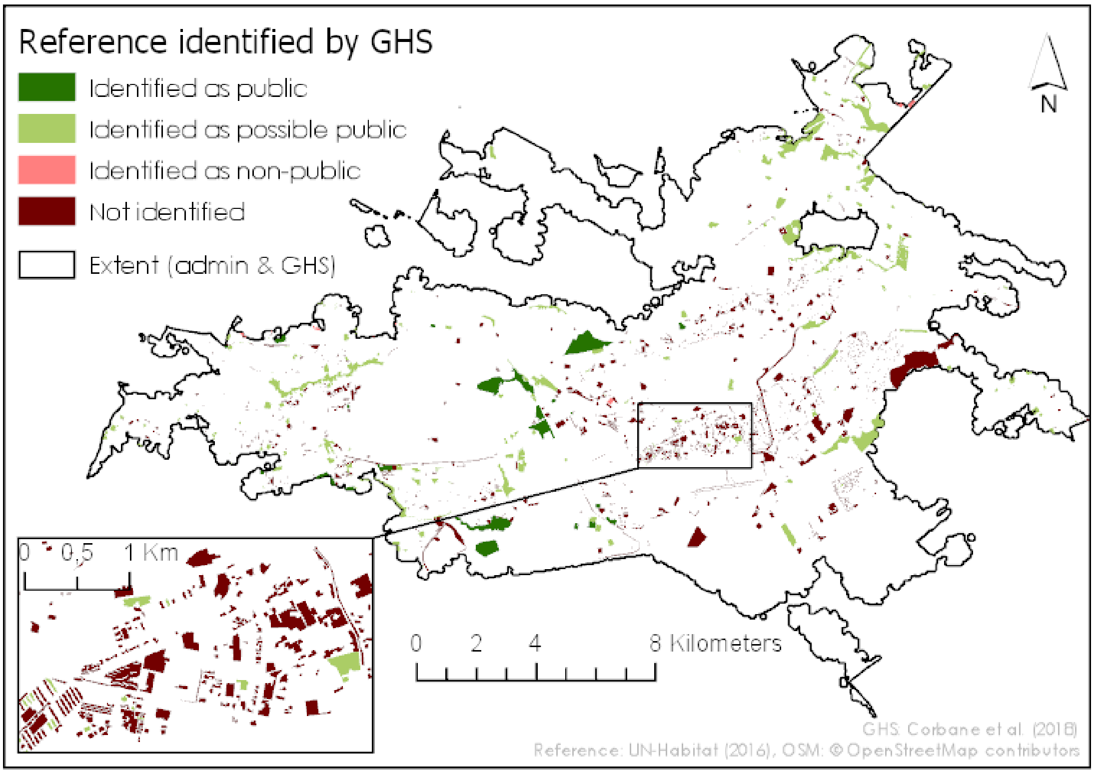


Appendix C. Figure 1. *Percentage of soft textured reference open spaces identified per size class and product.*

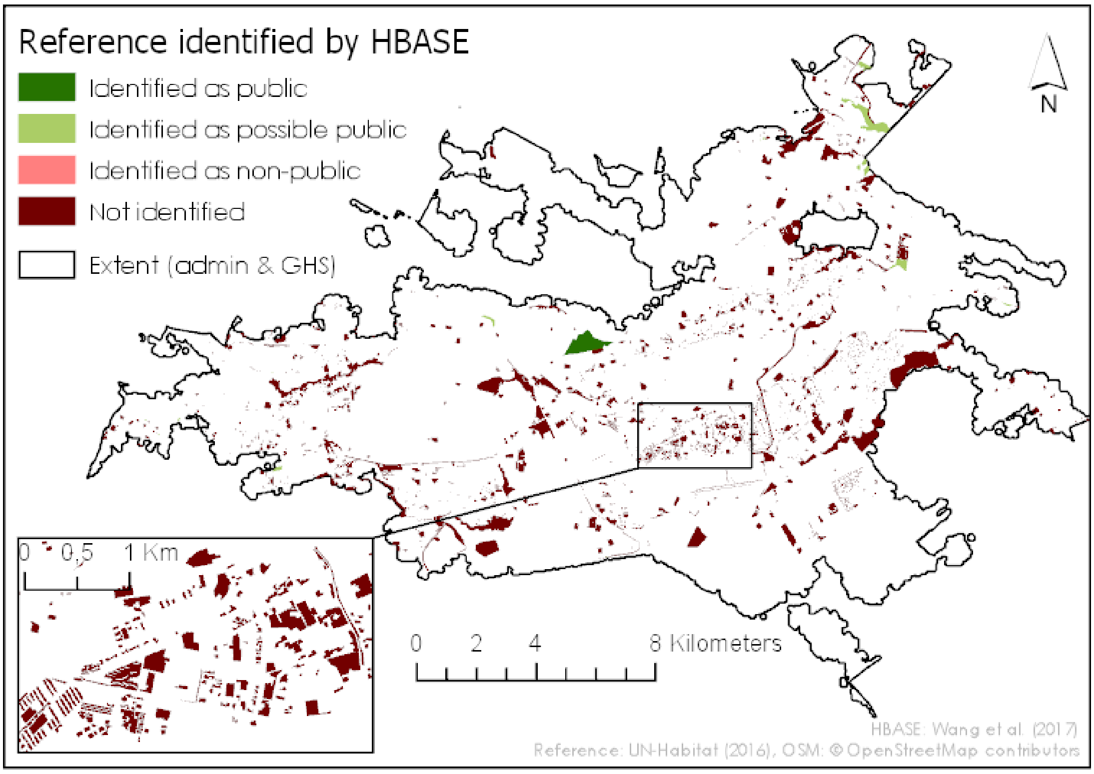


Appendix C. Figure 2. *Percentage of hard textured reference open spaces identified per size class and product.*

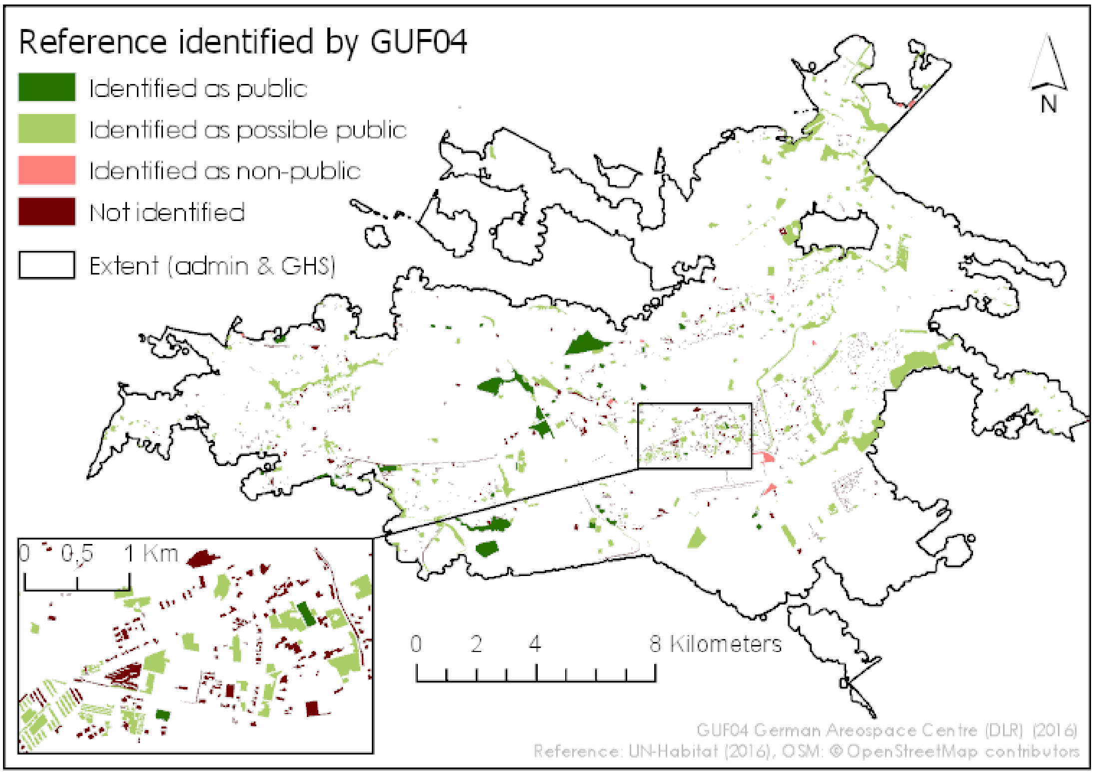
APPENDIX D: MAPS OF REFERENCE SPACES IDENTIFIED PER PRODUCT



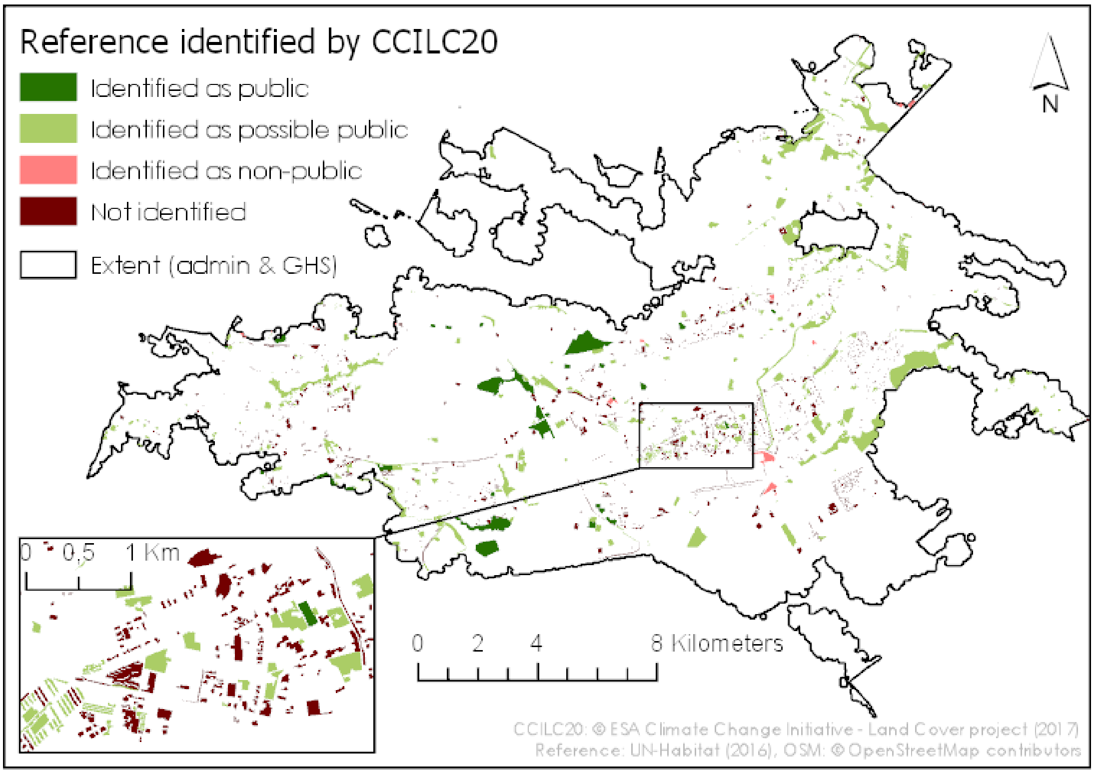
Appendix D. Figure 1. *Reference public open spaces identified as public, possible public, non-public, or not identified by GHS and OSM.*



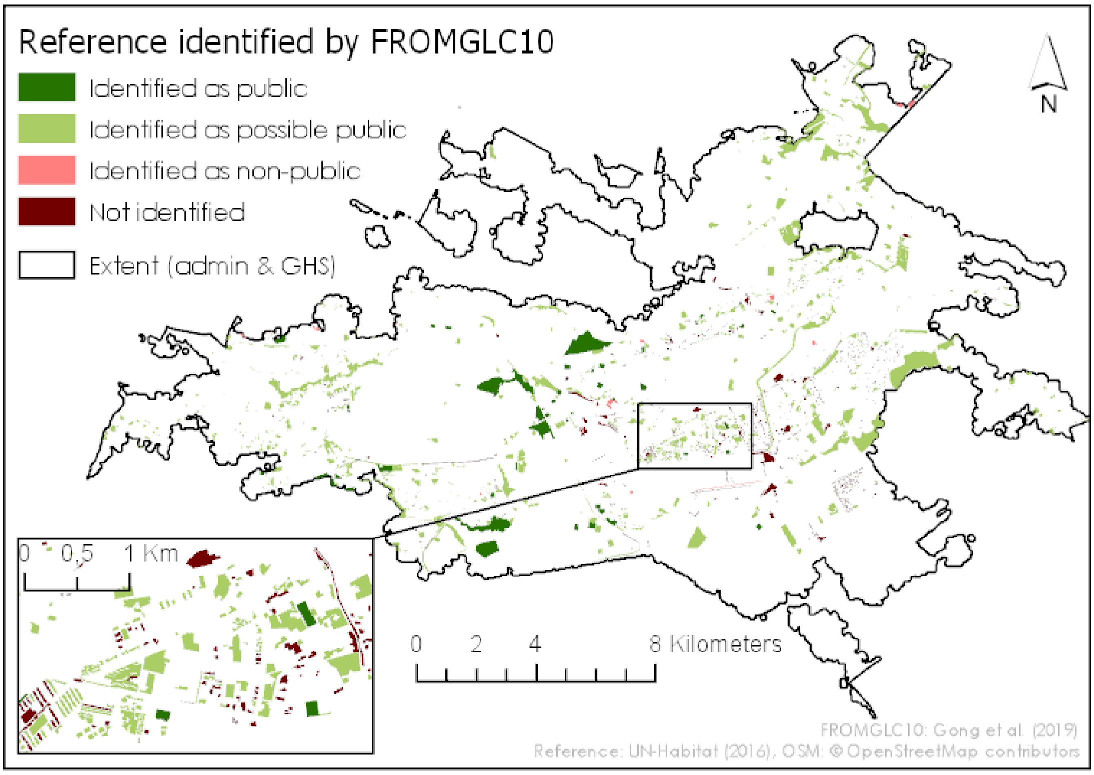
Appendix D. Figure 2. *Reference public open spaces identified as public, possible public, non-public, or not identified by HBASE and OSM.*



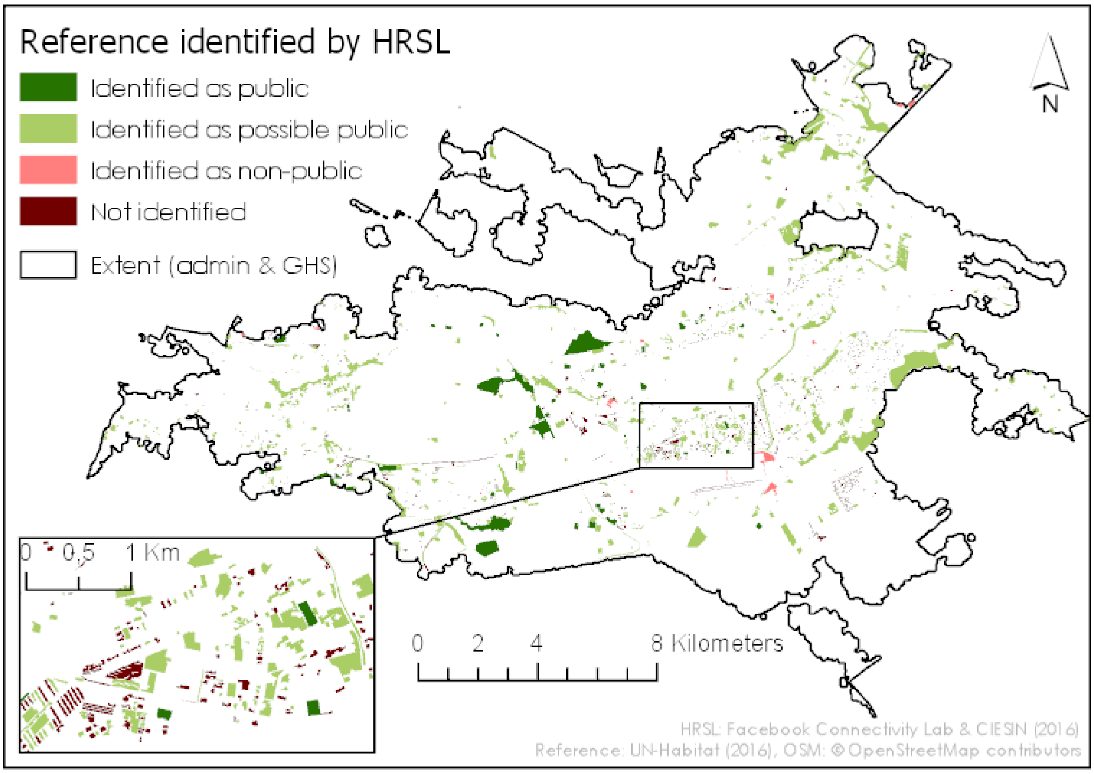
Appendix D. Figure 3. *Reference public open spaces identified as public, possible public, non-public, or not identified by GUF04 and OSM.*



Appendix D. Figure 4. *Reference public open spaces identified as public, possible public, non-public, or not identified by CCILC20 and OSM.*



Appendix D. Figure 5*. Reference public open spaces identified as public, possible public, non-public, or not identified by FROMGLC10 and OSM.*



Appendix D. Figure 6*. Reference public open spaces identified as public, possible public, non-public, or not identified by HRSL and OS.*