WORKING PAPER

Development of a Methodology for Land Cover Classification Validation

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Acronyms and Abbreviations

ACC Dar – Adapting to Climate Change in Coastal Dar es Salaam
ESA – European Space Agency
GIS – Geographic Information System
GPS – Global Positioning System
ISPRA – Italian National Institute for Environmental Protection and Research
LC – Land Cover
LCC – Land Cover Change
LU – Land Use
SPOT – Satellite Pour l'Observation de la Terre
UDEM – Urban Development and Environment Management
USGS – United States Geological Survey

Glossary

Accuracy Assessment – The process which "determines the quality of the map created from remotely sensed data. Accuracy assessment can be qualitative or quantitative, expensive or inexpensive, quick or time consuming, well designed and efficient or haphazard. The goal of quantitative accuracy assessment is the identification and measurement of map errors." (Congalton & Green, 2009, p. 2). It is often performed with the calculation of an error matrix.

Error Matrix – A matrix that "compares information from reference sites to information on the map for a number of sample areas" (Congalton & Green, 2009, p. 16).

Fuzzy Error Matrix – A modification of the Error Matrix that "allows the analyst to compensate for situations in which the classification scheme breaks represent artificial distinctions along a continuum of land cover and/or where observer variability is often difficult to control" (Congalton & Green, 2009, p. 135).

Land Cover – The "physical material at the surface of the earth. It is the material that we see and which directly interacts with electromagnetic radiation and causes the level of reflected energy that we observe as the tone or the digital number at a location in an aerial photograph or satellite image. Land covers include grass, asphalt, trees, bare ground, water, etc." (Fisher, et al., 2005, p. 89).

Land Cover Change – The detection of changes in Land Cover, usually analysing multitemporal data; in remote sensing, Land Cover Change will result in changes in reflectance values (Lu, et al., 2011).

Land Use – The "description of how people use the land. Urban and agricultural land uses are two of the most commonly recognised high-level classes of use. Institutional land, sports grounds, residential land, etc. are also all land uses" (Fisher, et al., 2005, p. 89).

Reflectance – The "ratio of reflected versus total power energy" (NASA, 2011, p. 47).

Remote Sensing – The measurement of the energy emanating from the earth's surface, using a sensor mounted on an aircraft or spacecraft platform, in order to obtain an image of the landscape beneath the platform (Richards & Jia, 2006).

Urban Sprawl – The unplanned, low-density urban expansion, characterized by a mix of land uses on the urban fringe (EEA, 2006).

Vulnerability – The "degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes" (IPCC, 2001, p. 21).

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Foreword

The population of Dar es Salaam (Tanzania) has grown rapidly in recent decades; at the same time Dar es Salaam experienced a rapid urban expansion, in particular because of informal peri-urban settlements growing at the fringe. The environment has consequently been subjected to several pressures, which can eventually cause several impacts and therefore affect people's vulnerability.

Spatial planning need to understand urbanization processes (especially informal ones), and their consequences on the environment, by the monitoring of Land Cover (LC).

This study is part of Activity 2.1 of the "Adapting to Climate Change in Coastal Dar es Salaam" (ACC Dar) project. This Activity aims to improve Dar City Council's planning services in understanding LC patterns, by the development of methodologies, based on remote sensing and GIS techniques, for monitoring changes in peri-urban settlements.

Two methodologies were already developed for the LC classification, which are described in the following working papers:

- "Development of a Methodology for Land Cover Classification in Dar es Salaam using Landsat Imagery";
- "Development of a Methodology for Land Cover Classification in Dar es Salaam using SPOT Imagery".

Those methodologies for LC monitoring, are very similar and meet the same requirements; in particular the LC classification are: very affordable, in order to be suitable to needs and resources of Dar's municipalities; rapid and easy to update, and therefore able to keep pace with the growth of the city.

The developed methodologies allowed for the LC classifications of Dar es Salaam over the years, in order to assess Land Cover Change (LCC).

This working paper presents a methodology developed for the validation of LC classifications, which completes the production process of LC maps, described in the previous working papers.

The validation of LC classifications has the purpose of assessing the quality of produced maps, and highlighting the source of errors in the classifications. In particular, this working paper shows the accuracy assessment of two LC classifications of Dar es Salaam (a Landsat derived and a SPOT derived, for the year 2011), produced by this Activity.

The accuracy assessment was performed comparing the LC classification to ground truth data, obtained by the photo interpretation of high resolution images. In addition, a field survey was performed for improving and checking the photo interpretation process.

The accuracy assessment showed good quality of the LC classifications, especially for the Landsat one. This suggests that Landsat classifications are adequate for LC monitoring of Dar es Salaam, while SPOT classification can be suitable for local studies.

Executive Summary

This study is part of the Activity 2.1 of the ACC Dar project. This activity has developed two similar methodologies for the semi-automatic classification of LC, using two different image sources (Landsat and SPOT satellites), which have different resolutions. This study developed a methodology for the assessment of the LC classification quality.

The objectives of the ACC Dar project are:

- to enhance the capacity of Dar's municipalities in understanding Climate Change (CC) issues specific to coastal areas;
- to assess CC impacts on the livelihood of those dwellers, partially or totally depending on natural resources, increasing knowledge about autonomous adaptive capacity;
- to develop methodologies for integrating adaptation activities into strategies and plans for Urban Development and Environment Management (UDEM) in coastal unplanned and underserviced settlements.

Dar es Salaam is located in the east of Tanzania, on the Indian Ocean coast, and its Municipality covers an area of 1 800km^2. During recent decades, Dar es Salaam experienced a rapid urban expansion, in particular because of informal peri-urban settlements growing at the fringe (Briggs & Mwamfupe, 2000).

Informal settlements and the rapid population growth are cause of environmental degradation and resource depletion. In fact, urban sprawl and the impermeabilization of soil surface, can worsen environmental issues (e.g. flooding) (Kironde, 2006).

Therefore, it is fundamental for spatial planning to monitor LC changes, in order to locate informal settlements and assess the related environmental impacts (e.g. groundwater salinization and pollution); those impacts increase the vulnerability of people to CC effects, in particular for those inhabitants who depend on natural resources for their livelihood (Paavola, 2008).

This Activity has developed two similar methodologies for LC monitoring, which rely on the classification (i.e. semi-automatic supervised classification) of free remote sensing images (Landsat and SPOT), allowing for the very affordable production of LC maps. Those methodologies are described in as many working papers.

Landsat images, which are provided for free by the United States Geological Survey (USGS), are characterized by coarse spatial resolution (i.e. 30m) and medium spectral resolution (i.e. 7 bands). SPOT images are provided for free by the European Space Agency (ESA), and have medium spatial resolution (i.e. 10m) but low spectral resolution (i.e. 4 bands).

Therefore, several LC maps of Dar es Salaam were produced by this Activity, which allowed for the assessment of LCC (using Landsat images) for the years: 2002, 2004, 2007, 2009 and 2011. Also a LC classification based on SPOT images, was produced for the year 2011 (the classification does not include Temeke District because of unavailability of images).

The LC classifications identified the following classes:

- “Continuous Urban”, a very dense built-up class;
- “Discontinuous Urban”, a class of low density built-up, characterized by mixed pixels of impervious surfaces and vegetation or soil;
- “Full Vegetation”, a very green vegetation class with high NDVI;
- “Most Vegetation”, a vegetation class with low NDVI;
- “Soil”, a bare soil class;
- “Water”, a surface water class.

This paper, presents the methodology developed for the accuracy assessment of LC classifications, which is a required step for their validation and to prove their reliability.

The process of accuracy assessment is performed through the calculation of an error matrix, which is a table that allows for the comparison of LC classification data to ground truth data (Richards & Jia, 2006). The approach used in this study is inspired to the one used by ISPRA (ex-APAT), the Italian National Institute for Environmental Protection and Research, for the accuracy assessment of the Corine Land Cover 2000 (APAT, 2005).

The reference data were obtained by the photo interpretation of 500 sample units (which are circles with 400m radius) that were selected randomly. The photo interpretation was performed using the high resolution images available in the free software Google Earth (developed by Google). In addition, a field survey was performed in order to improve the photo interpretation process, and check its results.

In order to consider and compensate the cases where the rules of classification represent artificial distinctions along a continuum of LC, a fuzzy approach was defined for the creation of error matrices. It is useful when reference data is acquired in a different season than the LC classification is referred to. A set of rules is required to define what type of classes can have more than one acceptable classification value.

The fuzzy error matrix allows to consider the presence of secondary classes in the sample units, and therefore improve the accuracy assessment where there is a mix of LC classes.

Several statistics can be calculated for each LC classification:

- the overall accuracy;
- the user's and producer's accuracies for every class;
- the K statistics.

In particular, the user's accuracy is calculated as the number of samples correctly identified for the *i* class, divided the total number of samples classified as the same *i* class; the producer accuracy is calculated as the number of samples correctly identified for the *j* class, divided the total number of samples belonging to the same *j* class of the reference (Congalton & Green, 2009).

This study assessed the accuracy of Landsat and SPOT LC classifications referred to the year 2011.

According to the error matrix of the Landsat classification, the urban classes have very high values of accuracy:

- the "Continuous Urban" class shows 98.0% of user's accuracy, and 93.1% of producer's accuracy;
- the "Discontinuous Urban" class shows high values of user's accuracy (i.e. 96.7%), although its producer's accuracy is fairly good (i.e. 71.9%).

The other LC classes have lower accuracies, because of:

a) the seasonal variation of LC classes;
b) the time difference between LC classification and reference images that were photo interpreted;
c) spectral similarities between LC classes (which is the error due to the LC classification process).

In order to better assess the LC accuracy, a new error matrix was calculated by limiting the reference images to the years 2010 and 2011. Nevertheless, the results showed no accuracy improvement, probably due to the location of reference images (that are mainly over the city centre).

The accuracy results for the SPOT classification are:

- the "Continuous Urban" class has very high values of the user's accuracy (i.e. 100.0%) and producer's accuracy (88.8%);
- the "Discontinuous Urban" class has good user's accuracy (i.e. 88.1%) and fairly good producer's accuracy (i.e. 69.4%).

Therefore, the SPOT results are slightly lower than Landsat ones; the main reason of its lower accuracy is the spectral confusion between the "Discontinuous Urban" class and the "Soil" class. In fact, the low spectral resolution of SPOT images makes very difficult the distinction between spectrally similar classes. However, the high spatial resolution of SPOT images allows for very good identification of spectrally defined classes like "Continuous Urban".

Considering the objectives of this Activity, Landsat classifications are the most suitable for monitoring LCC, as indicated by the good accuracies obtained for the urban classes.

In order to improve the photo interpretation process, it would be preferable to use high resolution images acquired at the same time of the acquisition of LC classification images.

The field survey confirmed the reliability of the perforemed photo interpretation, and allowed for the creation of a photographic database, which is a product of value itself. In addition, it could be performed cyclically (for example once a year) by Dar’s planning services, in order to create a database of ground truth data which will be useful for the future LC classifications.

1. Introduction, Scope, and Motivation

1.1 Background

Dar es Salaam's population has rapidly grown during the recent 20 years. In particular, Dar had 1.4 million of inhabitants in 1988, 2.4 million in 2002 (Kironde, 2006), and is estimated to reach 3 million in 2012 (United_Republic_of_Tanzania, 2006).

The built-up area of the city has expanded according to that population growth. The development of Dar has started in 1967, and continued during the 1980s. People's need to reduce travel time to the city centre has caused urban development, especially along the arterial roads. In the 1990s, the increase of private transportation and the efficient public transportation system provoked the urban expansion away from the arterial roads, thus producing an irregular spatial pattern (Briggs & Mwamfupe, 2000).

About one half of population is poor or very poor, and lives in informal settlements, especially at the fringe. In particular, informal peri-urban settlements grow along the radial roads that connect to the city centre (Kombe, 2005).

Dar es Salaam has a major role in the economy of Tanzania. Because of this, migrants from all over the country come in Dar, attracted by job opportunities; thus they acquire land and build houses in poverty, bypassing formal urban land management (Kombe, 2005). That informal urban growth is caused by the type of regulatory framework of Dar es Salaam, because administrative procedures take too long to make land available to people (Kironde, 2006).

Unfortunately, those settlements lack of services like electricity, transportation networks (Olvera, et al., 2003), potable water (Kyessi, 2005). People try to compensate for those lacks with the creation of social networks, supported by cultural norms (Kombe, 2005).

Nevertheless, informal settlements can cause environmental degradation and resource depletion, in particular, urban sprawl and soil sealing (the impermeabilization of soil surface), can exacerbate environmental issues like flooding (Kironde, 2006) or groundwater salinization and pollution (Mtoni, et al., 2012).

Those environmental issues can increase people's vulnerability to CC effects, in particular for those inhabitants who depends on natural resources for their livelihood (Paavola, 2008). In addition, rapid LCC is a serious challenge for urban planners and decision-makers, because the lack of financial makes very difficult to monitor LC.

The Activity 2.1 of the ACC Dar Project has developed an affordable methodology for LC monitoring; in particular, that methodology relies on the supervised classification of remotes sensing images, which are provided for free (i.e. Landsat and SPOT).

Landsat images (provided for free by the USGS) were classified using this methodology, which allowed for the LC classification of Dar es Salaam Region in several years (2002, 2004, 2007, 2009 and 2011). Therefore, it has been possible to assess the LCC for those years. The details of that study are described in the working paper "Development of a Methodology for Land Cover Classification in Dar es Salaam using Landsat Imagery".

The same methodology was adapted to the use of SPOT images (delivered for free by the ESA); the working paper "Development of a Methodology for Land Cover Classification in Dar es Salaam using SPOT Imagery" describes the methodology and the differences with the Landsat's one.

A brief description of those methodologies, together the LC maps for year 2011, is contained in "Appendix 1 – Land Cover Classifications" of this working paper. The main objective of the LC classifications is the identification of urban classes, and the change of urban patterns, with the purpose of assessing LC fragmentation.

1.2 Goals and scope

This study is part of Activity 2.1 of the ACC Dar Project, which has the objective to enhance the capacity of Dar's municipalities in understanding CC issues specific to coastal areas. This working paper describes the methodology developed for the assessment of LC classification accuracy.

The main objective is to validate the LC classifications produced during the previous phases of this Activity (i.e. the development of a methodology for the LC classification in Dar es Salaam, based on remote sensing and GIS techniques).

This validation methodology shares the main goals with the LC classification methodology, which are the rapid production and validation of LC maps of Dar es Salaam, which are easy to update, and therefore able to keep pace with the growth of the city.

1.3 Motivation

People's vulnerability to CC is influenced by the efficacy of urban planning. In particular, the lack of planning in informal settlements can increase CC impacts; for example, the effects of flooding in peri-urban settlements are aggravated by the use of pit-latrines, which can pollute groundwater and cause epidemics (Paavola, 2003).

Urban sprawl is a cause of environmental changes and has involved many regions of the World, Africa included. For example, it can provoke the stress of water-related ecosystems; can cause environmental degradation, such as deforestation, waste pollution, and the decrease of water quality and quantity; and it can exacerbate health problems like malaria cases. Therefore, it can increase people's vulnerability to CC (DST, 2008).

This Activity has already developed a methodology for LC monitoring (using Landsat and SPOT images). However, the reliability of the LC maps must be verified, especially when the LC classifications are developed with supervised, semi-automatic methods (Congalton & Green, 2009).

This study describes the methodology developed for the validation of LC classifications. This methodology, together with the previous ones, aims to improve capacity building of Dar's municipalities, improving the LC monitoring. Dar's municipalities will be able to create LC maps, and therefore assess the LC classification accuracy, using the methodology described in this paper.

The developed methodologies should increase the adaptive capacity of Institutions, should improve their knowledge about LCC, allowing for more effective planning.

The final beneficiaries of the developed methodologies will be Dar's inhabitants who live in unplanned areas, and whose livelihood depends on natural resources. In fact, their vulnerability to CC should decrease, because spatial planning should improve their adaptive capacity.

2. Approach and Methods

This study, aims to develop a methodology for the validation of LC classifications. This activity has developed two similar methodologies for semi-automatic LC classification, using two different satellite sources (Landsat and SPOT), with different resolutions. As shown in Figure 1, this is a preliminary step in order to assess LC fragmentation (which will be described in another working paper).

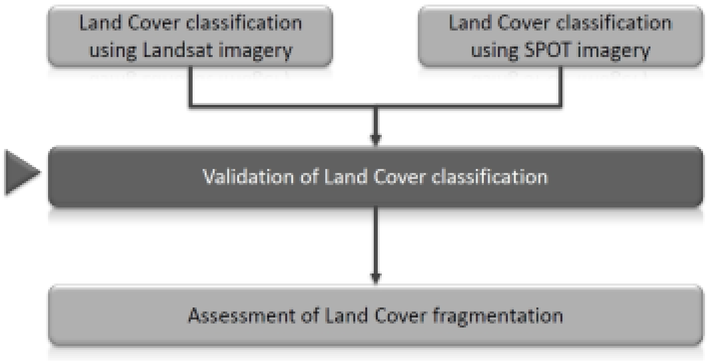

Figure 1: Developed methodologies of Activity 2.1; validation of LC classification

2.1 Overall Approach

LC monitoring is a planning need, which is useful to understand urbanization processes and their consequences on the environment; for example, the expansion of impervious areas (i.e. soil sealing) can lead to drainage problems, and consequently contribute to flooding issues (Swan, 2010).

Migration is one of the causes of LCC (DPU, 2005), but it is also a form of autonomous adaptation (and often the only one) to environmental change, especially for poor people, in order to reduce their exposure to hazards (FORESIGHT, 2011). In particular, migration in Dar is influenced by socio-economic factors, which lead to rapid urban growth (Kombe, 2005). Therefore, LC monitoring can provide useful information about the location of new settlements, and the trend of urbanization.

The relationship between LCC and environmental change can increase the exposure of population to environmental hazards (IPCC, 2001). Consequently, LCC can increase people vulnerability to CC, defined by IPCC (2001) as a function of:

- the sensitivity, that is “the degree to which a system will respond to a given change in climate, including beneficial and harmful effects”;
- the “exposure of the system to climatic hazards”;
- the adaptive capacity, that is “the degree to which adjustments in practices, processes, or structures can moderate or offset the potential for damage or take advantage of opportunities created by a given change in climate”.

However, LU changes can have stronger effects than CC has on some environmental issues, like water stress (Lioubimtseva & Henebry, 2009). For example, urban sprawl can be considered as an indicator of sensitivity to water shortage, because of the amount and variety of water uses in peri-urban areas (ESPON, 2011).

The overall research approach of this Activity is to provide useful and affordable tools for LCC monitoring to the planning services of Dar; the developed methodologies should allow for the adaptation of planning strategies to environmental change.

In particular, the developed methodologies rely on remote sensing and GIS techniques, which are useful for performing LC classifications and therefore for monitoring LCC. The requirements of developed methodology for the LC classification were:

- to be based on free or affordable data and software;
- to provide LC maps suitable for monitoring urban sprawl patterns.

In order to meet these requirements, free multispectral satellite images were acquired and analysed using image processing software, which allows for semi-automatic LC classifications.

The accuracy assessment of LC classifications is required in order to understand the reliability of any potential analysis using LC data. Moreover, the accuracy assessment can increase the quality of LC maps, by identifying the sources of errors (Congalton & Green, 2009).

This working paper describes the methodology developed to assess the accuracy of LC classifications. The assessment is performed through the comparison of LC classification to reference data, which represent the ground truth.

2.2 Data Collection and Analysis Methodology

This Activity has produced LC classifications using Landsat and SPOT images; this study has developed a methodology for assessing the classification accuracy.

The process of accuracy assessment is required in order to determine the quality of the created map; it is performed with the calculation of an error matrix, which is a table that allows for the comparison of classification data to ground truth data (Richards & Jia, 2006). For this purpose, it is convenient to define a number of sample units (selected in a random fashion) where the coherence between the thematic map (i.e. classification result) and reference data (i.e. ground truth) is calculated (Congalton & Green, 2009).

In this study, the LC classification maps for the year 2011, previously produced by this Activity, were used as main data; in particular, one map was derived from Landsat images, and one from SPOT images.

The reference data was obtained by the photo interpretation of several sample units, using the high resolution images available in Google Earth (that is free software developed by Google). That allowed for the comparison between the LC classifications and the photo interpretation, for each sample unit. Also, a field survey was performed in order to improve the photointerpretation process, and check its results.

In order to consider and compensate the cases where the classification rules represent artificial distinctions along a continuum of LC, a fuzzy approach was defined for the creation of the error matrices. For example, it is useful when, inside a sample unit, there is not a unique LC class, but two or more main classes. This can also remove some errors of photointerpretation (Congalton & Green, 2009).

Therefore, several statistics were calculated from the error matrices, in order to define the accuracy level of each classification.

3. Findings

3.1 Classification Accuracy

The accuracy of a LC classification is the measure of its quality, by assessing the coherence between the LC map and what is truly at ground. There are several ways to assess classification accuracy, which allow for the identification of sources of error and for the comparison of LC classification techniques (Congalton & Green, 2009).

The following paragraphs describe the methodology of LC accuracy assessment and the results of this methodology applied to the LC classification of Dar es Salaam.

3.1.1 Error Matrix

Classification accuracy is assessed by the coherence between the thematic map (i.e. classification result) and reference data (i.e. ground truth), for a defined number of sample units. Sample units should be selected in a random manner, if possible. Also, sample units can be a single pixel, a cluster of pixels, or a polygon, depending on the spatial resolution of LC classification and the minimum mapping unit thereof (Congalton & Green, 2009).

The reference data (i.e. definition of ground truth for the sample units) are produced by field survey, or by the photo interpretation of remote sensing images that have higher spatial resolution than LC maps.

It is convenient to create a table (an example is shown in Table 1), referred to as “error matrix” (or “confusion matrix”), where ground truth classes are in columns, and thematic maps classes are in rows (Richards & Jia, 2006). The samples that are correctly classified are located in the major diagonal of the matrix, while the other elements of the matrix are classification errors.

Table 1: Example of error matrix

	Ground truth 1	**Ground truth 2**	**…**	**Ground truth k**	**Total**
Class 1	a_{11}	a_{12}	…	a_{1k}	a_{1+}
Class 2	a_{21}	a_{22}	…	a_{2k}	a_{2+}
…	…	…	…	…	…
Class k	a_{k1}	a_{k2}	…	a_{kk}	a_{k+}
Total	a_{+1}	a_{+2}	…	a_{+k}	n

The example of Table 1 shows an error matrix where k is the number of LC classes identified in the map, and n is the total number of collected sample units. For each i row a number of samples (i.e. a_{1+}) is classified in the corresponding i class, which can be defined as (Congalton & Green, 2009):

$$a_{i+} = \sum_{j=1}^{k} a_{ij} \quad (1)$$

Similarly, for each j column, a number of samples (i.e. a_{+j}) is classified in the corresponding j class; this number can be calculated as:

$$a_{+j} = \sum_{i=1}^{k} a_{ij} \quad (2)$$

The overall accuracy of a LC classification is defined as the ratio between the number of samples that are correctly classified (which are in the major diagonal), and the total number of sample units (Congalton & Green, 2009):

$$overall\ accuracy = \frac{\sum_{i=1}^{k} a_{ii}}{n} \quad (3)$$

The number of sample units that are not in the major diagonal are classification errors. They can be differentiated in omission errors and commission errors. Omission errors refer to columns, and are the number of sample units belonging to the j class that were not recognized in the LC classification. Commission errors refer to rows, and are the number of sample units classified erroneously in the i class, but that belong to other LC classes in the reference data (Richards & Jia, 2006). "*Every error on the map is an omission from the correct category and a commission to an incorrect category*" (Congalton & Green, 2009, p. 17).

Therefore, in addition to the overall accuracy, other statistics can be calculated for the purpose of highlighting the accuracy of each class, such as user's accuracy and producer's accuracy.

User's accuracy assesses the number of samples correctly identified for the i class, divided the total number of samples classified as the same i class (Congalton & Green, 2009):

$$user's\ accuracy\ i = \frac{a_{ii}}{a_{i+}} \tag{4}$$

Producer's accuracy is calculated as the number of samples correctly identified for the j class, divided the total number of samples belonging to the same j class of the reference (Congalton & Green, 2009):

$$producer's\ accuracy\ j = \frac{a_{jj}}{a_{+j}} \tag{5}$$

A classification can be considered fairly good if user's accuracy and producer's accuracy are more than 70%, and very good if they are more than 90%.

Another statistic that can be calculated for assessing classification accuracy is K_{hat}. It is an estimate of the Kappa analysis, which is a discrete multivariate technique for comparing several error matrices (Congalton & Green, 2009).

K_{hat} can be expressed by the overall accuracy (i.e. p_o) and the "chance agreement" (i.e. p_c). The chance agreement is calculated by (Congalton & Green, 2009)

$$p_c = \sum_{i=1}^{k} p_{i+} p_{+i} \tag{6}$$

Where the equations of p_{i+} and p_{+j} for the row i and for the column j are expressed by:

$$p_{i+} = \sum_{j=1}^{k} p_{ij} \tag{7}$$

$$p_{+j} = \sum_{i=1}^{k} p_{ij} \tag{8}$$

And p_{ij} is the proportion of samples of the error matrix's ij cell, calculated by:

$$p_{ij} = \frac{a_{ij}}{n} \tag{9}$$

Therefore, K_{hat} is expressed by (Congalton & Green, 2009):

$$K_{hat} = \frac{p_o - p_c}{1 - p_c} = \frac{n \sum_{i=1}^{k} a_{ii} - \sum_{i=1}^{k} a_{i+} a_{+i}}{n^2 - \sum_{i=1}^{k} a_{i+} a_{+i}} \tag{10}$$

It is also possible to calculate the K_{hat} value for a specific i class (Congalton & Green, 2009):

$$K_{hat\ i} = \frac{n a_{ii} - a_{i+} a_{+i}}{n a_{i+} - a_{i+} a_{+i}} \tag{11}$$

A classification is considered moderately good if K_{hat} is between 0.4 and 0.8, and very good if K_{hat} is greater than 0.9 (Congalton & Green, 2009).

3.1.2 Fuzzy Error Matrix

The error matrix is the result of a deterministic accuracy assessment, where each sample unit can only belong to one class. In many cases, LC variability (for example due to seasonality) can be a source of error during accuracy assessment. In fact, the phenological state of vegetation changes considerably during the year (Helmer & Ruefenacht, 2007), and this can lead to different LC classifications.

Therefore, it can be useful to consider more than one acceptable classification for certain classes that suffer seasonal changes. This is useful when reference data is acquired in a different season than the one to which the LC classification refers. A set of rules is required to define what types of classes can have more than one acceptable classification (e.g. dense vegetation and sparse vegetation can be classified as the same class).

In particular, it is convenient to consider the LC class proportions for each sample unit (e.g. 60% of a sample unit is covered by the main LC class and 35% covered by the second LC class). Therefore, it is possible to set a threshold that defines the minimum area for the second class in order to be considered acceptable in the accuracy assessment (e.g. the second class is considered acceptable if its proportion is greater than 25% of the sample unit).

In order to consider that LC variability in the error matrix, it is possible to create a fuzzy error matrix. The fuzzy error matrix is a modification of the standard error matrix, previously described. As for the standard error matrix, the major diagonal contains the number of sample units that were correctly classified (agreement between classification and reference data) for each class.

However, each off-diagonal cell of the fuzzy matrix contains two values (differently from the off-diagonal cells of the standard error matrix, which contain only one value). The first of the two values represents the number of sample units that can be considered acceptable, while the second of the two values is the number of unacceptable sample units (i.e. the error) (Congalton, 2010).

Table 2 shows an example of fuzzy error matrix, where:

- a_{ii} are the number of sample units that are classified correctly;
- b_{ij} are the number of sample units that are considered classified correctly for the class i and the ground truth j;
- c_{ij} are the classification errors.

Table 2: Example of fuzzy error matrix

	Ground truth 1	Ground truth 2	…	Ground truth k	Total
Class 1	a_{11}	$(b_{12})(c_{12})$	...	$(b_{1k})(c_{1k})$	$a_{11}+b_{1+}+c_{1+}$
Class 2	$(b_{21})(c_{21})$	a_{22}	...	$(b_{2k})(c_{2k})$	$a_{22}+b_{2+}+c_{2+}$
…	...	...	...	...	...
Class k	$(b_{k1})(c_{k1})$	$(b_{k2})(c_{k2})$	...	a_{kk}	$a_{kk}+b_{k+}+c_{k+}$
Total	$a_{11}+b_{+1}+c_{+1}$	$a_{22}+b_{+2}+c_{+2}$	...	$a_{kk}+b_{+k}+c_{+k}$	n

Therefore, it is possible to calculate traditional accuracy statistics from the fuzzy error matrix (overall, user's and producer's accuracies) by considering the correct values reported in the major diagonal. In addition, fuzzy accuracy statistics can be calculated by adding the major diagonal value (a_{ii}) to the first numbers in the other cells (b_{ij}) (Congalton, 2010).

Hence, the equations 3, 4, and 5 become:

$$fuzzy\ overall\ accuracy = \frac{\sum_{i=1}^{k} a_{ii}+b_{i+}}{n} \tag{12}$$

$$fuzzy\ user\ accuracy\ i = \frac{a_{ii}+ b_{i+}}{a_{ii}+ b_{i+}+c_{i+}} \tag{13}$$

$$fuzzy\ producer\ accuracy\ j = \frac{a_{jj}+ b_{+j}}{a_{jj}+ b_{+j}+c_{+j}} \tag{14}$$

In this study, the fuzzy error matrix was calculated. In particular, a secondary class was considered acceptable if its proportion in the sample unit was greater than 25%. In addition, a set of combinations between primary and secondary class was defined. The secondary class is considered acceptable only if it belongs to one of the rules shown in Table 3.

Table 3: Combinations of classes considered acceptable in the fuzzy matrix

Primary Class	Secondary Class
Continuous Urban	Discontinuous Urban
Discontinuous Urban	Continuous Urban
Discontinuous Urban	Most Vegetation
Discontinuous Urban	Soil
Full Vegetation	Most Vegetation
Most Vegetation	Full Vegetation
Most Vegetation	Soil
Soil	Discontinuous Urban
Soil	Most Vegetation

3.2 Photo Interpretation of Reference Images

The photo interpretation of reference images is a required step in order to create the reference data for accuracy assessment of LC classifications. For this purpose, it is necessary to select the sample units, in a random fashion, all over the classification area.

In this study, a set of 500 points was selected randomly over the whole Dar es Salaam Region, using the ArcGIS tool: "Create Random Points". In particular, the location of the household questionnaire (performed in Activity 1.1 of this project) was considered during the random selection of points belonging to urban LC classes. That allowed for a better integration between the project activities, and in particular between the results of the LC classification and of the household questionnaire.

Therefore, the point selection was defined as:

- 100 points selected randomly inside the "Continuous Urban" class (according to the Landsat classification of 2011), among the points selected for the questionnaire performed in the Activity 1.1;
- 100 points selected randomly inside the "Discontinuous Urban" class (according to the Landsat classification of 2011), among the points selected for the questionnaire performed in the Activity 1.1;
- 100 points selected randomly inside the "Full Vegetation" class (according to the Landsat classification of 2011);
- 100 points selected randomly inside the "Most Vegetation" class (according to the Landsat classification of 2011);
- 100 points selected randomly inside the "Soil" class (according to the Landsat classification of 2011);
- No point was selected inside the "Water" class, because of its very little surface.

After the random selection, a buffer of 400m was created for every point; as such, the photo interpretation was performed inside each buffer, which represent the sample unit. The approach followed in this study is similar to the one used for the Corine Land Cover 2000 accuracy assessment (APAT, 2005) by ISPRA (ex-APAT, now the Italian National Institute for Environmental Protection and Research).

Google Earth (free software developed by Google) was used for the photo interpretation of the sample units; that software allows for the visualization of high resolution images acquired over Dar, in several years.

The sample units were exported to KML format (a GIS format that can be imported in Google Earth) using the ArcGIS tool "Layer to KML". That allowed for the visualization of the sample units in Google Earth, and therefore the photo interpretation of LC classes.

In ArcGIS, a polygon shapefile was created in order to manually draw the main classes. The primary class was the one with the greatest surface inside each buffer; a secondary class was considered if the buffer was not completely covered by the primary class.

For each class, one or more polygons were drawn inside the sample unit area, and for each polygon additional data was recorded. In particular, the attribute table contains the following fields:

- Identification code of the sample unit (which is useful during the accuracy calculation);
- Primary LC class;
- Secondary LC class;
- Latitude and longitude of the sample unit center;
- Date of the reference image (that is reported by Google Earth).

Figure 2 shows sample units, which were photo interpreted.

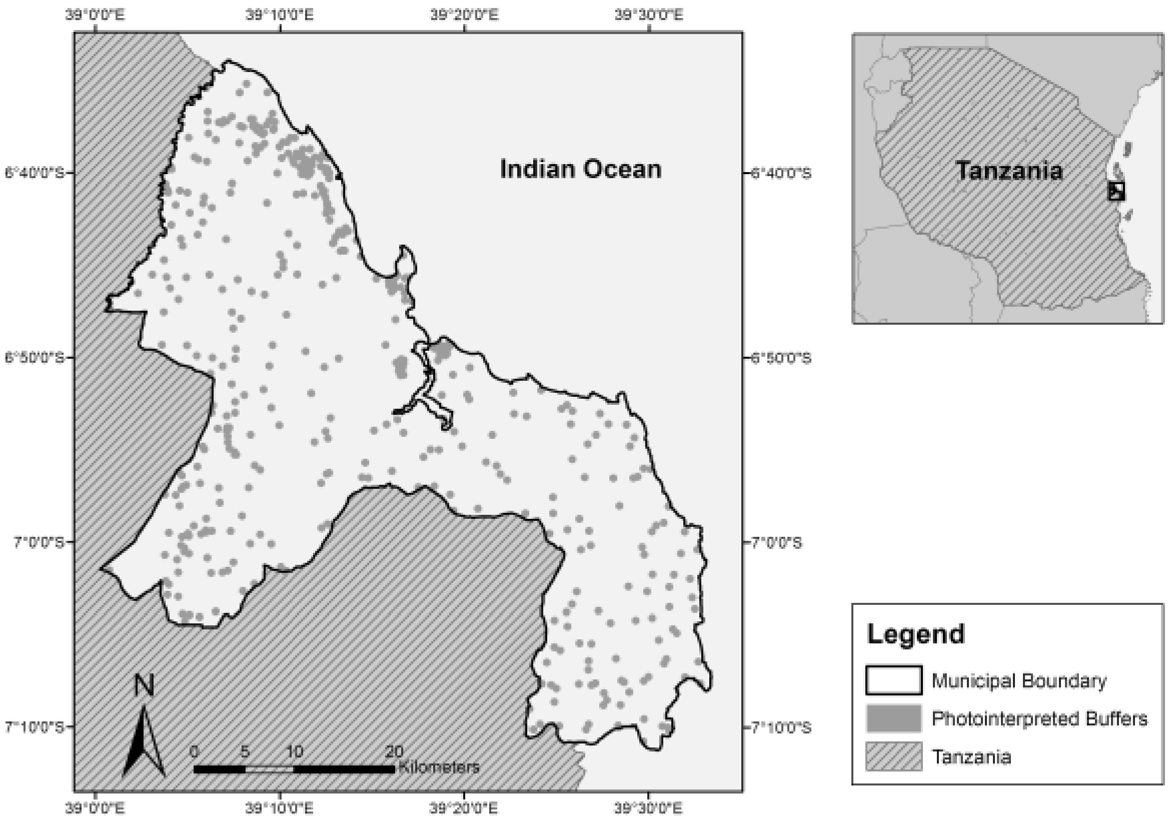

Figure 2: The location of the sample units that were photo interpreted

3.3 Field Survey

A field survey is necessary in order to improve and check the photo interpretation process. In fact, the field survey is useful for the refinement of the polygons drawn during the photo interpretation process. The file survey can be performed by reaching the location of each sample unit, or of a subset of sample units.

For this purpose, a subset of 20 points for each LC class was selected from among the 100 previously defined. In order to reduce the logistic problems of the field survey, which had to be performed in a very large area such as Dar es Salaam, a criterion of road proximity was defined for the point selection. The points were selected using the ArcGIS tools “Proximity” for measuring the distance between each point and the road network, and therefore choosing the 20 points that have the lowest distance from roads.

During the field survey, all the selected points have to be visited with the help of a GPS, and 4 pictures for each point have to be taken in all 4 cardinal directions. These pictures allow for the documentation, and the creation of a database, which is useful for the visual comparison of the photo interpretation and field data.

3.4 Results

3.4.1 Accuracy of Landsat LC classification

In this paragraph, the accuracy assessment of the LC classification (based on Landsat images) of 2011 is reported. The cloud cover limited the photo interpretation of the 500 sample units selected randomly. In particular, the assessment was performed comparing the classification to 465 sample units.

An example of a sample unit that was photo interpreted is shown in Figure 9.

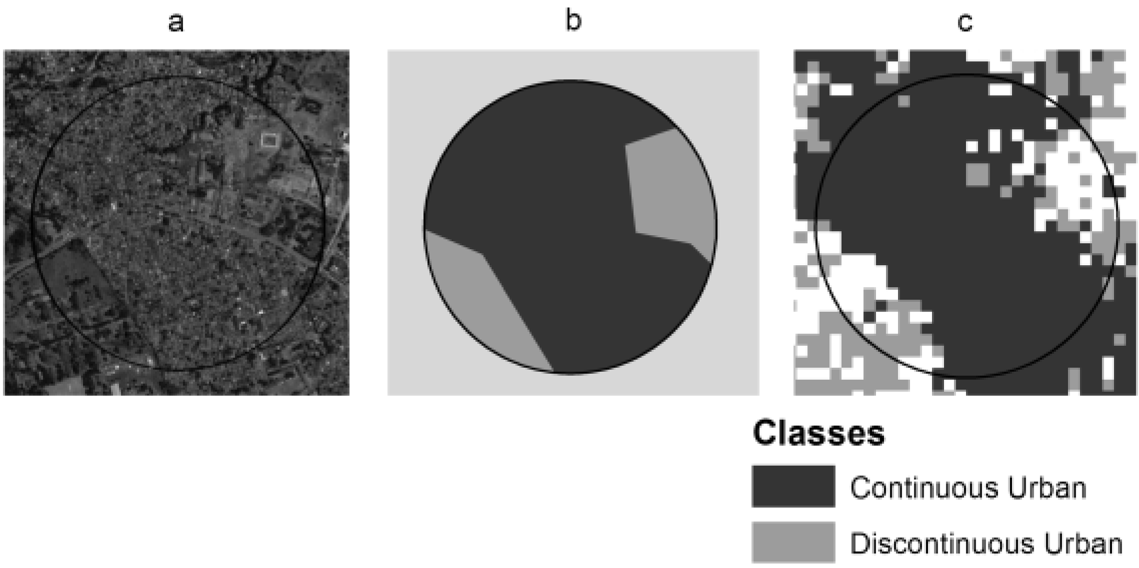

Figure 3: (a) Example of a sample unit over a Google Earth image; (b) the photo interpretation of the sample unit; (c) the Landsat LC classification

The Table 4 shows the fuzzy error matrix that was calculated for the LC classification.

Table 4: Fuzzy error matrix calculated for the LC classification based on Landsat images of 2011

		Reference Data					
		Continuous Urban	*Discontinuous Urban*	*Full Vegetation*	*Most Vegetation*	*Soil*	*Total*
Classification	*Continuous Urban*	93	(4)(2)	(0)(0)	(0)(0)	(0)(0)	99
	Discontinuous Urban	(1)(2)	81	(0)(0)	(3)(1)	(3)(0)	91
	Full Vegetation	(0)(0)	(0)(0)	29	(5)(7)	(0)(3)	44
	Most Vegetation	(0)(0)	(0)(0)	(3)(4)	56	(6)(16)	85
	Soil	(0)(5)	(2)(32)	(0)(3)	(2)(55)	47	146
	Total	101	121	39	129	75	465

The overall accuracy of the LC classification is:

- Overall Accuracy = 306/465 = 65.8%

The overall accuracy is quite low; however the main objective of the LC classification was the identification of urban classes, therefore it is useful to calculate the user's and producer's accuracies.
Following, the statistics obtained from the deterministic error matrix are listed in Table 5, and a chart is shown in Figure 4.

Table 5: The accuracies of user and producer

Class	**User's accuracy** [%]	**Producer's accuracy** [%]
Continuous Urban	93.9	92.1
Discontinuous Urban	89.0	66.9
Full Vegetation	65.9	74.4
Most Vegetation	65.9	43.4
Soil	32.2	62.7

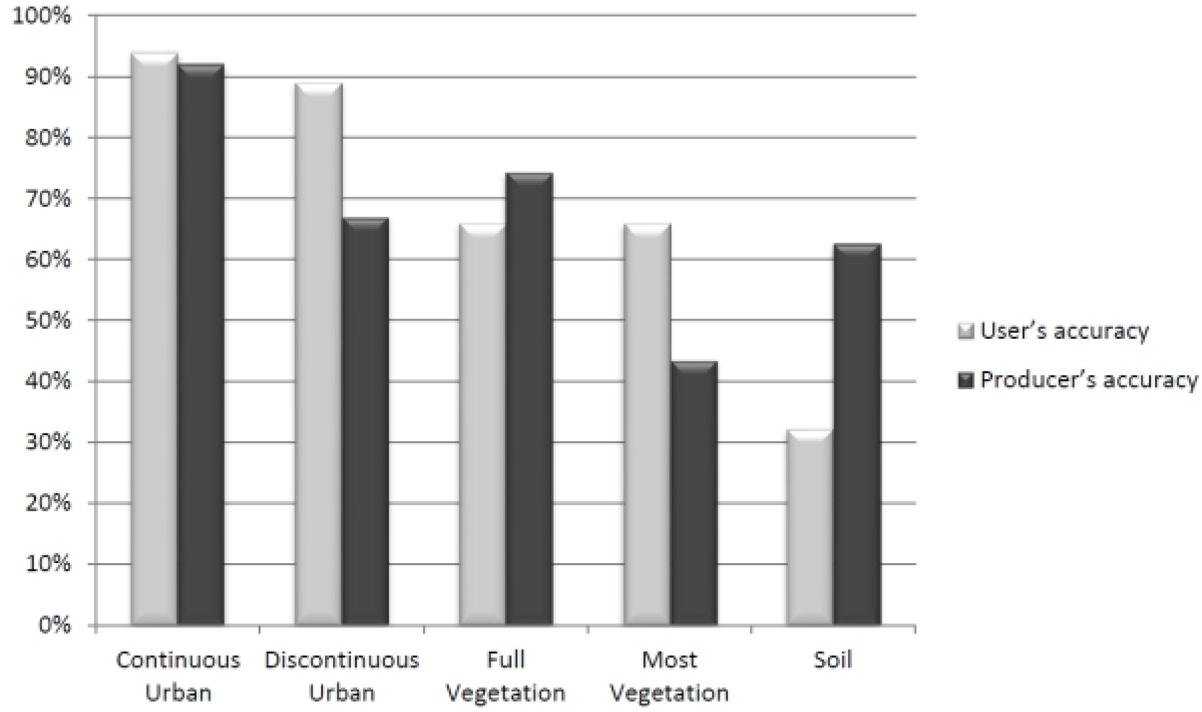

Figure 4: Chart of the accuracies of user and producer

The user's and producer's accuracies indicate that the overall accuracy is highly influenced by the poor identification of "Soil" and "Most Vegetation" classes. Nevertheless, the user's and producer's accuracies of "Continuous Urban" class are very good (i.e. over 90%). Also, the user's accuracy of the "Discontinuous Urban" class is quite good (i.e. 89.0%), while its producer's accuracy is slightly lower than good (i.e. 66.9%).
The Kappa statistic of the error matrix is:

- K_{hat} = 0.57

As for the overall accuracy, the K_{hat} is quite low. Following, the Kappa statistics, calculated for each LC class, are reported in Table 6.

Table 6: Kappa statistics for each LC class

Class	K_{hat}
Continuous Urban	0.92
Discontinuous Urban	0.85
Full Vegetation	0.63
Most Vegetation	0.53
Soil	0.19

The Kappa statistics summarize the results obtained for the user's and producer's accuracies; the identification of the "Continuous Urban" class is very good (K_{hat} = 0.92) and also the identification of the "Discontinuous Urban" class is good (K_{hat} = 0.85). The vegetation classes have a quite good accuracy, while the "Soil" class has a very low K_{hat} value. Obviously, the LC classification error is driven by the similarity between endmembers.

However, for a better assessment of LC accuracy, the fuzzy statistics were also calculated. The fuzzy overall accuracy of the error matrix is:

- Fuzzy Overall Accuracy = 72.0%

Therefore, considering the sample units where the secondary class has a considerable presence, the overall accuracy was increased from 65.8% to 72.0%.

Following, the statistics obtained from the fuzzy error matrix are shown in Table 7, and a chart is shown in Figure 5.

Table 7: The fuzzy accuracies of user and producer

Class	**User's Accuracy** [%]	**Producer's Accuracy** [%]
Continuous Urban	98.0	93.1
Discontinuous Urban	96.7	71.9
Full Vegetation	77.3	82.1
Most Vegetation	76.5	51.2
Soil	34.9	74.7

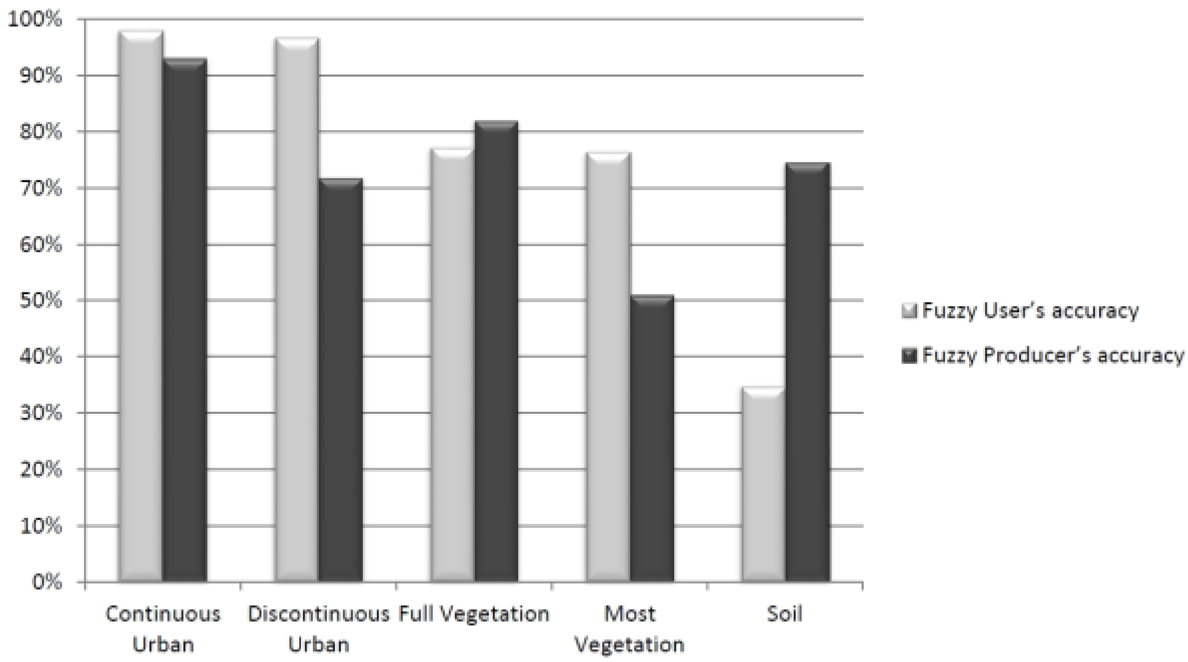

Figure 5: Chart of the fuzzy accuracies of user and producer

The fuzzy statistics show a very high accuracy for the "Continuous Urban" class and high accuracy for the "Discontinuous Urban" class, although its producer's accuracy (71.9%) is considerably lower than its user's accuracy (i.e. 96.7%) Moreover, the fuzzy assessment has increased all the accuracy values, also for the vegetation and soil classes.

However, LC classifications rely on the seasonality of acquired images. In particular, the accuracy assessment is highly influenced by seasonality if the LC classification and reference data are acquired in different times.

In order to cover the whole area of Dar es Salaam, the photo interpretation was performed using all the available images, which were acquired in the years 2001, 2004, 2005, 2006, 2007, 2008, 2009, 2010, and 2011. Obviously, the use of old images affects the accuracy assessment, especially for those classes that change rapidly, such as the “Discontinuous Urban”. For this reason, a filter was created in order to only select the sample units belonging to reference images acquired between 2010 and 2011 (a sufficiently narrow range of time, in order to assess the LC classification of 2011). Applying this temporal filter, the fuzzy error matrix was calculated for the remaining 373 sample units.

Table 8 shows the fuzzy error matrix calculated for the LC classification of 2011.

Table 8: Fuzzy matrix calculated for the LC classification of 2011 (using limited reference images)

		Reference Data					
		Continuous Urban	*Discontinuous Urban*	*Full Vegetation*	*Most Vegetation*	*Soil*	*Total*
Classification	*Continuous Urban*	93	(4)(2)	(0)(0)	(0)(0)	(0)(0)	99
	Discontinuous Urban	(1)(2)	75	(0)(0)	(3)(0)	(0)(0)	81
	Full Vegetation	(0)(0)	(0)(0)	20	(5)(6)	(0)(2)	33
	Most Vegetation	(0)(0)	(0)(0)	(2)(3)	44	(1)(8)	58
	Soil	(0)(5)	(1)(31)	(0)(2)	(2)(49)	12	102
	Total	101	113	27	109	23	373

The overall accuracy of the new error matrix is:

- Overall Accuracy = 244/373 = 65.4%

The new overall accuracy (i.e. 65.4%) is quite similar to the one calculated for the previous error matrix (i.e. 65.8%), therefore there is no general improvement.

The statistics obtained from the deterministic error matrix are shown in

Table 9, and in the chart of Figure 6.

Table 9: The accuracies of user and producer (using limited reference images)

Class	User's accuracy [%]	Producer's accuracy [%]
Continuous Urban	93.9	92.1
Discontinuous Urban	92.6	66.4
Full Vegetation	60.6	74.1
Most Vegetation	75.9	40.4
Soil	11.8	52.2

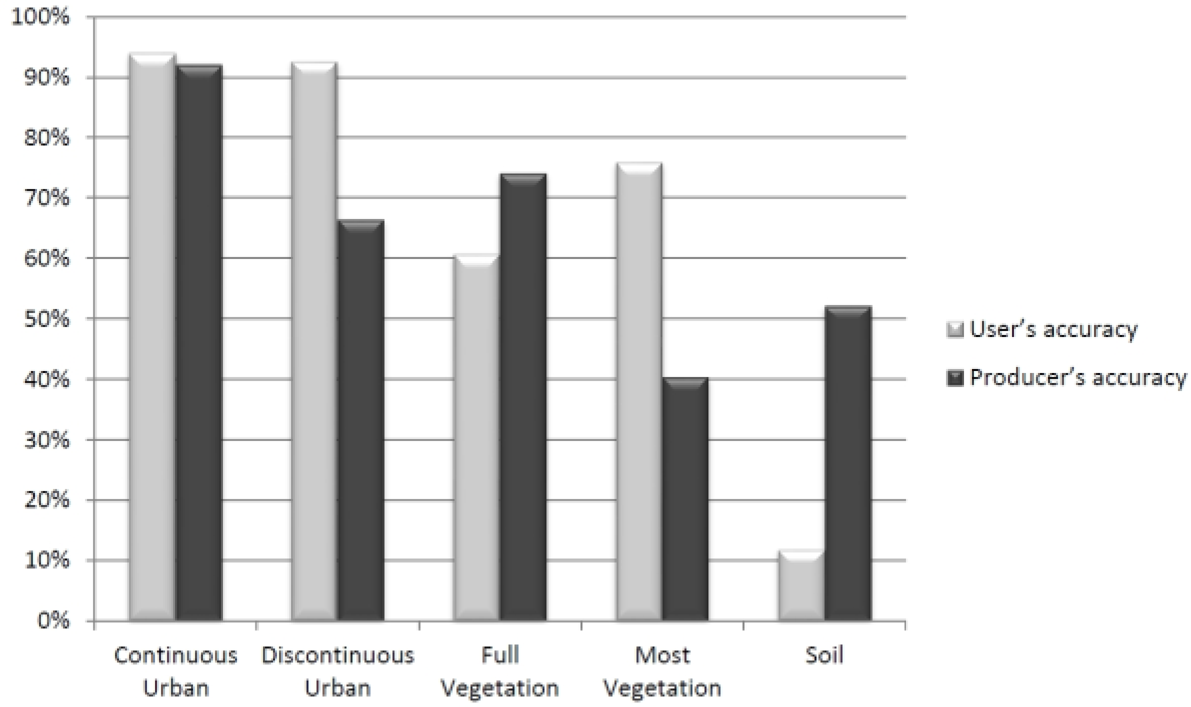

Figure 6: Chart of the accuracies of user and producer (using limited reference images)

The new user's and producer's accuracies are similar to the ones calculated for the previous error matrix. The "Continuous Urban" class has exactly the same values for accuracies of user (i.e 93.9%) and producer (92.1%). The "Discontinuous Urban" class has the user's accuracy increased from 89.0% to 92.6%, while has the producer's accuracy lightly decreased (from 66.9% to 66.4%).

Therefore, it is useful to calculate the Kappa statistics for the new error matrix, as following described:

- K_{hat} = 0.56

K_{hat} has almost the same value (from 0.57 to 0.56). The Kappa statistics, calculated for each LC class, are reported in Table 10.

Table 10: Kappa statistics for each LC class (using limited reference images)

Class	K_{hat}
Continuous Urban	0.92
Discontinuous Urban	0.89
Full Vegetation	0.58
Most Vegetation	0.66
Soil	0.06

The K_{hat} calculated for the urban classes reflects the considerations derived from the user's and producer's accuracies. The K_{hat} of the "Continuous Urban" class is the same of the previous error matrix, while the K_{hat} calculated for the "Discontinuous Urban" class has slightly increased (from 0.85 to 0.89).

For the new matrix, the fuzzy overall accuracy was also calculated:

- Fuzzy Overall Accuracy = 70.5%

Following, the statistics obtained from the fuzzy error matrix are shown in Table 11, and a chart is shown in Figure 7.

Table 11: The fuzzy accuracies of user and producer (using limited reference images)

Class	**User's accuracy** [%]	**Producer's accuracy** [%]
Continuous Urban	98.0	93.1
Discontinuous Urban	97.5	70.8
Full Vegetation	75.8	81.5
Most Vegetation	81.0	49.5
Soil	14.7	56.5

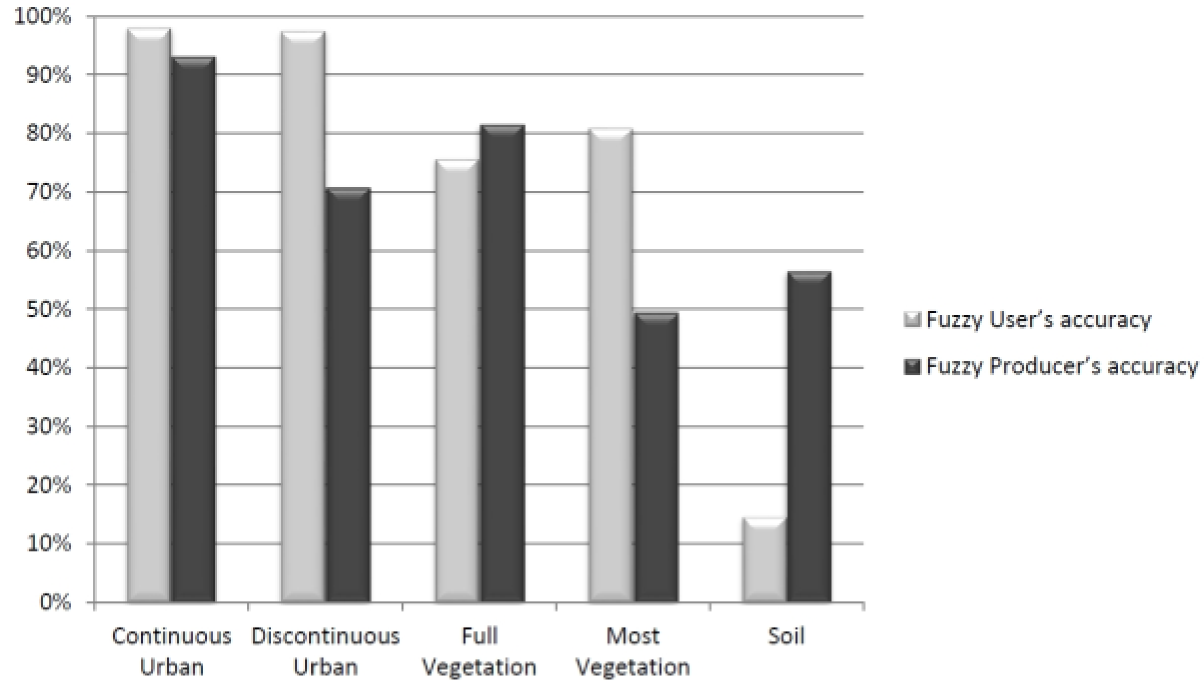

Figure 7: Chart of the fuzzy accuracies of user and producer (using limited reference images)

The fuzzy accuracies are higher than the respective deterministic accuracies. However, there is no improvement compared to the fuzzy accuracies calculated for the previous error matrix (i.e. using all the available images). Therefore, the limitation to the sample units, belonging to reference images acquired between 2010 and 2011, does not affect positively the accuracy assessment, mainly because the reference images are concentrated over the centre of Dar. Moreover, limiting the number of sample units affects the statistic reliability of the error matrix. In this case, it is preferable to use all the sample units available, without limitations to the acquisition year of reference images.

Another main issue of the accuracy assessment is the seasonality, which can lead to considerable variations of the vegetated surfaces (e.g. vegetation changes to soil and vice versa), as shown in Figure 8. This issue has been partially addresses using the fuzzy error matrix. The ideal solution would be the use of reference images acquired in the same season of the LC classification time; however, it is difficult to obtain such images, because of the limited availability of data over Dar es Salaam.

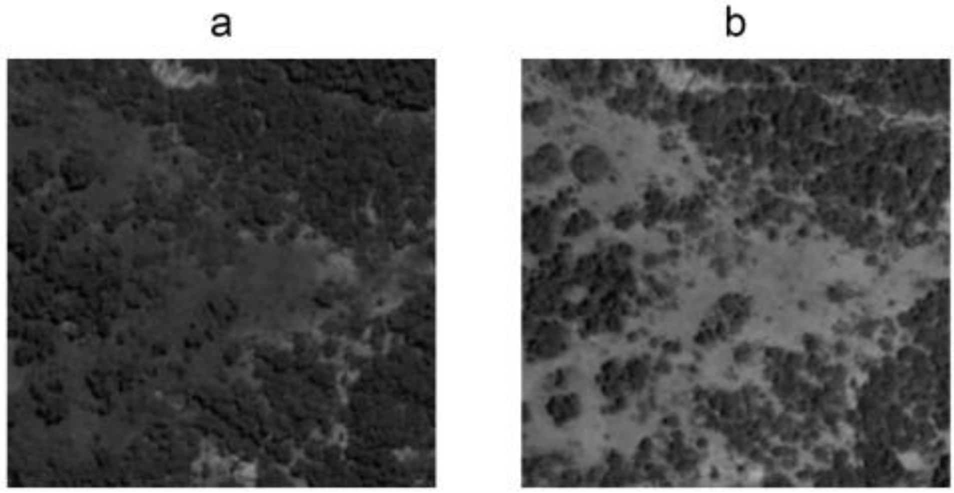

Figure 8: Example of seasonal variation of the vegetated surfaces; (a) an image from Google Earth acquired on 11/06/2010; (b) an image from Google Earth acquired on 05/02/2011, where brighter areas are soil

3.4.2 Accuracy of SPOT LC classification

The accuracy assessment of the LC classification (based on SPOT images) of 2011 is reported in this paragraph. The assessment was performed using the same sample units, selected randomly, which were photo interpreted for the accuracy assessment of the Landsat LC classification.

Nevertheless, the SPOT classification does not cover the whole Dar es Salaam (i.e. without the Temeke District), therefore a subset of sample units was selected, resulting in 325 sample units which are inside the classified area.

An example of the photo interpretation and the accuracy assessment process is shown in Figure 9; the Table 12 shows the fuzzy error matrix that calculated for the LC classification.

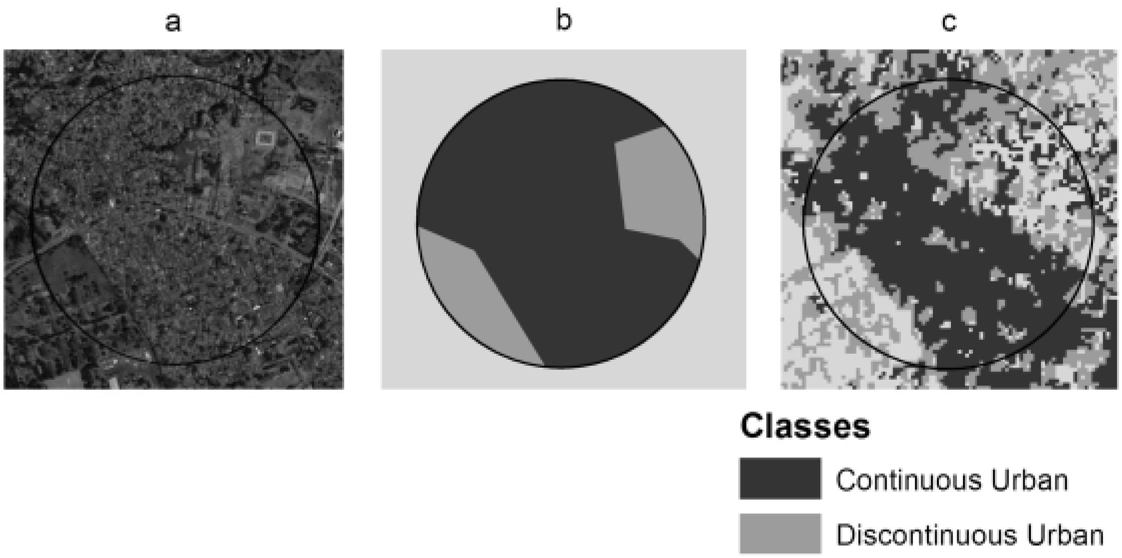

Figure 9: (a) Example of a buffer over a Google Earth image; (b) the photo interpretation of the buffer; (c) the LC classification of SPOT images

Table 12: Fuzzy error matrix calculated for the LC classification based on SPOT images of 2011

		Reference Data					
		Continuous Urban	*Discontinuous Urban*	*Full Vegetation*	*Most Vegetation*	*Soil*	*Total*
Classification	*Continuous Urban*	76	(0)(0)	(0)(0)	(0)(0)	(0)(0)	76
	Discontinuous Urban	(3)(8)	56	(0)(0)	(0)(0)	(0)(0)	67
	Full Vegetation	(0)(0)	(0)(0)	12	(0)(0)	(0)(0)	12
	Most Vegetation	(0)(0)	(15)(9)	(0)(6)	79	(2)(10)	121
	Soil	(0)(2)	(4)(24)	(0)(1)	(3)(6)	9	49
	Total	89	108	19	88	21	325

The overall accuracy of the LC classification is:

- Overall Accuracy = 232/325 = 71.4%

The overall accuracy is quite good; however, it is fundamental to calculate the statistics for the singular classes. These statistics calculated from the deterministic error matrix are shown in Table 13 and in the chart of Figure 10.

Table 13: The accuracies of user and producer

Class	**User's accuracy** [%]	**Producer's accuracy** [%]
Continuous Urban	100.0	85.4
Discontinuous Urban	83.6	51.9
Full Vegetation	100.0	63.2
Most Vegetation	65.3	89.8
Soil	18.4	42.9

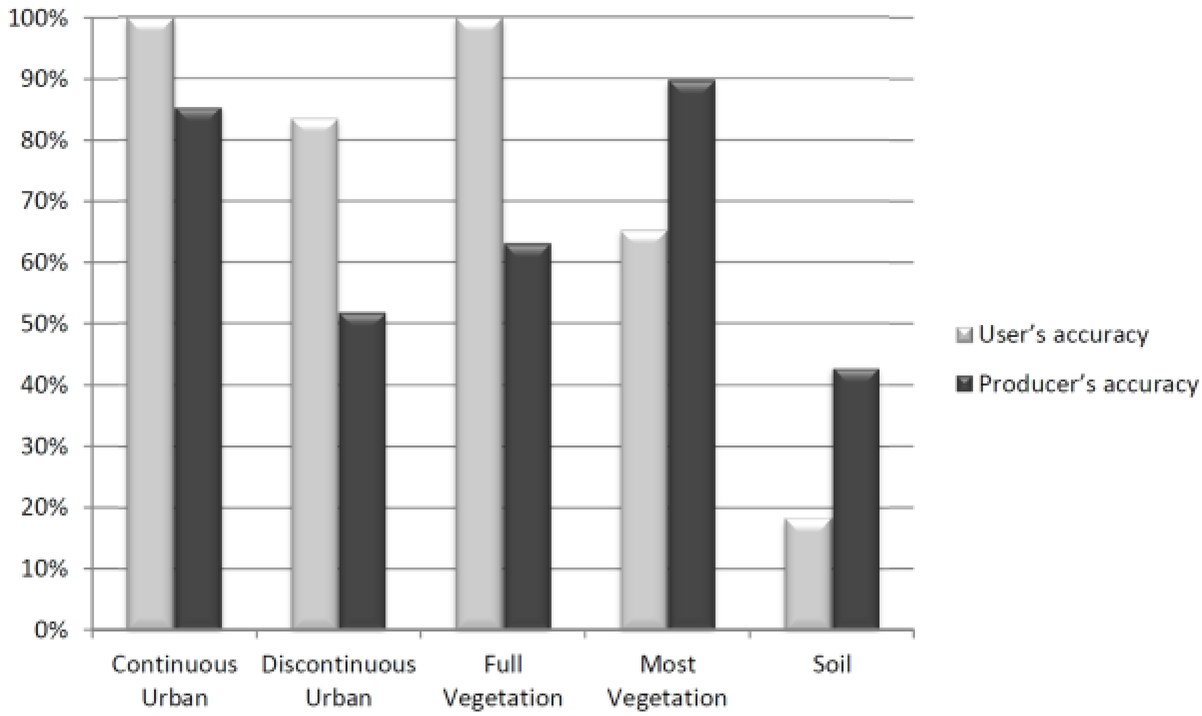

Figure 10: Chart of the accuracies of user and producer

The user's and producer's accuracies of the "Continuous Urban" class are very good; the "Discontinuous Urban" class has good user's accuracy (i.e. 83.6%), while the producer's accuracy is quite low (i.e. 51.9%). Fairly good results are for the vegetation classes, while the "Soil" has very low values of accuracy.

It is useful to calculate the Kappa statistic for the error matrix, which is:

- K_{hat} = 0.62

The Kappa statistics calculated for each LC class are reported in Table 14.

Table 14: Kappa statistics for each LC class

Class	K_{hat}
Continuous Urban	1.00
Discontinuous Urban	0.75
Full Vegetation	1.00
Most Vegetation	0.52
Soil	0.13

The K_{hat} of "Continuous Urban" and "Full Vegetation" classes show perfect agreement between the LC classification and the ground truth. The "Discontinuous Urban" class has a good value of K_{hat}.

Considering the fuzzy error matrix, the overall accuracy is:

- Fuzzy Overall Accuracy = 80.3%

Therefore, the fuzzy error matrix has increased considerably the overall accuracy (from 71.4% to

80.3%). The statistics obtained from the fuzzy error matrix are shown in Table 15 and in the chart of Figure 11.

Table 15: The fuzzy accuracies of user and producer

Class	User's accuracy [%]	Producer's accuracy [%]
Continuous Urban	100.0	88.8
Discontinuous Urban	88.1	69.4
Full Vegetation	100.0	78.9
Most Vegetation	79.3	93.2
Soil	32.7	52.4

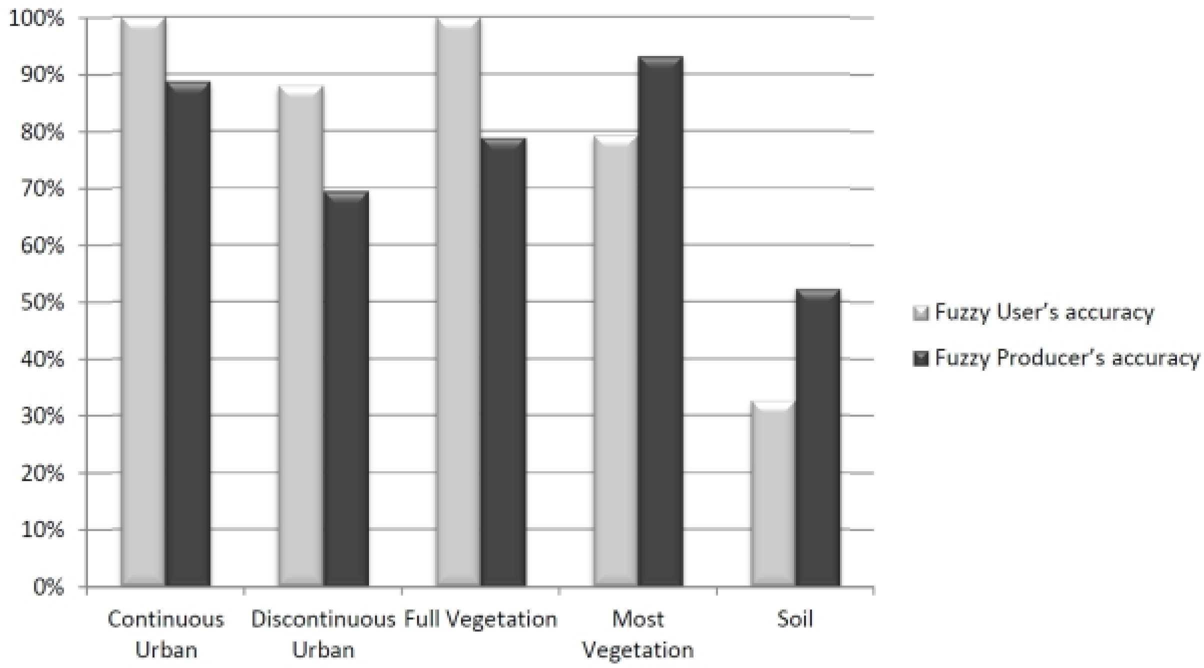

Figure 11: Chart of the fuzzy accuracies of user and producer

The "Continuous Urban" class has very high values of the user's and producer's accuracy; the "Discontinuous Urban" class has improved its accuracies, especially the user's one that increased from 51.9% to 69.4%. For the vegetation classes there is also a good agreement with the ground truth. The "Soil" is the class with most critique values of accuracy, in particular because of the spectral confusion with the "Discontinuous Urban" class.

The low spectral resolution (i.e. 4 bands) of SPOT images makes very difficult the distinction between the "Discontinuous Urban" and "Soil" classes; at the same time, the high spatial resolution (i.e. 10m) allows for very good identification of spectrally defined classes like "Continuous Urban" and "Full Vegetation".

3.4.3 Field Survey

A total of 100 points (which are the centre of 100 sample units) were selected for the field survey, as shown in Figure 12.

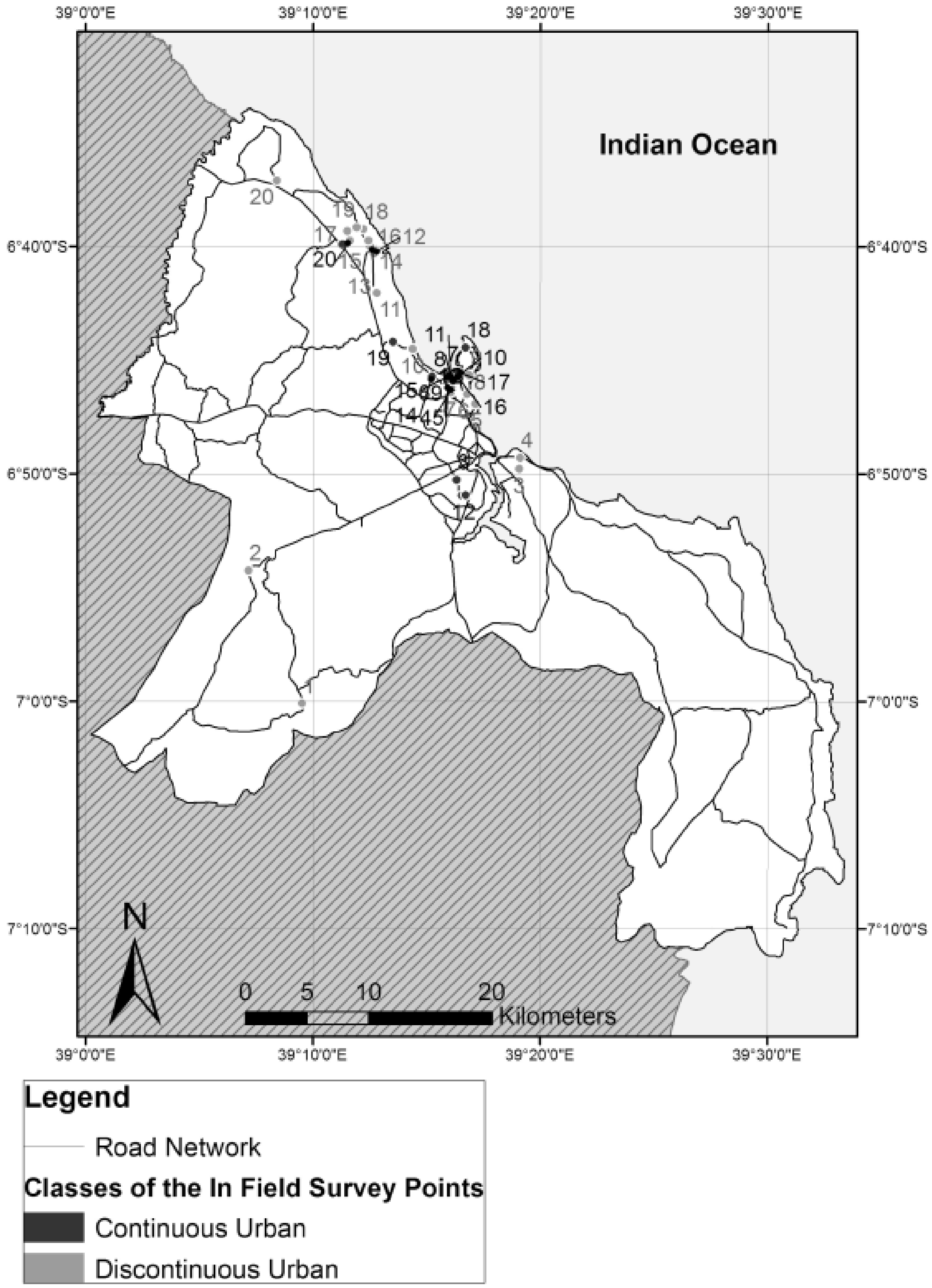

Figure 12: Points selected for the field survey, for the urban classes of LC

The field survey took place from 24th March 2012 to 6st May 2012. The points were reached with the help of a GPS, and 4 images were taken in all 4 cardinal directions. The photo interpretation was therefore compared to the field survey, and in some cases the drawn polygons were modified accordingly.

Because of logistic problems, 17 points were not visited, as reported in Table 16.

Table 16: List of points not visited during the field survey

Temeke	Kinondoni	Ilala
Full Vegetation 11	Full Vegetation 2	Full Vegetation 5
Full Vegetation 13	Full Vegetation 9	Full Vegetation 6
Full Vegetation 14	Most Vegetation 5	Most Vegetation 4
Full Vegetation 15	Soil 6	
Full Vegetation 19	Soil 15	
Most Vegetation 3	Soil 18	
Most Vegetation 16		
Most Vegetation 20		

Some points were reached but it was not possible to take the pictures in all cardinal directions, because of logistic problems. Those points are following described:

- “Continuous Urban 1” and “Continuous Urban 2”, are inside a local police area, where photography is forbidden;
- “Soil 2” is inside a military area, where access is restricted;
- “Full Vegetation 8” is near the estuary of Msimbazi river, where the dense vegetation limits the accessibility;
- “Full Vegetation 1”, “Full Vegetation 17” and “Soil 5” are inside a natural reserve , where access is restricted;
- “Discontinuous Urban 8” is in front of an embassy where photography is forbidden.

The field survey produced a database of photos. The documentation for the points belonging to the “Continuous Urban” and “Discontinuous Urban” classes are reported in “Appendix 2 – Field Survey”.

4. Conclusions and Recommendations

Following, the conclusions derived from this study and the recommendations on the future steps of the project implementation are described.

4.1 Conclusions

This study is part of the Activity 2.1 of the ACC Dar project, which aims to improve the Dar City Council's planning services in understanding LC patterns.

The Activity developed two similar methodologies for monitoring changes in peri-urban settlements, based on remote sensing and GIS techniques, which meet the following requirements for the LC map production:

- to be very affordable, in order to be suitable to needs and resources of Dar's municipalities;
- to be rapid and easy to update, for the purpose of keeping pace with the growth of the city.

In particular, those methodologies for LC classification are described in the following working papers:

- "Development of a Methodology for Land Cover Classification in Dar es Salaam using Landsat Imagery";
- "Development of a Methodology for Land Cover Classification in Dar es Salaam using SPOT Imagery".

In order to assess LCC and urban sprawl evolution, several LC classifications of Dar es Salaam were produced by this Activity:

- Landsat based (for the years 2002, 2004, 2007, 2009 and 2011);
- SPOT based (for the year 2011).

Landsat images have coarse spatial resolution (i.e. 30m) but medium spectral resolution (i.e. 7 bands). SPOT images have medium spatial resolution (i.e. 10m) but low spectral resolution (i.e. 4 bands). However, those images are provided for free by the USGS and the ESA respectively; therefore they allowed for very affordable LC classifications.

The accuracy assessment of a LC classification is a required step for the monitoring process; in fact, it is the measure of the classification quality, and therefore a measure of LC monitoring reliability.

In this paper, the accuracy assessment was performed for the LC classifications produced using Landsat and SPOT images of 2011. The accuracy was performed through the calculation of error matrices, which allow for the valuation of statistics for every LC class. The error matrices are created comparing the classification to reference data. A total of 500 sample units were selected randomly, which were photo interpreted using high resolution images (freely available from Google Earth software, developed by Google). In addition, a field survey allowed for the refinement of the photo interpretation process, and the creation of a photographic database of 100 sample units.

The error matrices allowed for the calculation of several statistics like: the overall accuracy; the user's and producer's accuracies, for every LC class; the K statistics. Also, a fuzzy error matrix was calculated, for the purpose of considering the presence of secondary classes in the sample units, and therefore improving the accuracy assessment, especially where there is a mix of LC classes.

Considering the Landsat classification, the results of the fuzzy error matrix are significantly better than the deterministic matrix, especially for the urban classes: the "Continuous Urban" class indicates very high values of accuracy; the "Discontinuous Urban" class demonstrates high values of user's accuracy (i.e. 96.7%), although its producer's accuracy is fairly good (i.e. 71.9%).

In a similar fashion, the fuzzy error matrix improved the results for the SPOT classification: the "Continuous Urban" class has very high values of the user's and producer's accuracy; the "Discontinuous Urban" class has good user's accuracy (i.e. 88.1%) and almost good producer's accuracy (i.e. 69.4%). The main cause of this low accuracy is the spectral confusion between the "Discontinuous Urban" class and the "Soil" class. In fact, the low spectral resolution of SPOT images makes very difficult the distinction between spectrally similar classes; at the same time, their high spatial resolution allows for very good identification of spectrally defined classes like "Continuous Urban" and "Full Vegetation".

For the Landsat classification, an error matrix was calculated using limited reference images (which were acquired recently, in 2010 or 2011), with the purpose of a better accuracy assessment. Nevertheless, the accuracies obtained limiting the reference images were very similar to the accuracies obtained using all the images. The lack of improvement in the accuracy is due mainly to the concentration of the reference images acquired over the centre of Dar es Salaam, therefore missing the peri-urban areas that are characterized by new urbanization.

The field survey confirmed the reliability of the photo interpretation, and allowed for the creation of a photographic database, which is a product of value per se.

Considering the objectives of this Activity, and the target of the produced LC classifications (i.e. urban classes, and their evolution), the image availability (SPOT images are heavily affected by cloud cover), and the classification accuracy assessment, then: Landsat classifications , despite the lower spatial resolution thereof, are more suitable than SPOT ones.

Nevertheless, the results of SPOT classification (i.e. very good for the "Continuous Urban" class, and fairly good for the "Discontinuous Urban" class) suggest that SPOT images could be used for detailed studies, in areas of particular interest.

4.2 Recommendations

The accuracy assessment highlighted the seasonal variability of the vegetated LC classes. Because of the spectral confusion between "Soil" and "Discontinuous Urban" classes, the LC classification should be performed using images acquired when vegetation is in its maximum growing season; in this season the surfaces that are covered by bare soil are at their minimum, and therefore the spectral confusion should be limited.

Another main issue, highlighted by the accuracy assessment, is that the photo interpretation should be performed using high resolution images acquired at the same time of the acquisition of the LC classification image.

This methodology can assess the accuracy of the LC maps produced by this activity; however, the accuracy assessment methodology could be adapted in the near future to use new high resolution images that become available, for example from the European programme "Global Monitoring for Environment and Security" (GMES), for the purpose of improving the photo interpretation process.

In addition, the field survey could be performed cyclically (for example once a year) by the Dar's planning services, in order to create a database of ground truth data which will be useful for the future LC classifications.

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Appendix 1 – Land Cover Classifications

This Appendix contains the figure representing the LC classification of Dar es Salaam for the year 2011, derived from Landsat and SPOT images. Also the main characteristics of the semi-automatic classification process are described.

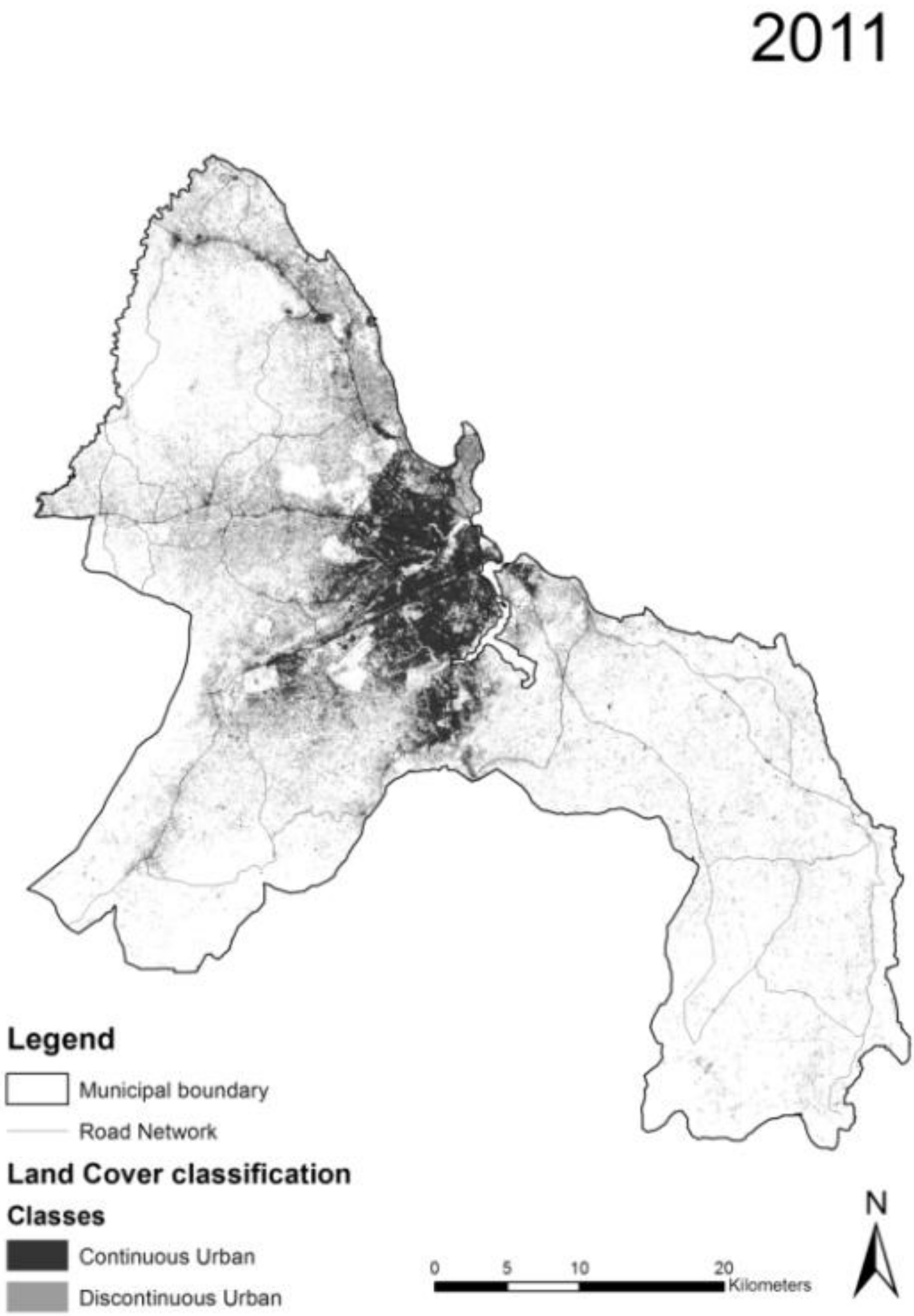

Figure 13: Land Cover classification of Landsat images for year 2011

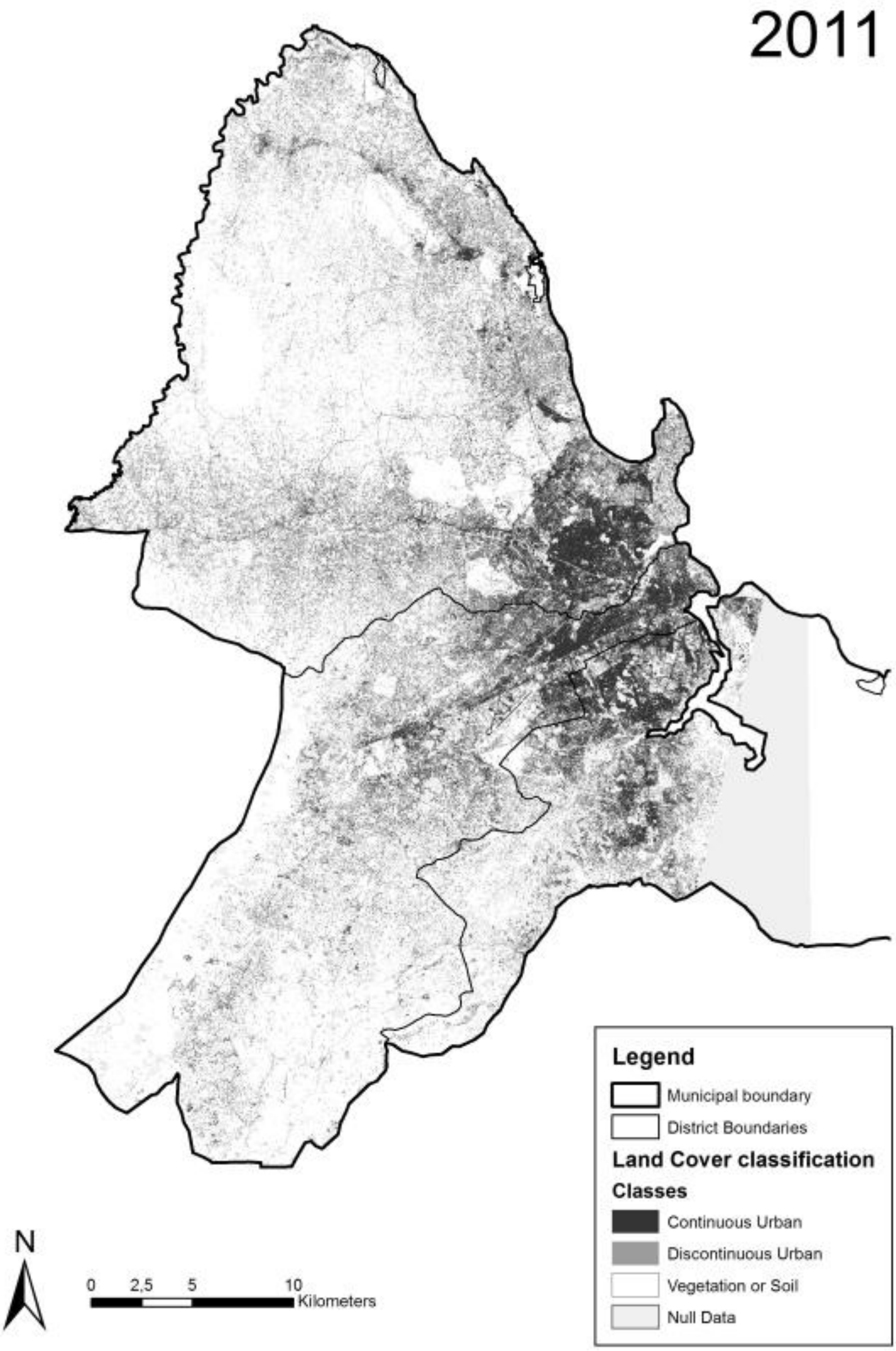

Figure 14: Land Cover classification of SPOT images for year 2011

Semi-Automatic Classification Process

The Landsat LC classifications were produced with a semi-automatic process, which is described in detail in the working paper "Development of a Methodology for Land Cover Classification in Dar es Salaam using Landsat Imagery"; a similar process applied to SPOT images is described in the working paper "Development of a Methodology for Land Cover Classification in Dar es Salaam using SPOT Imagery".

The main steps of that process are the following:

a) Image selection;
b) Preprocessing:
   1. Georeferencing images in order to assign spatial coordinates to pixels;
   2. Creating masks of clouds and shadows, and applying those masks to the bands of the images, in order to exclude pixels belonging to clouds or shadows from LC classification;
   3. Converting the multispectral bands from DN to reflectance, applying atmospheric correction;
   4. Mosaicking temporally different images, in order to obtain a cloud-free and gap-free image;
c) Processing:
   1. Classifying the image mosaic with Maximum Likelihood (ML) algorithm;
   2. Elaborating vegetation indices (in particular NDVI), which are useful for classifying vegetation;
   3. Classifying the ML classification and the vegetation indices through a Knowledge-Base classification.

The ML algorithm is one of the most used supervised classifiers; it assumes that the probability distributions for the classes are of the form of multivariate normal models (Richards & Jia, 2006). An adequate number of training areas (which represent the LC classes that are already known) are required to be input in the image, for the purpose of creating as many spectral signatures. Therefore, the ML algorithm uses the Gaussian threshold stored in each class signature to assign every pixel a class (Huang, et al., 2009).

A total of 6 classes were classified for each image:

- "Continuous Urban", a very dense urbanization class;
- "Discontinuous Urban", a low density urbanization class, characterized by a mixed pixel of urban and vegetation or soil;
- "Full Vegetation", a class of particularly healthy and green vegetation;
- "Most Vegetation", another vegetation class, less green than "Full Vegetation";
- "Soil";
- "Water".

The LC classification methodology was focused on the identification of urban patterns over the years. For this reason, several images (acquired in different months) were used for the creation of image mosaics, which allow for the LC classification of the whole area of Dar es Salaam. Nevertheless, this approach increased spectral variability for vegetation and soil classes, due to the phenological variation of vegetation.

Because urban landscapes are a composite combination of buildings, roads, grass, trees, soil, water, and so on (Lu, et al., 2011), the spectral similarities of those surfaces make the classification process more problematic. For example, bare soil and unpaved roads can be very similar to impervious surfaces, depending on the soil type (Van de Voorde, et al., 2008); also white soil and white roofs can be spectrally similar.

Therefore it is complicated to define a spectrally distinct "built" class, in particular when small, isolated patches of urban cover exist within a vegetated landscape, as is the case of periurban development (Shrestha & Conway, 2011).

Appendix 2 – Field Survey

The following paragraphs show the result of the field survey, performed by Eng. Carlo Norero in the context of his master's thesis. The points were reached with the help of a GPS, and 4 picture were taken in all 4 cardinal directions.

In particular, 20 points for each LC class (according to the Landsat LC classification of 2011) were visited.

Following, the documentation produced for the "Discontinuous Urban" points and the "Continuous Urban" points is shown. In particular, the Landsat LC classification of 2011 is compared to the pictures taken during the field survey.

Discontinuous Urban Points

The point 8 of the "Discontinuous Urban" class lacks of the pictures in the West and South directions, where photography is forbidden because of an embassy.

Discontinuous Urban Class - Point 1

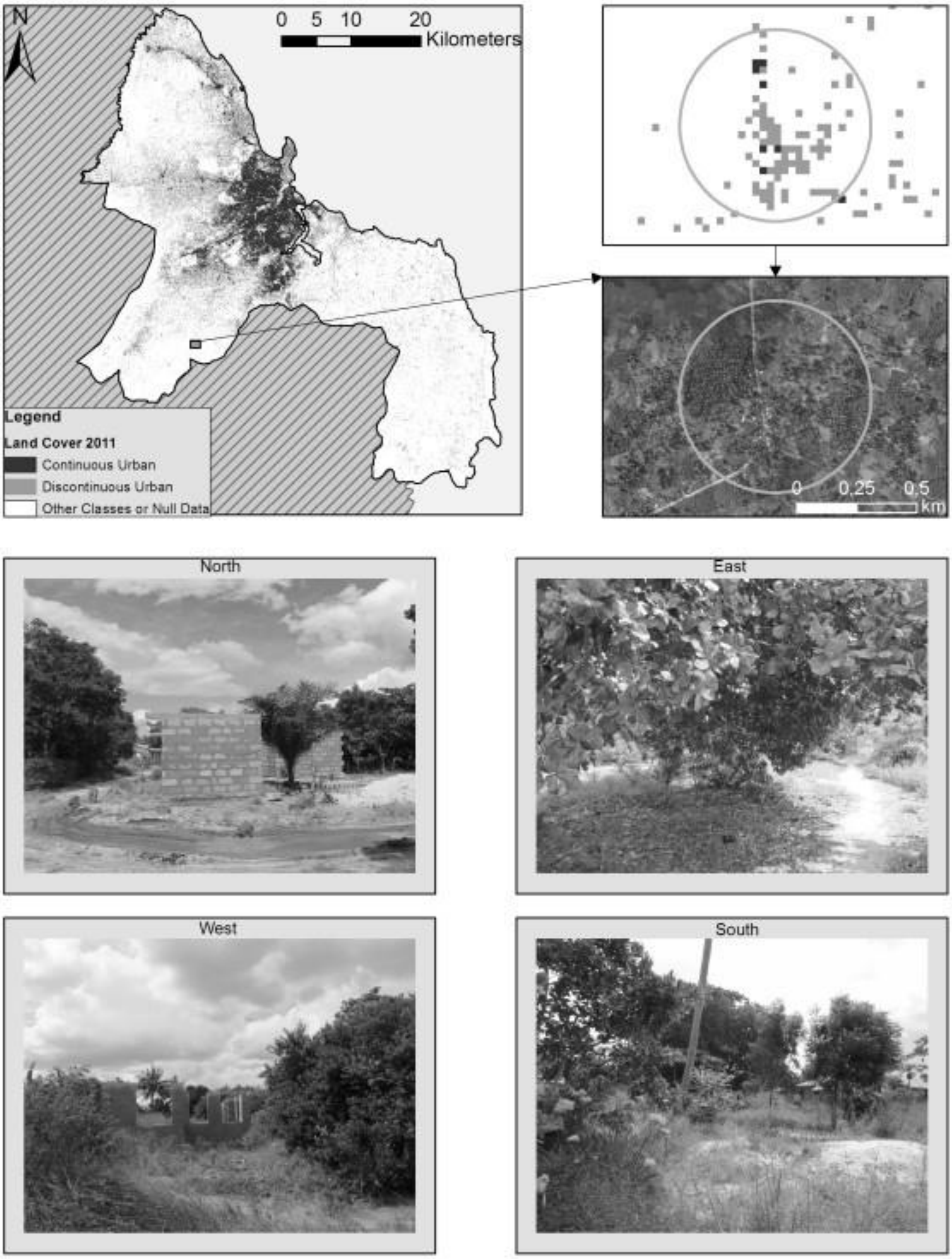

Figure 15: Discontinuous urban class, point 1

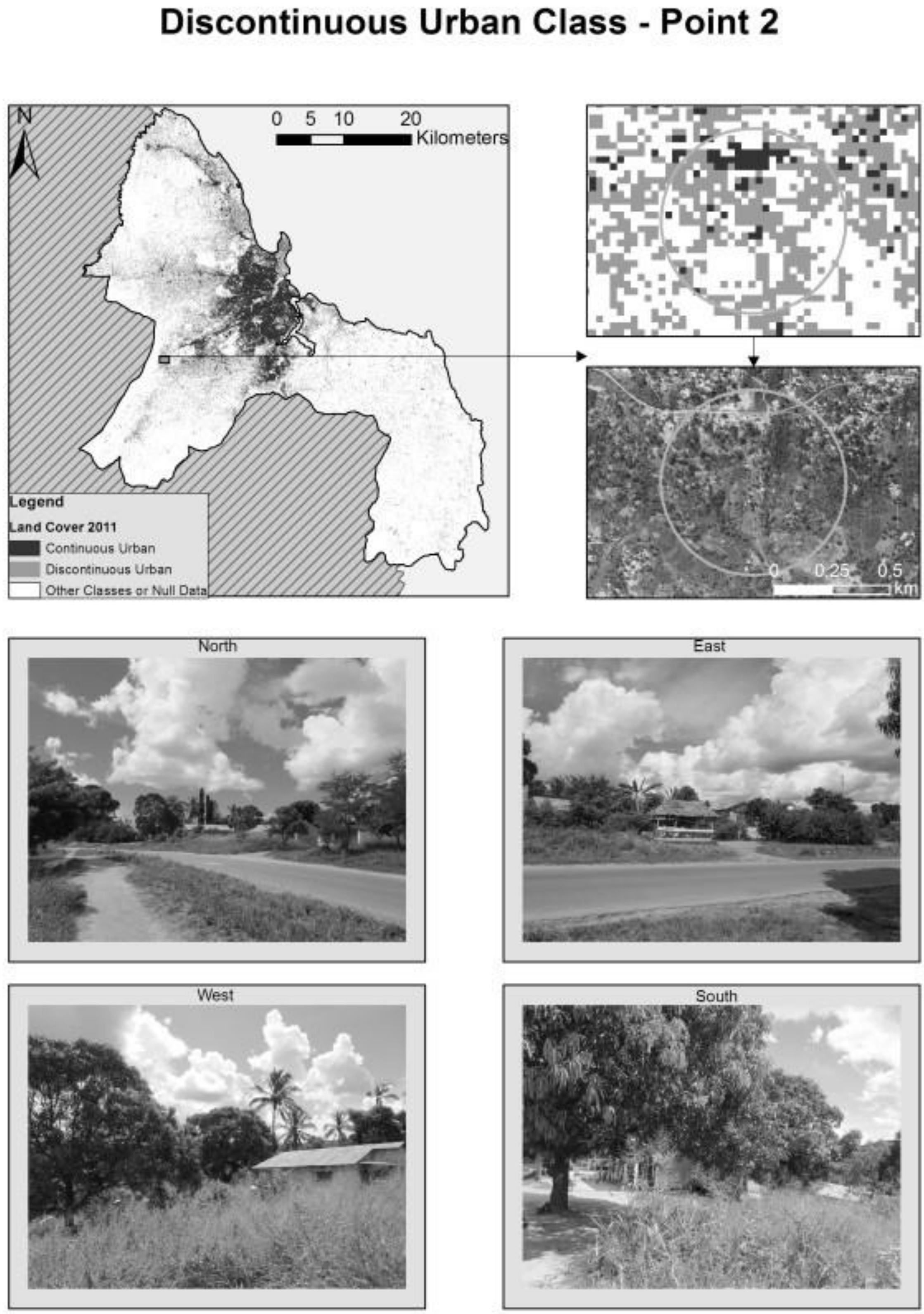

Figure 16: Discontinuous urban class, point 2

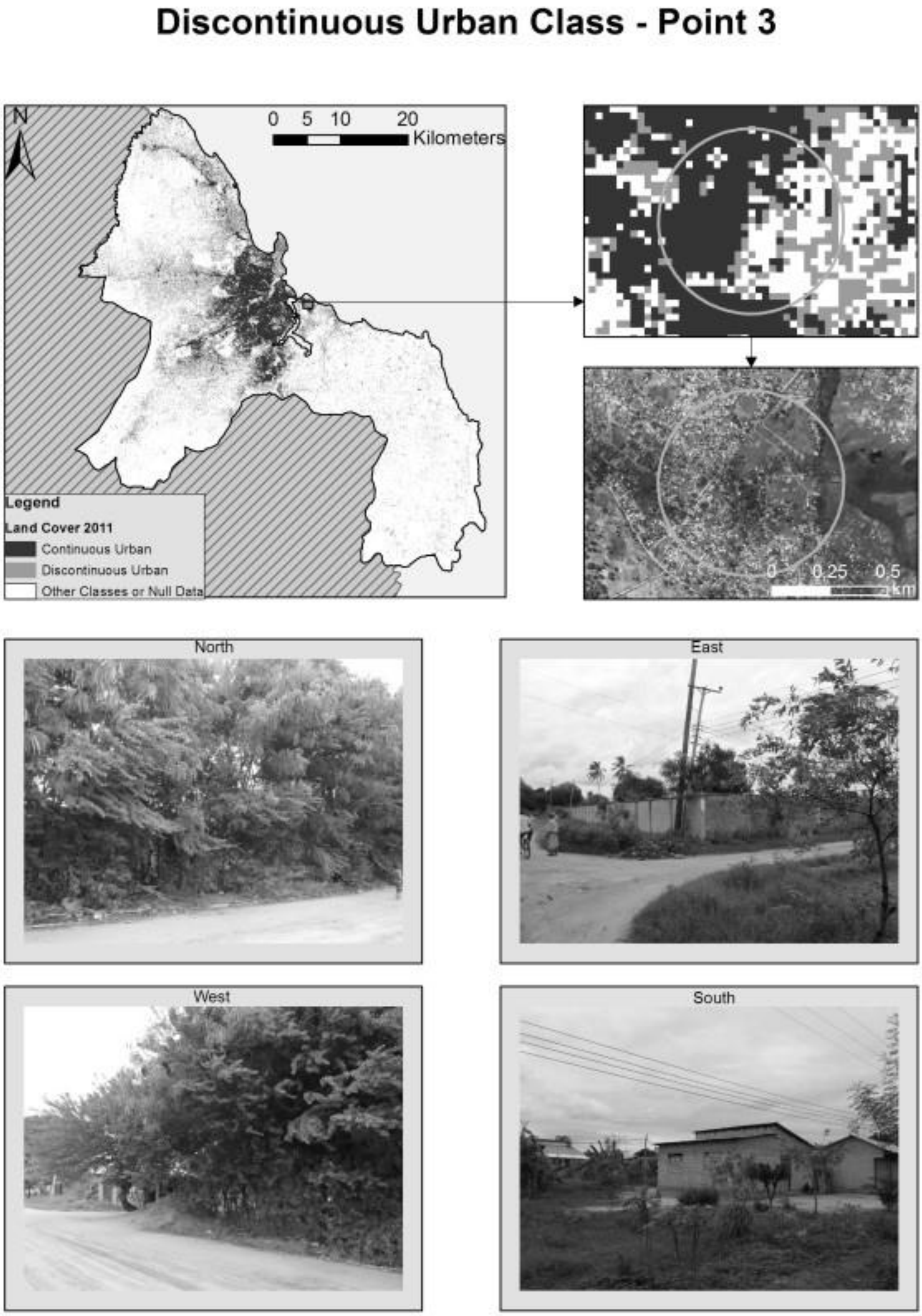

Figure 17: Discontinuous urban class, point 3

Discontinuous Urban Class - Point 4

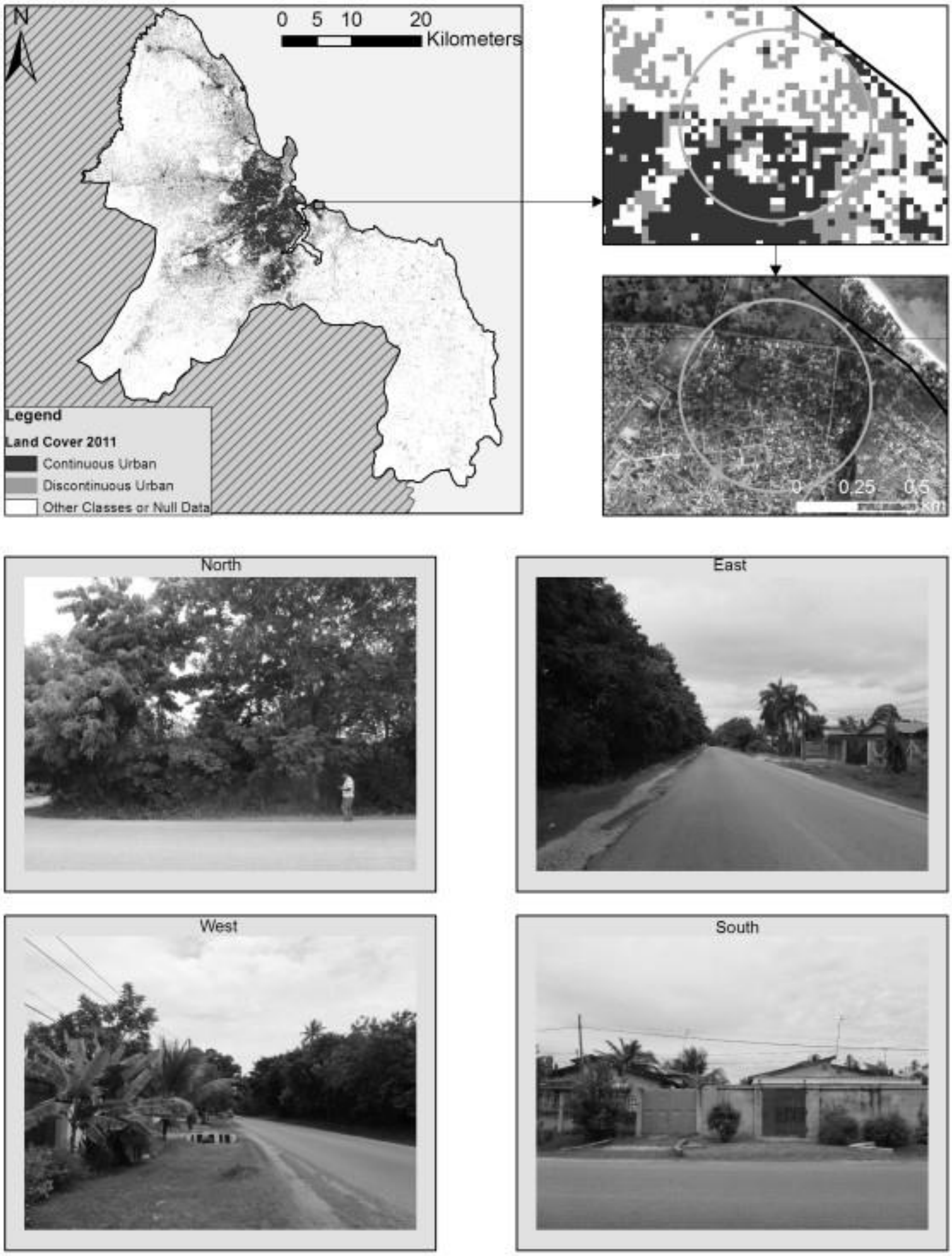

Figure 18: Discontinuous urban class, point 4

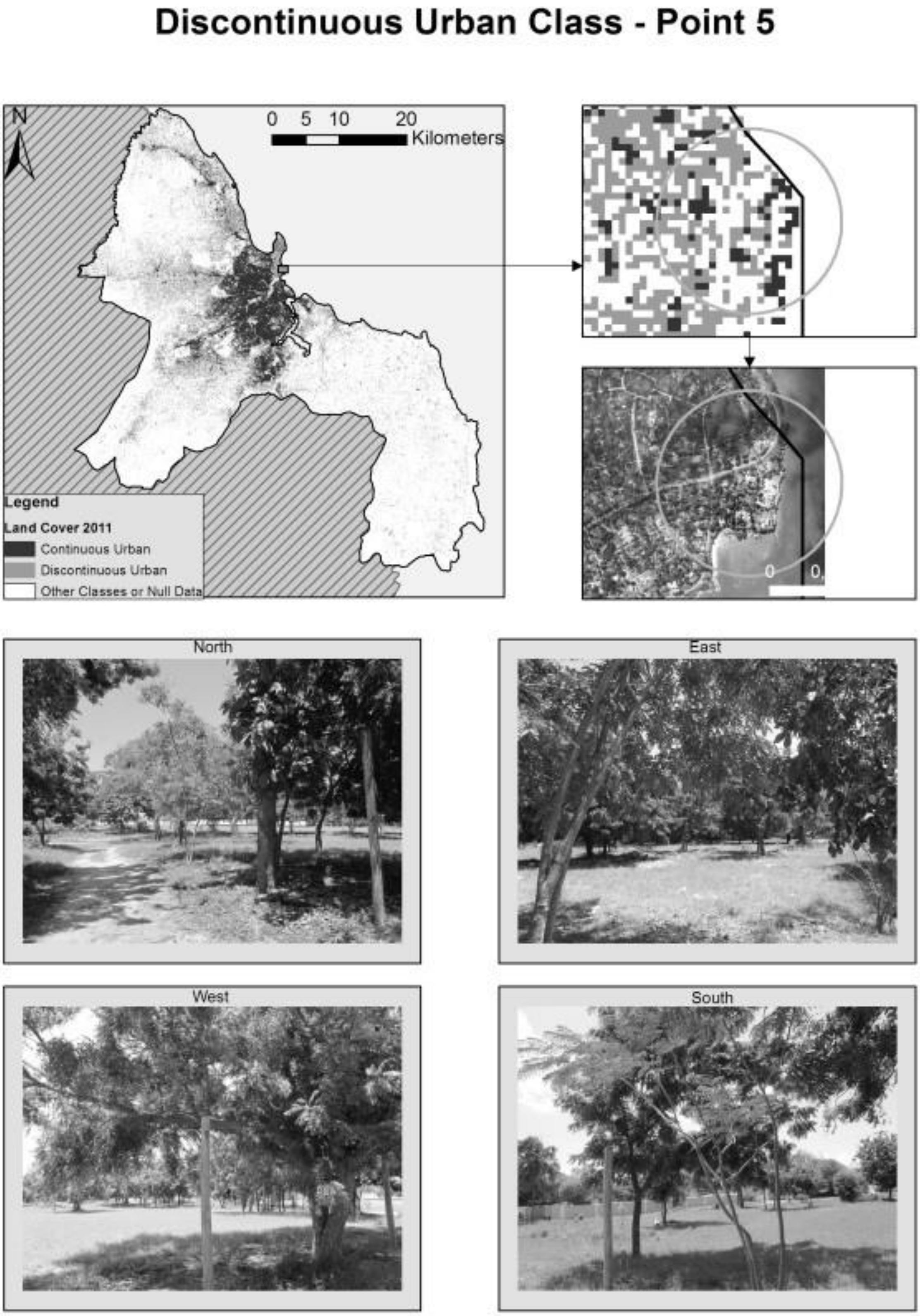

Figure 19: Discontinuous urban class, point 5

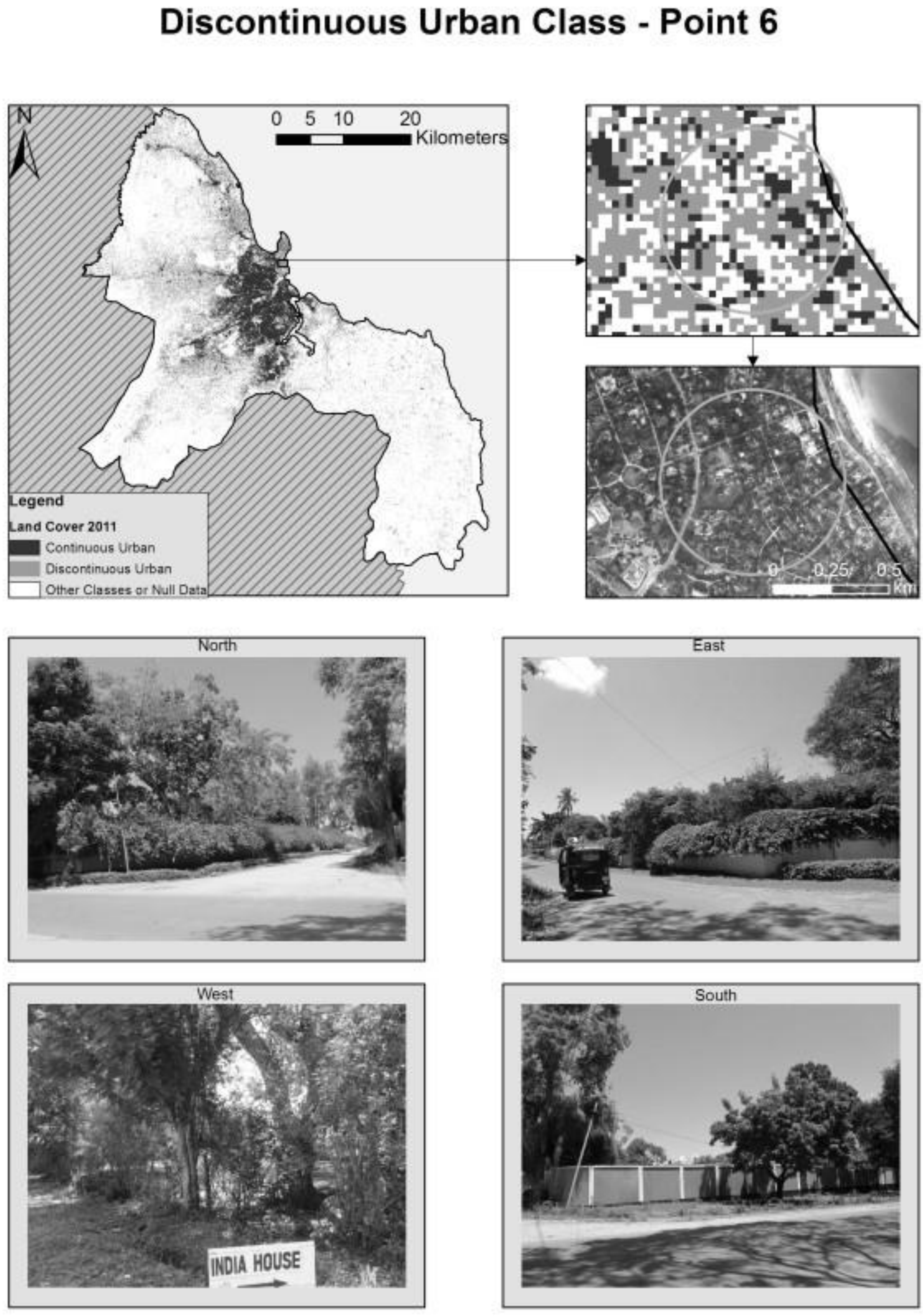

Figure 20: Discontinuous urban class, point 6

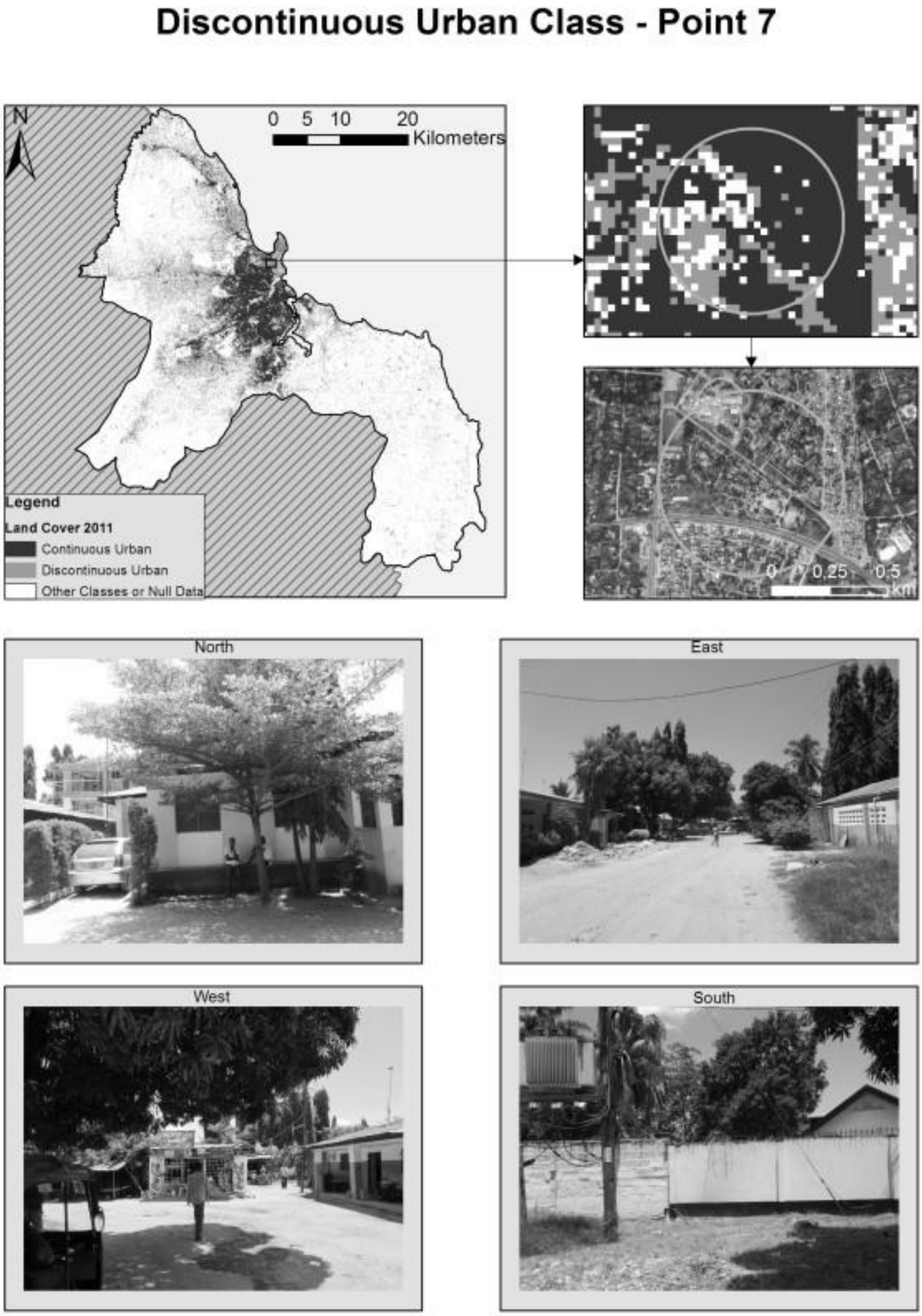

Figure 21: Discontinuous urban class, point 7

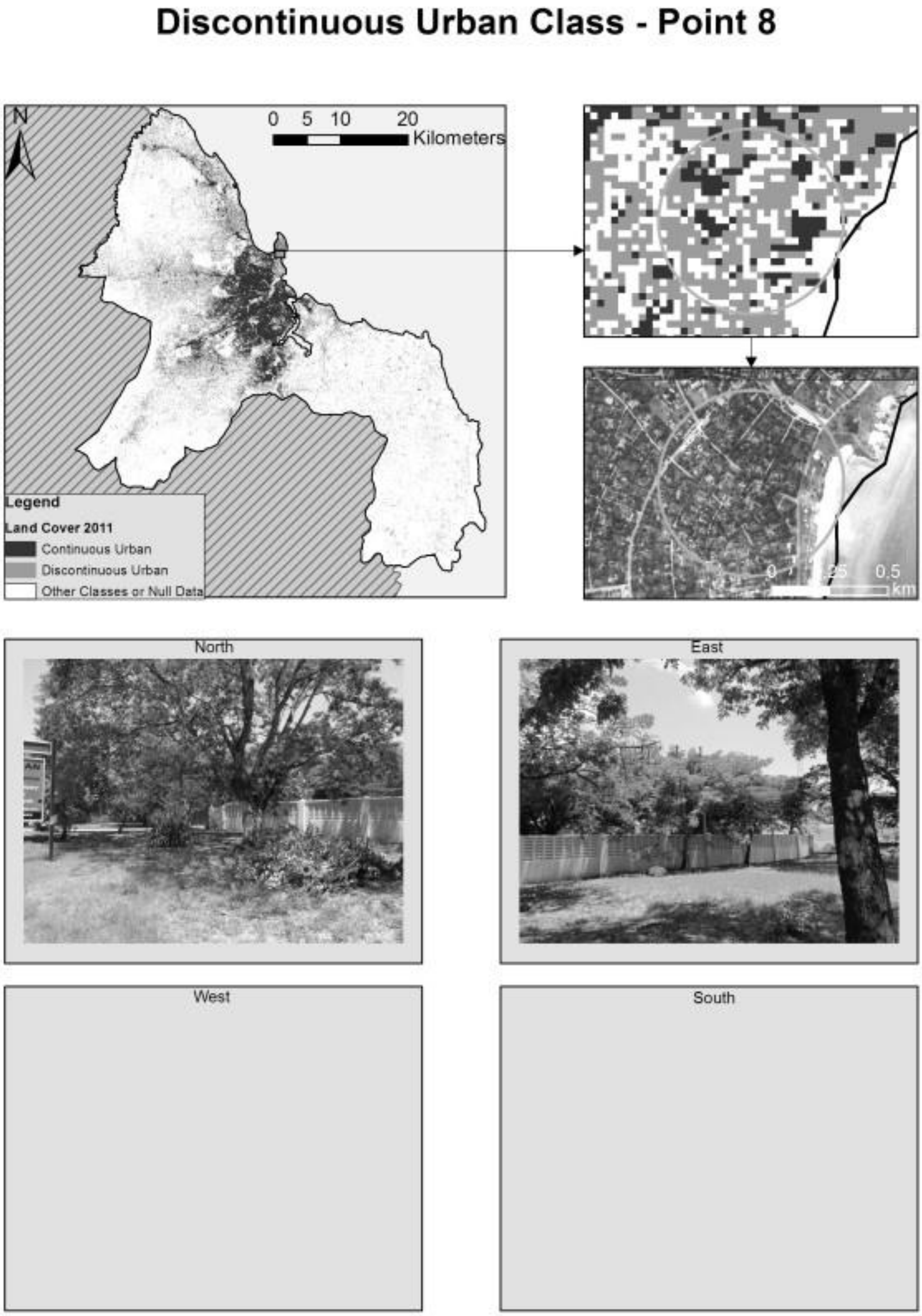

Figure 22: Discontinuous urban class, point 8

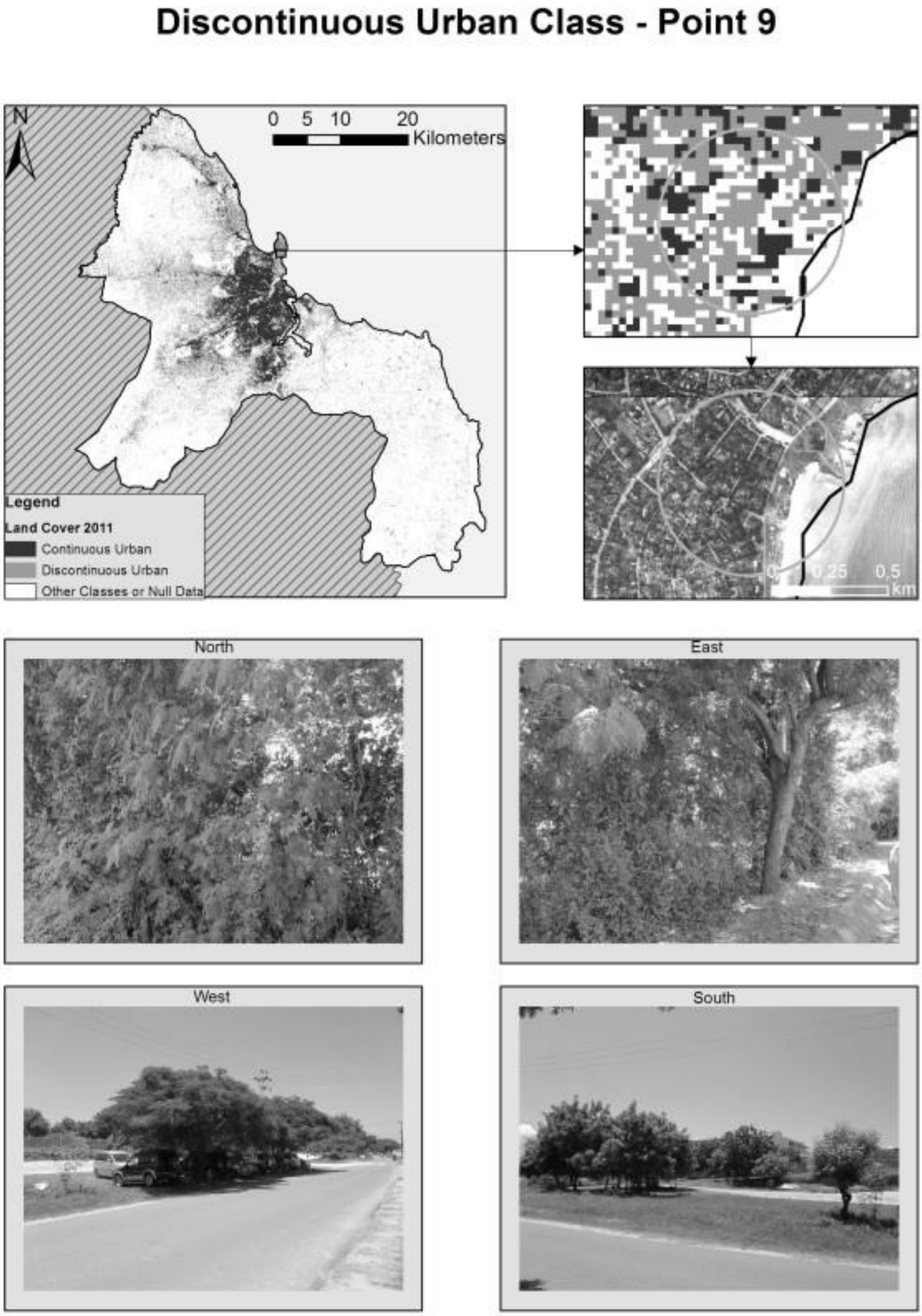

Figure 23: Discontinuous urban class, point 9

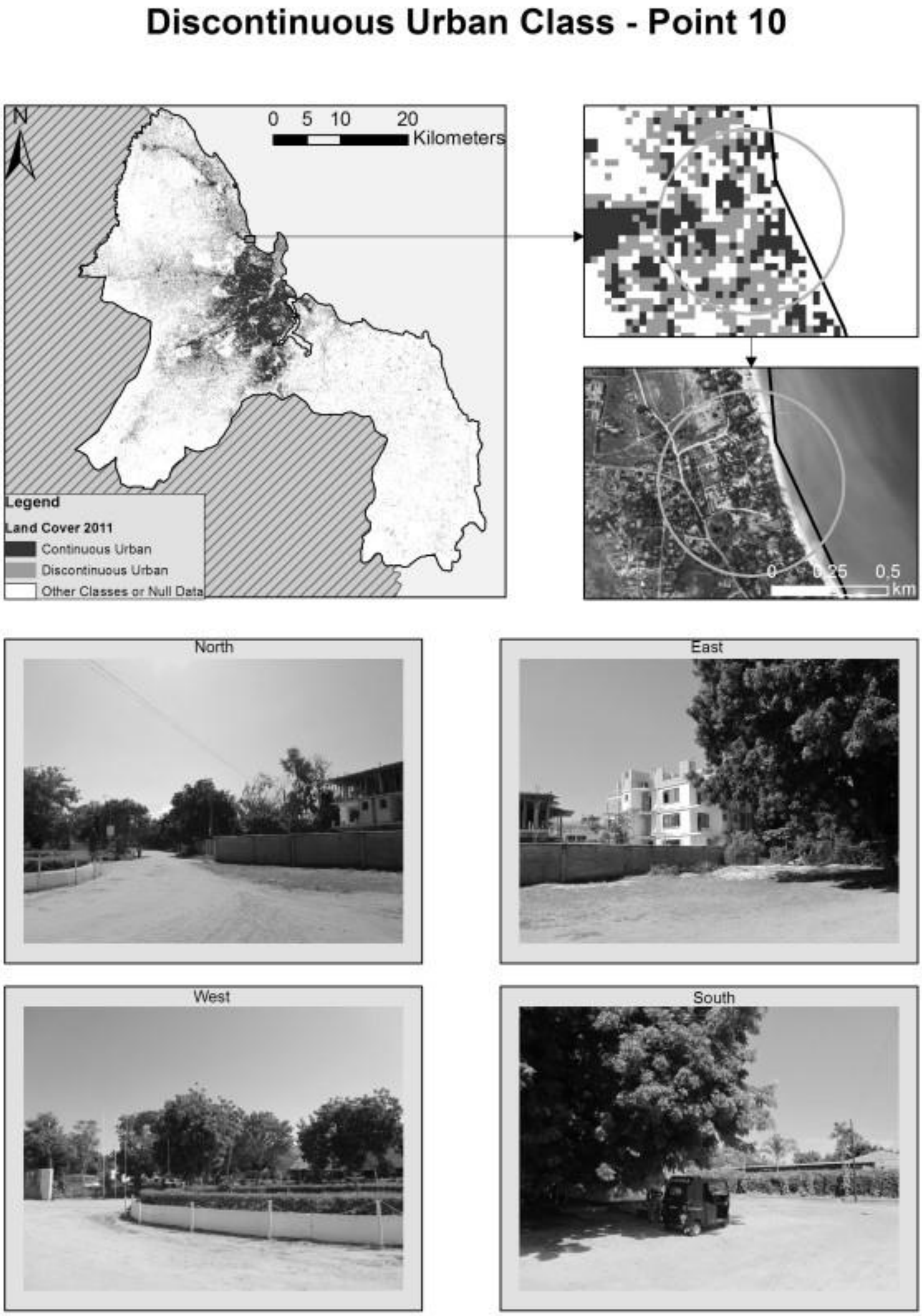

Figure 24: Discontinuous urban class, point 10

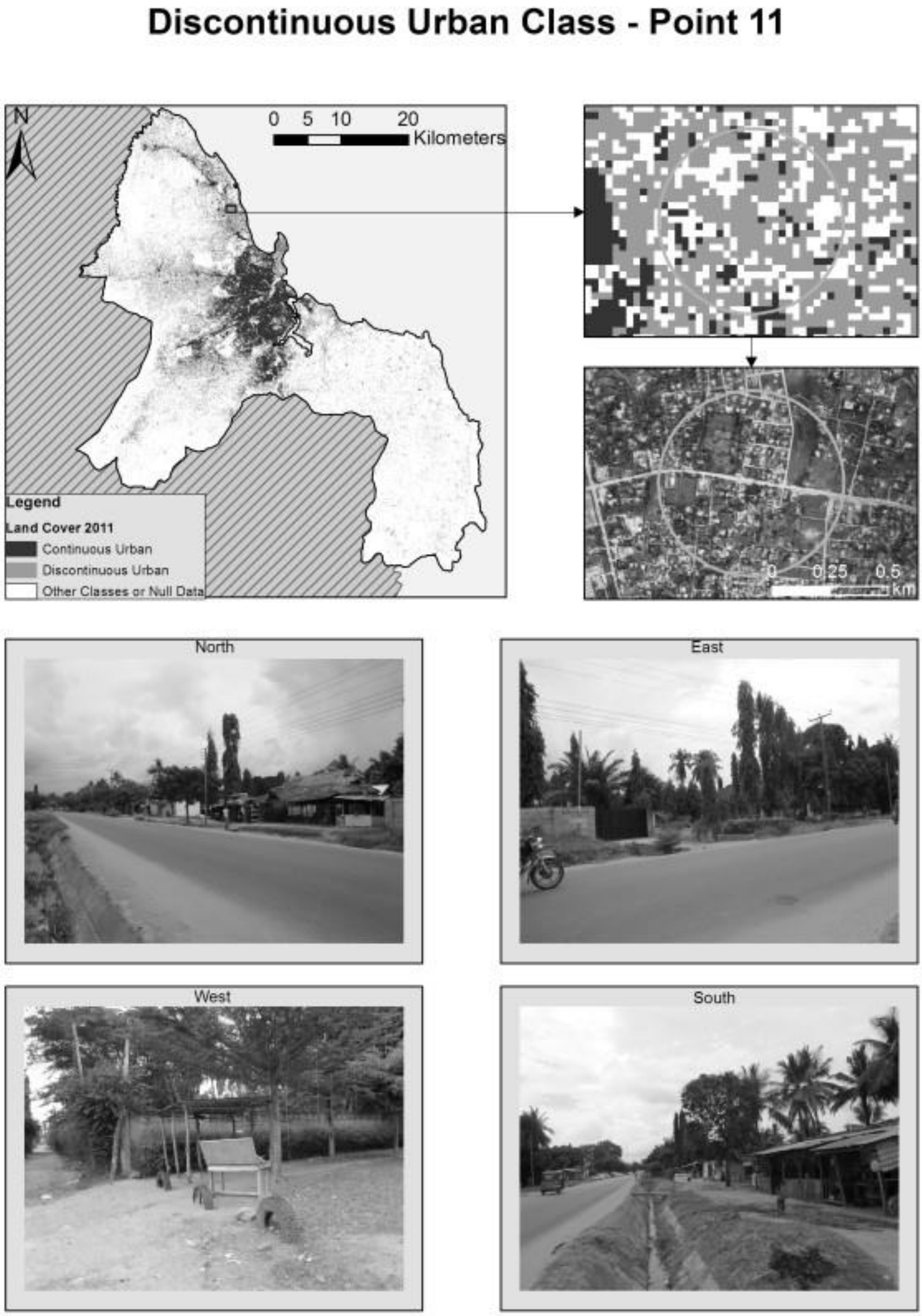

Figure 25: Discontinuous urban class, point 11

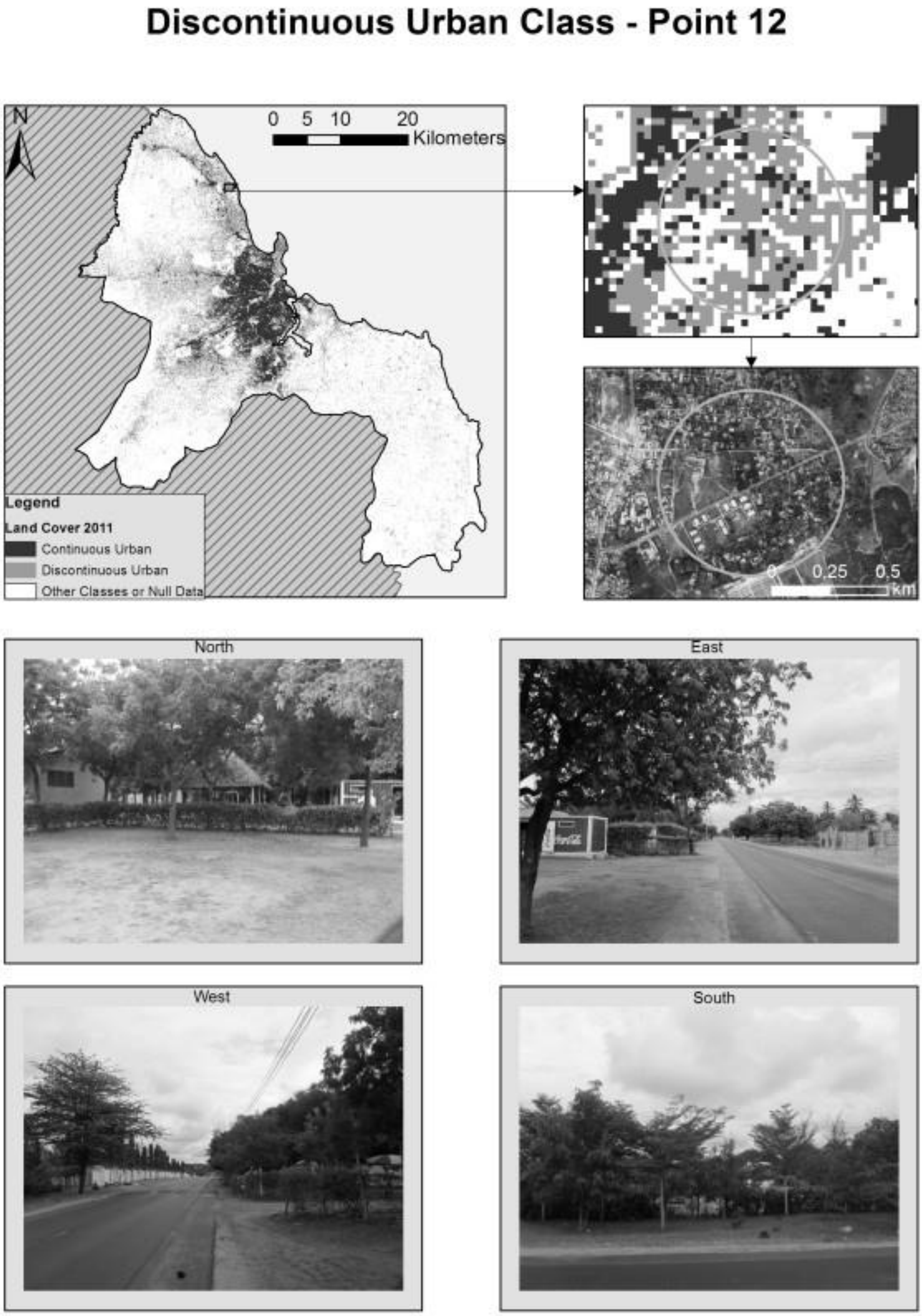

Figure 26: Discontinuous urban class, point 12

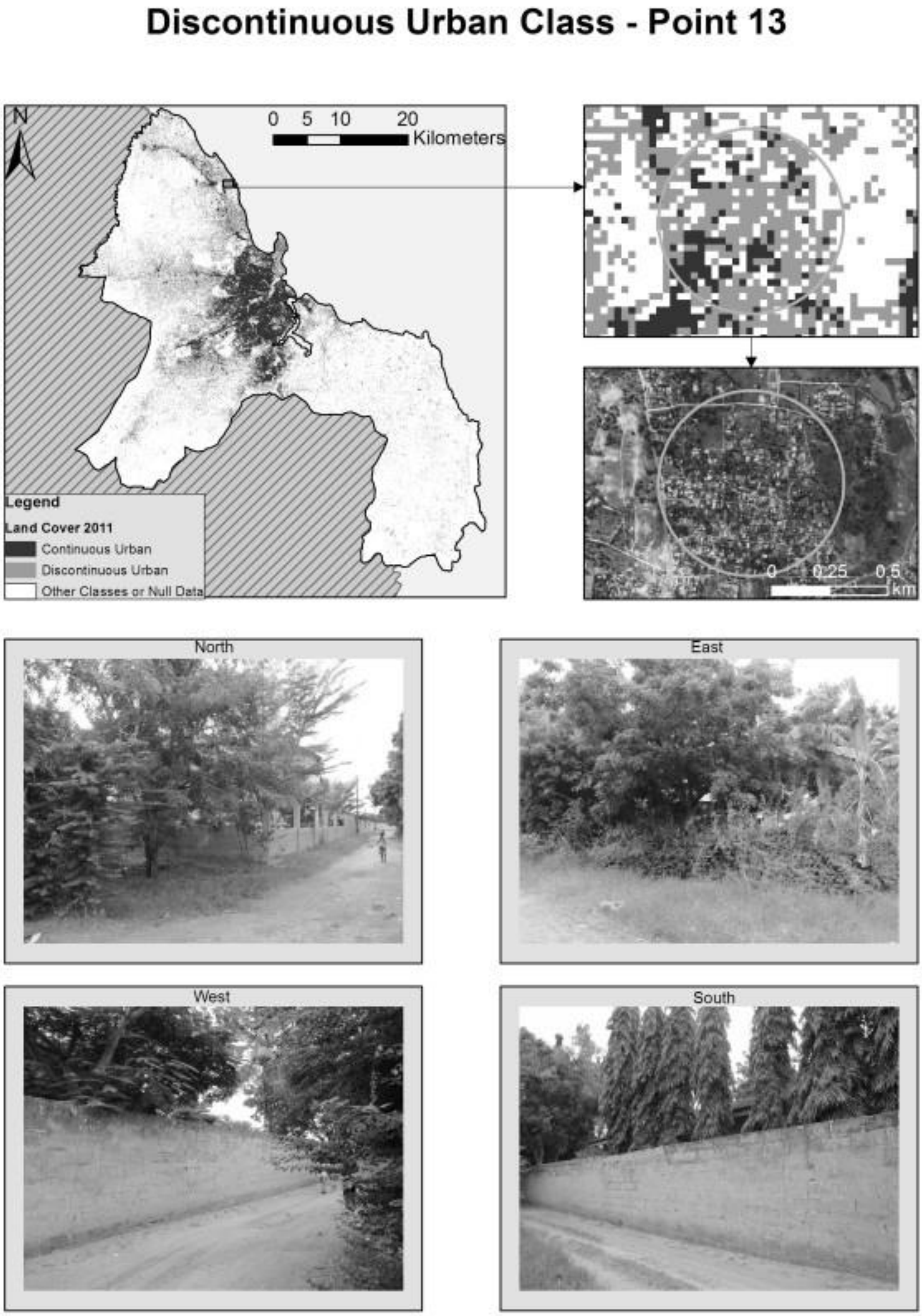

Figure 27: Discontinuous urban class, point 13

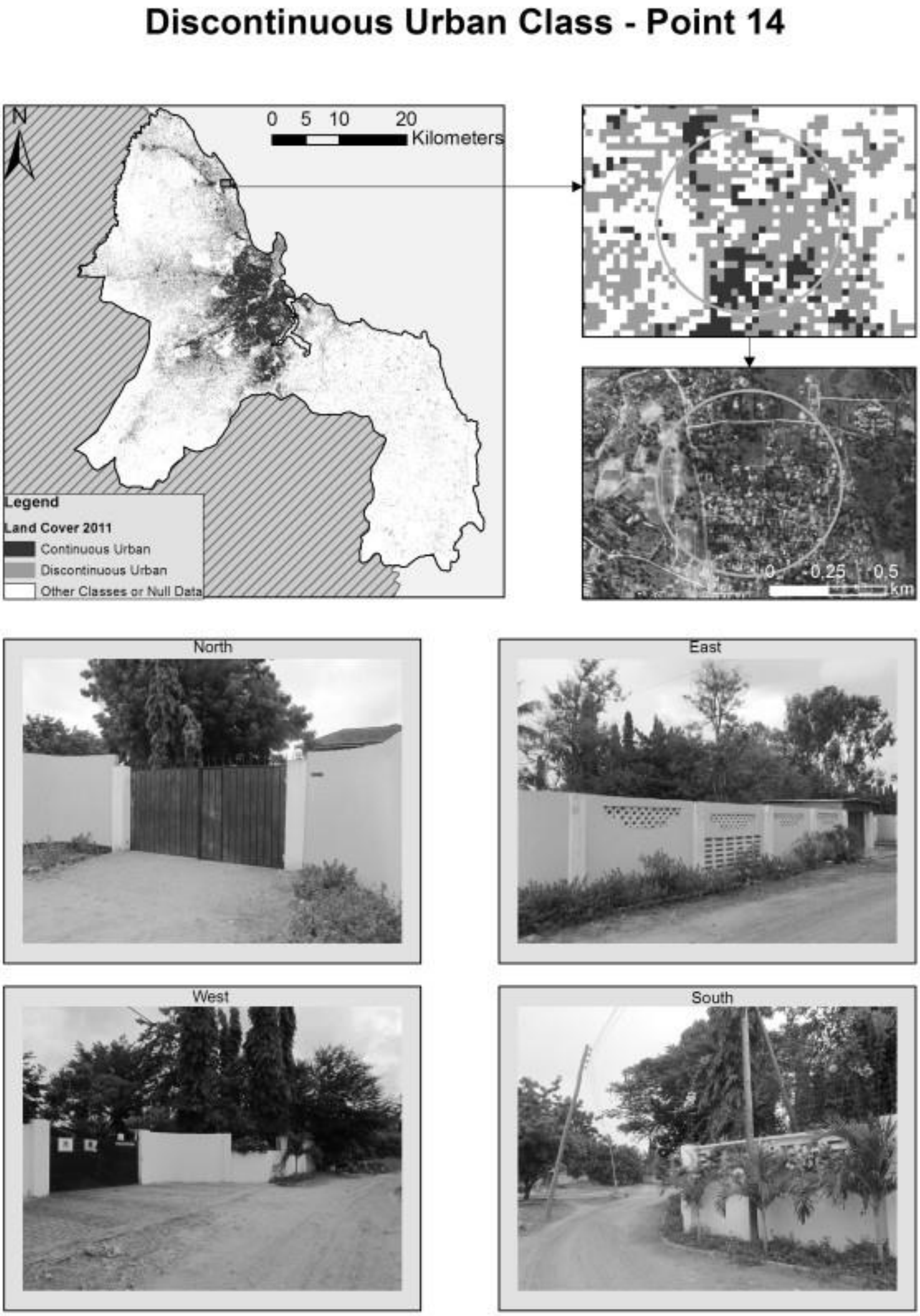

Figure 28: Discontinuous urban class, point 14

Discontinuous Urban Class - Point 15

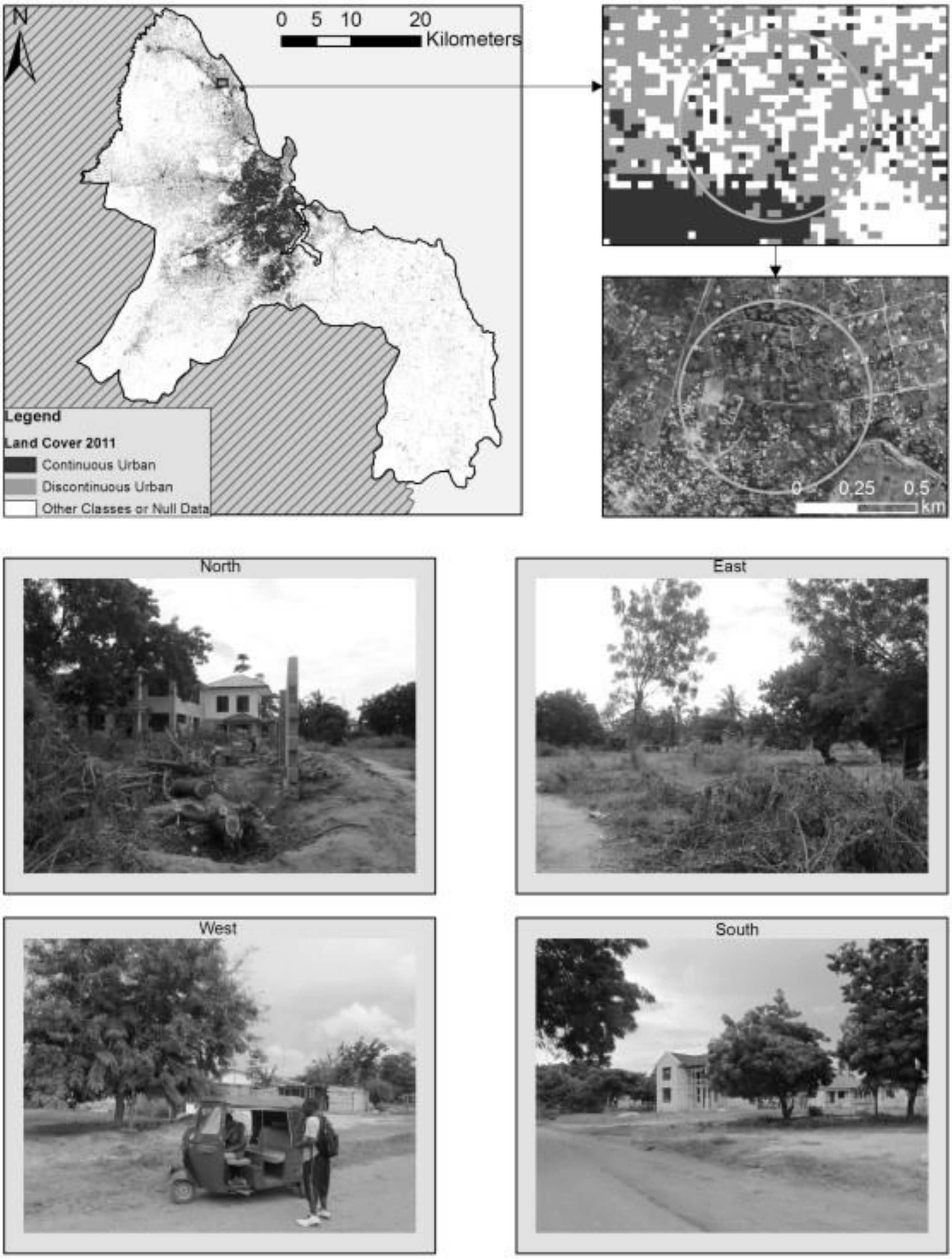

Figure 29: Discontinuous urban class, point 15

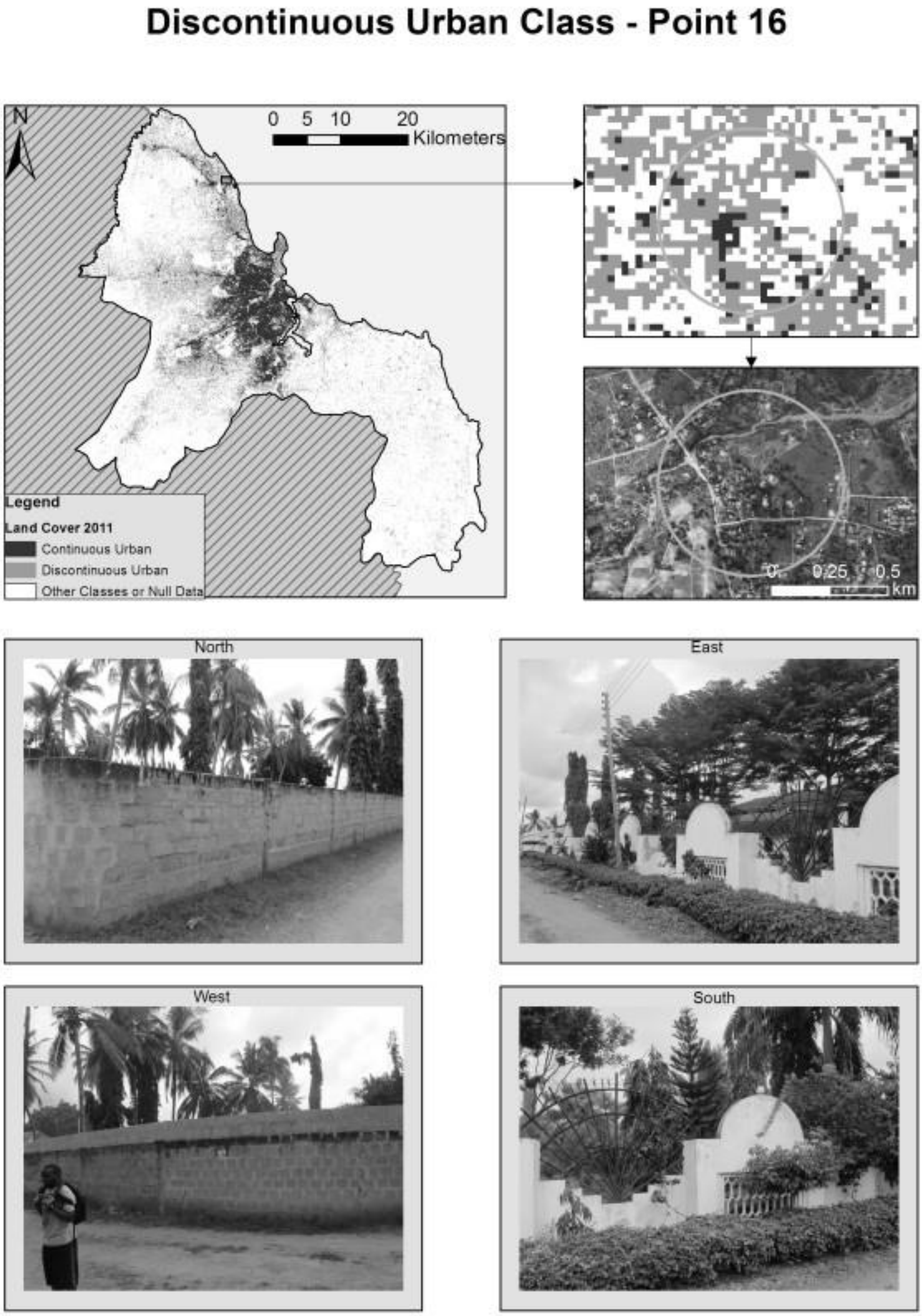

Figure 30: Discontinuous urban class, point 16

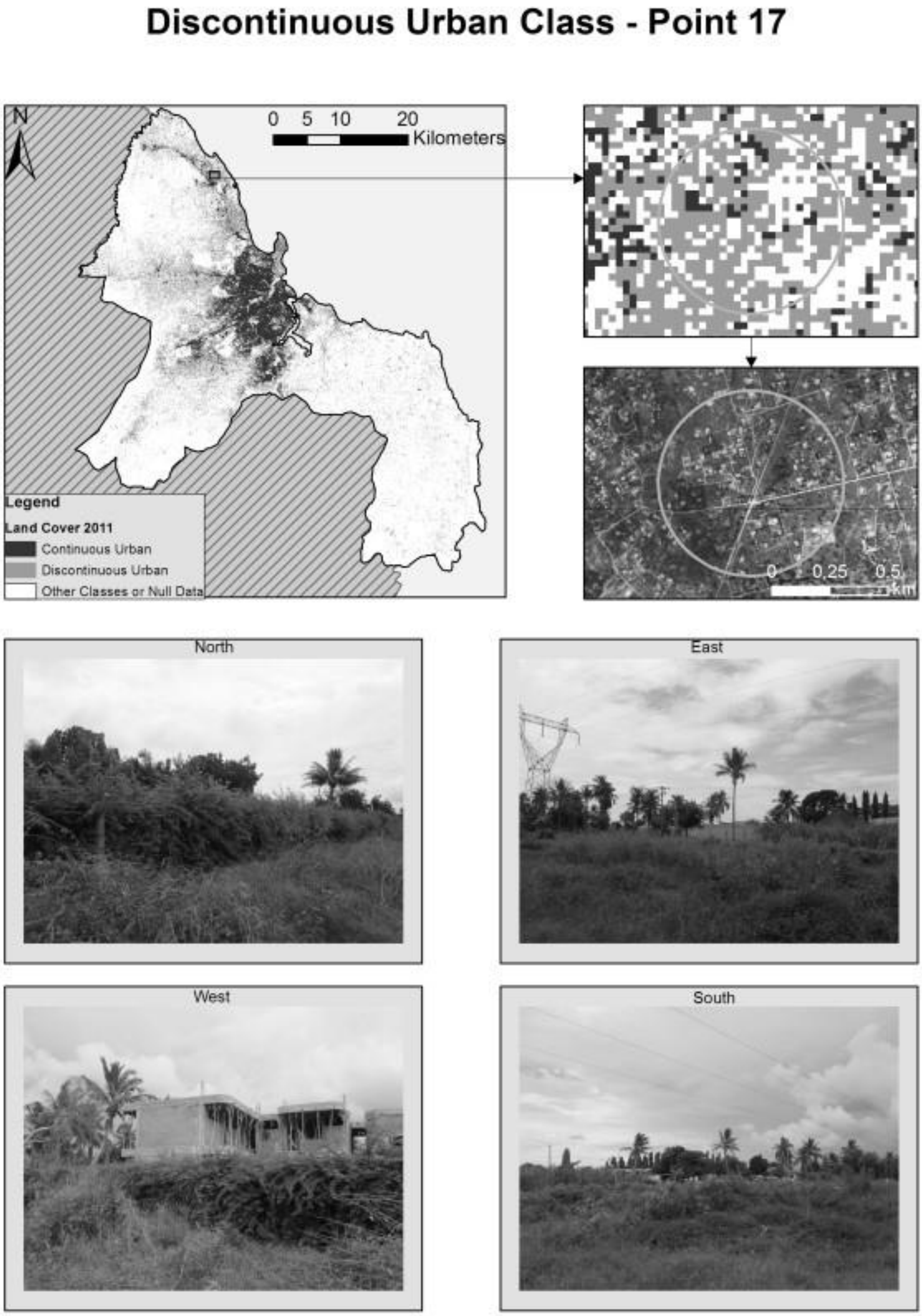

Figure 31: Discontinuous urban class, point 17

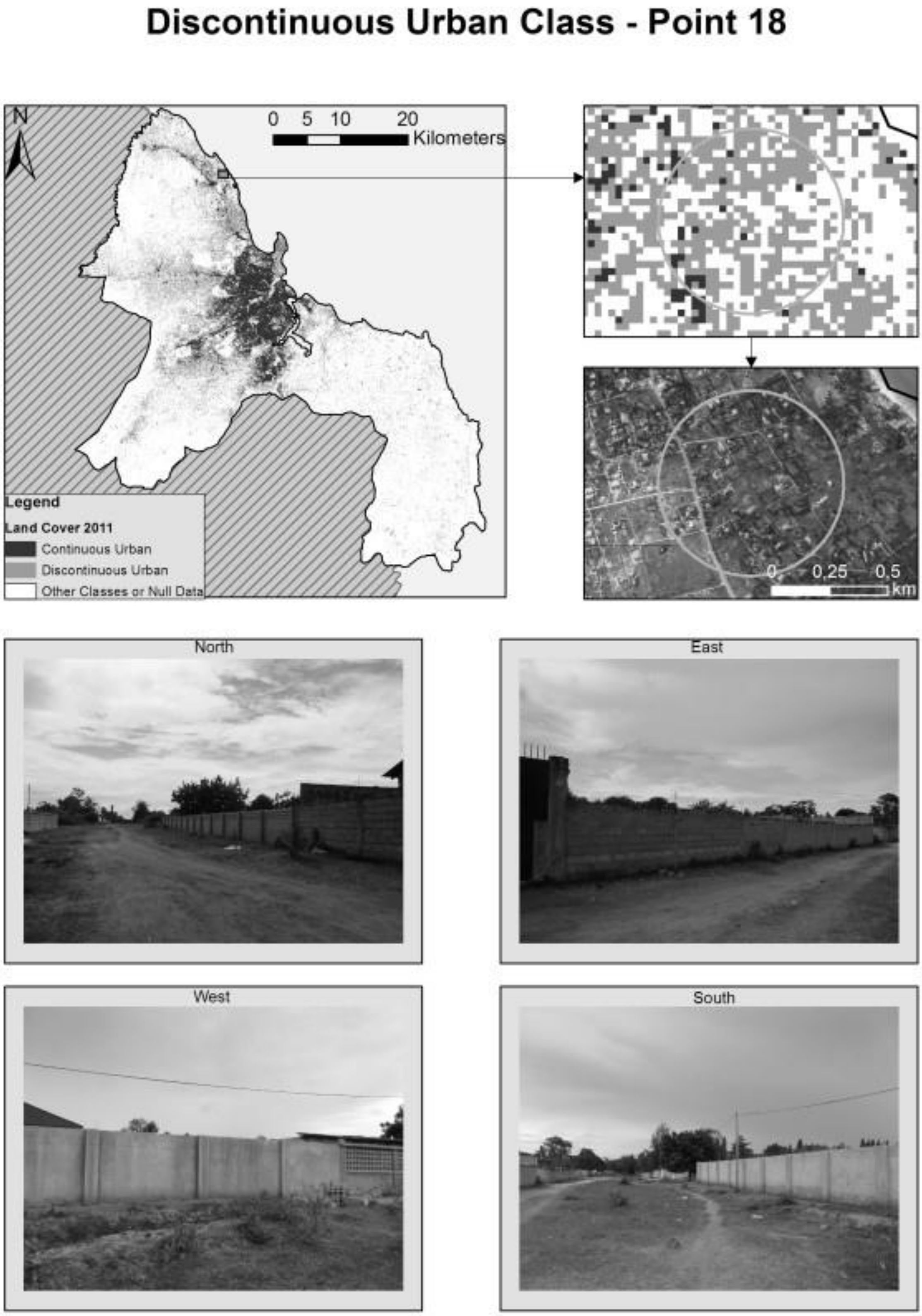

Figure 32: Discontinuous urban class, point 18

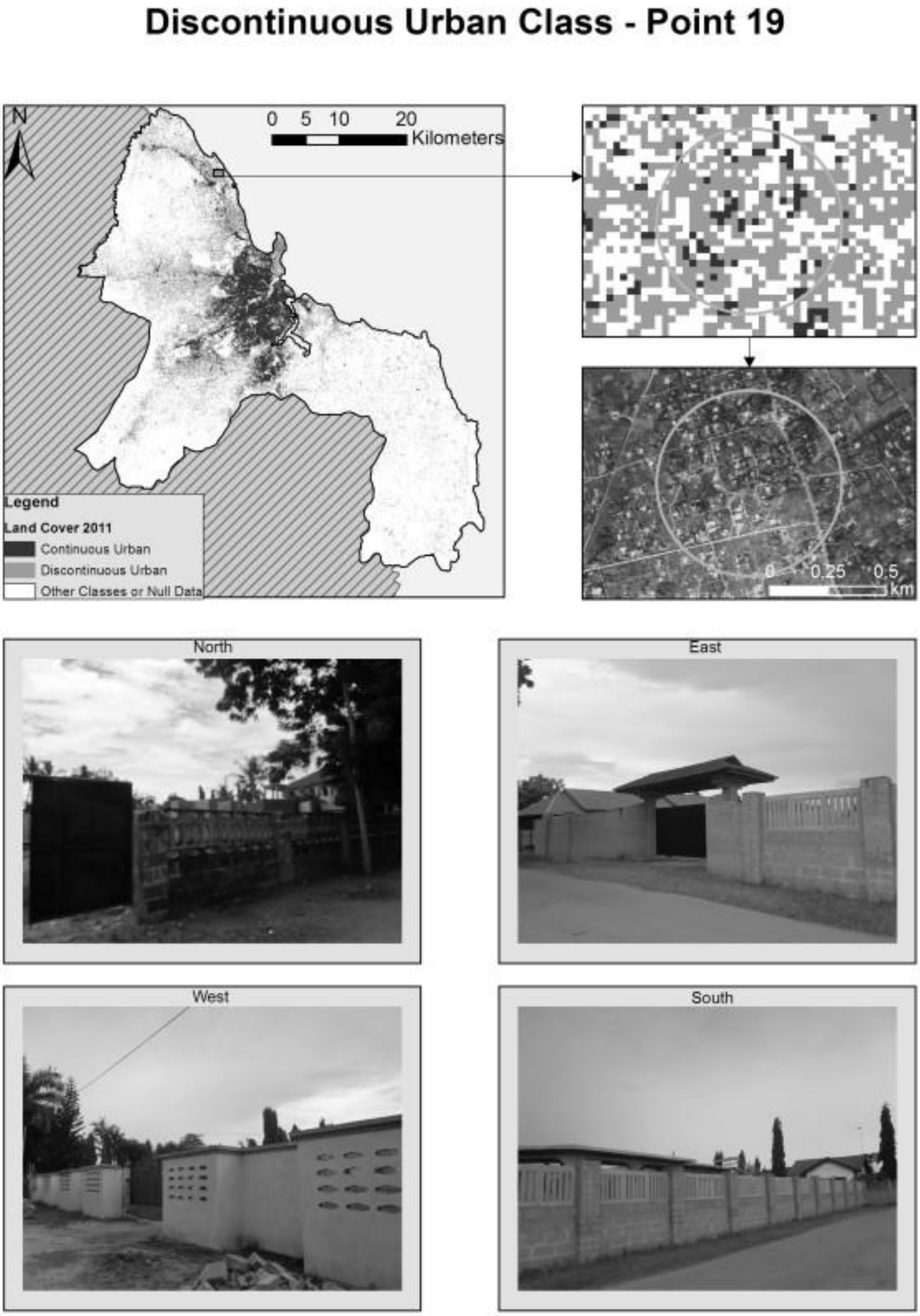

Figure 33: Discontinuous urban class, point 19

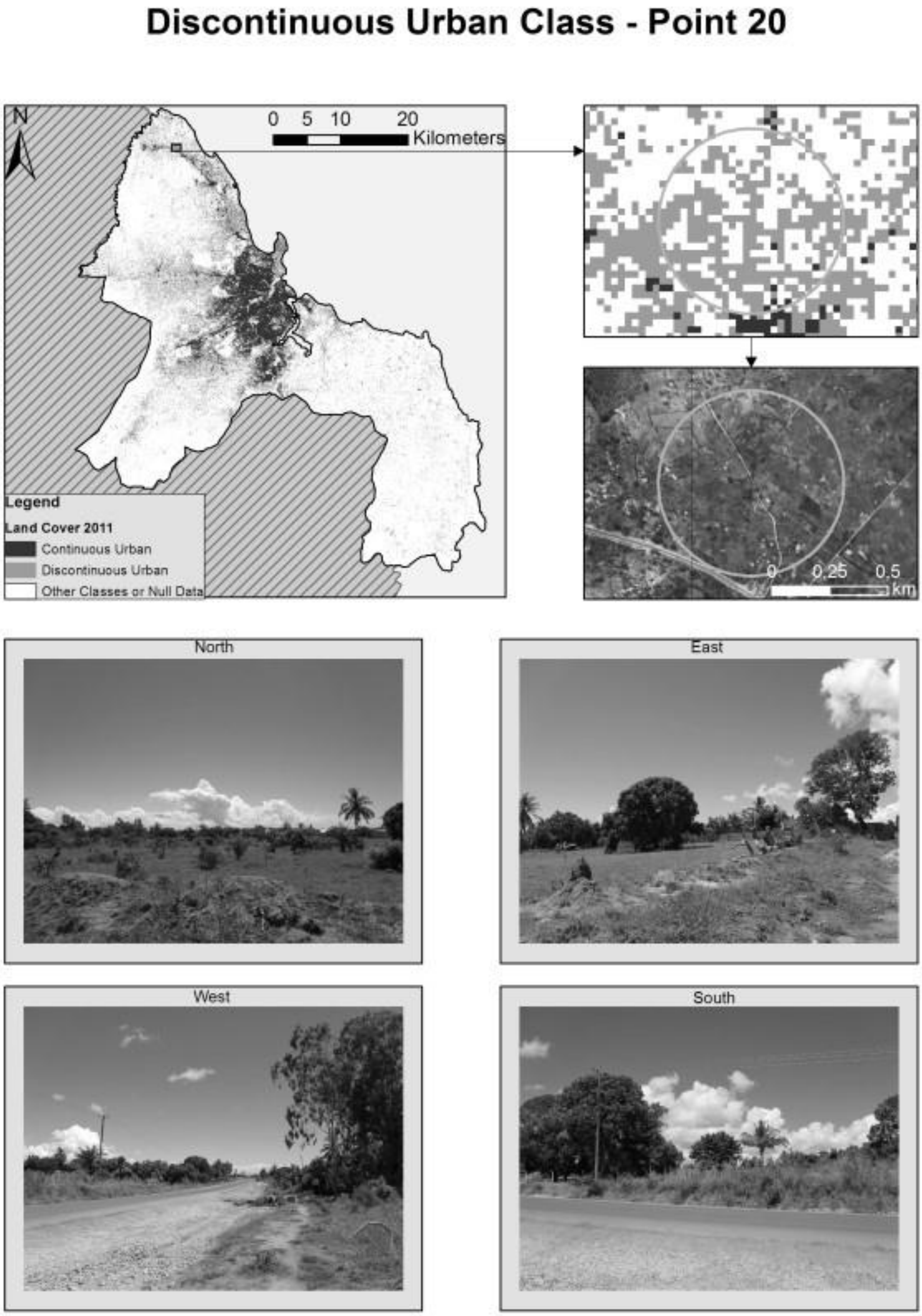

Figure 34: Discontinuous urban class, point 20

Continuous Urban Points

The points 1 and 2 of the “Continuous Urban” class are inside a local police area, where photography is forbidden.

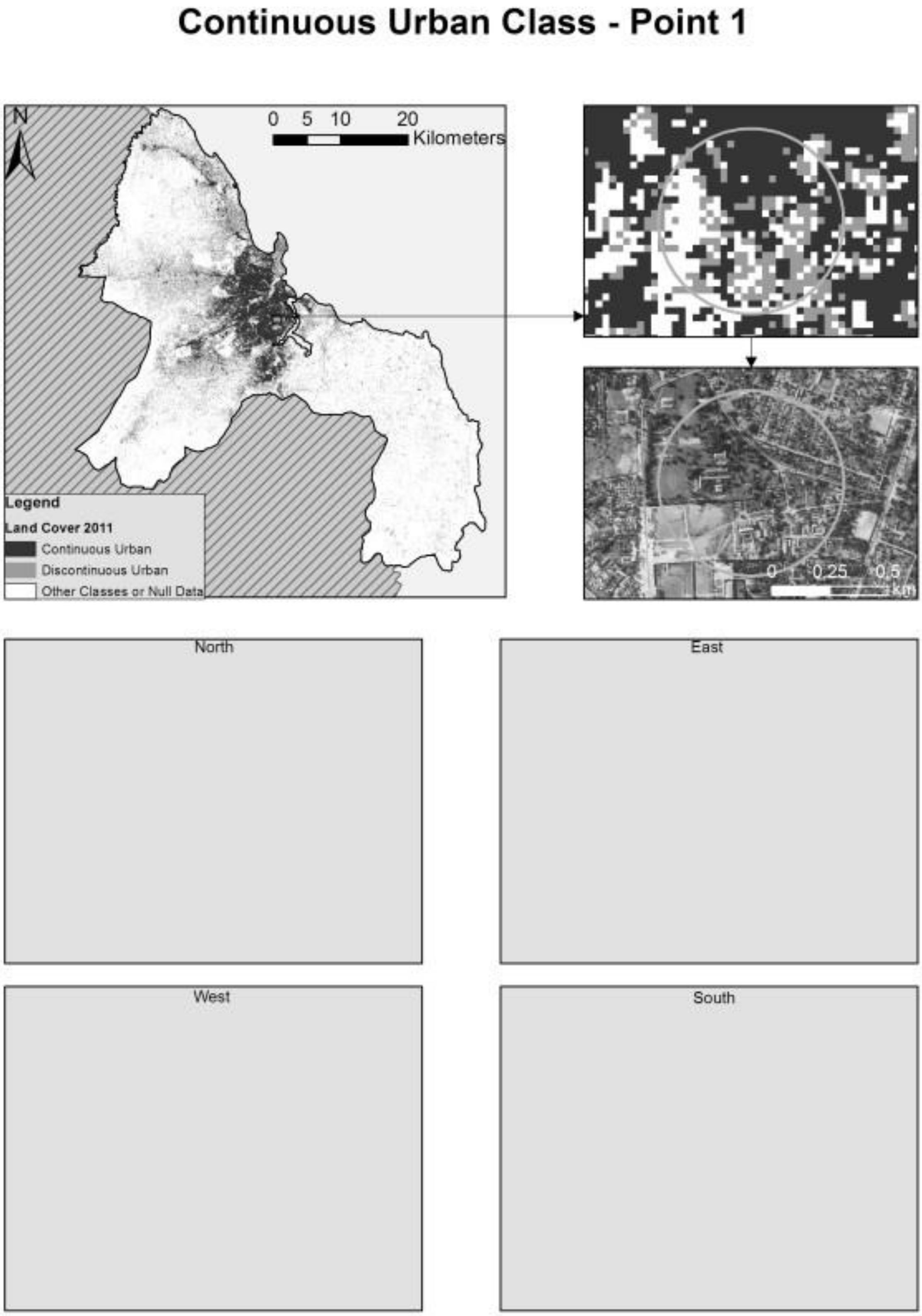

Figure 35: Continuous urban class, point 1

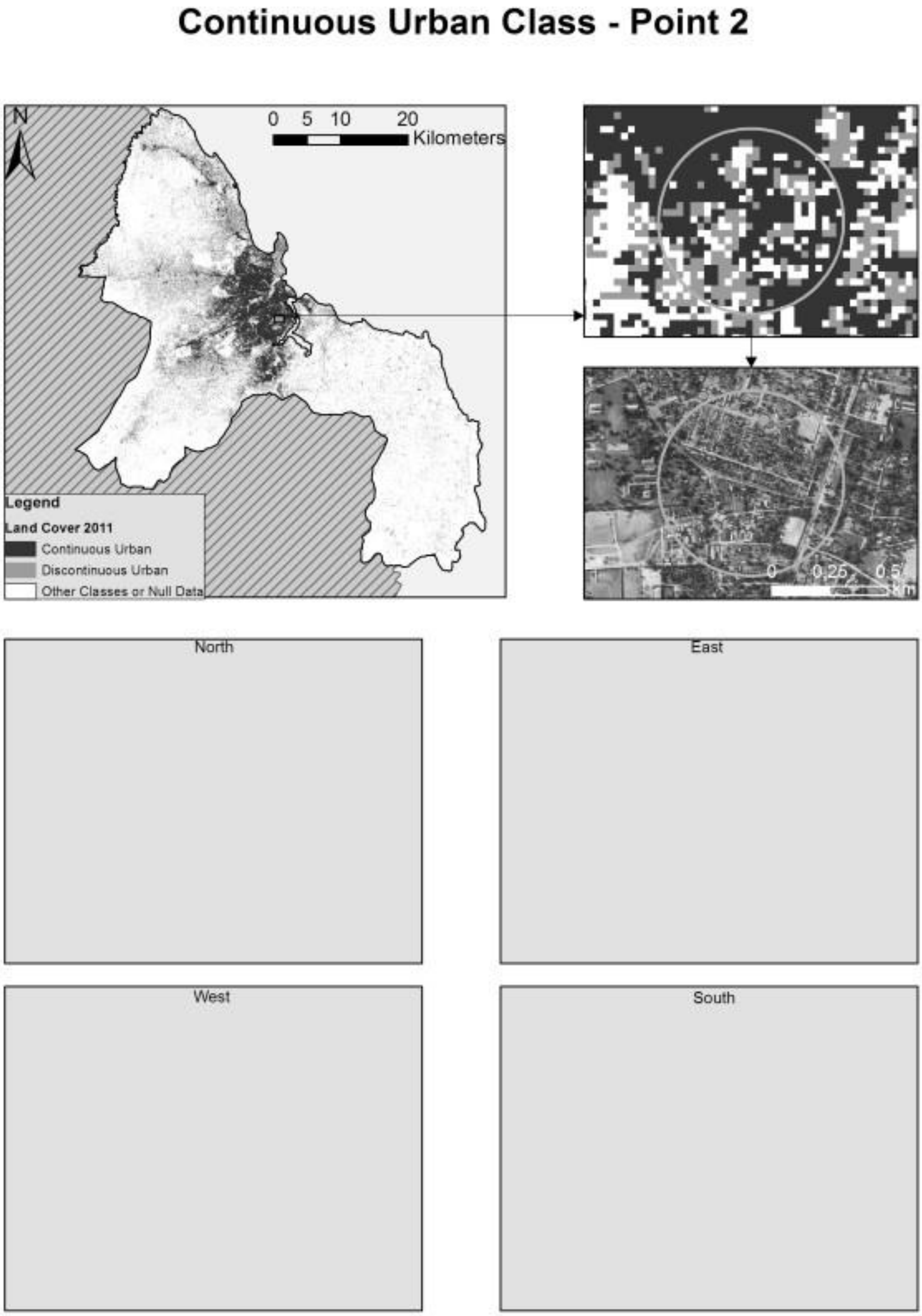

Figure 36: Continuous urban class, point 2

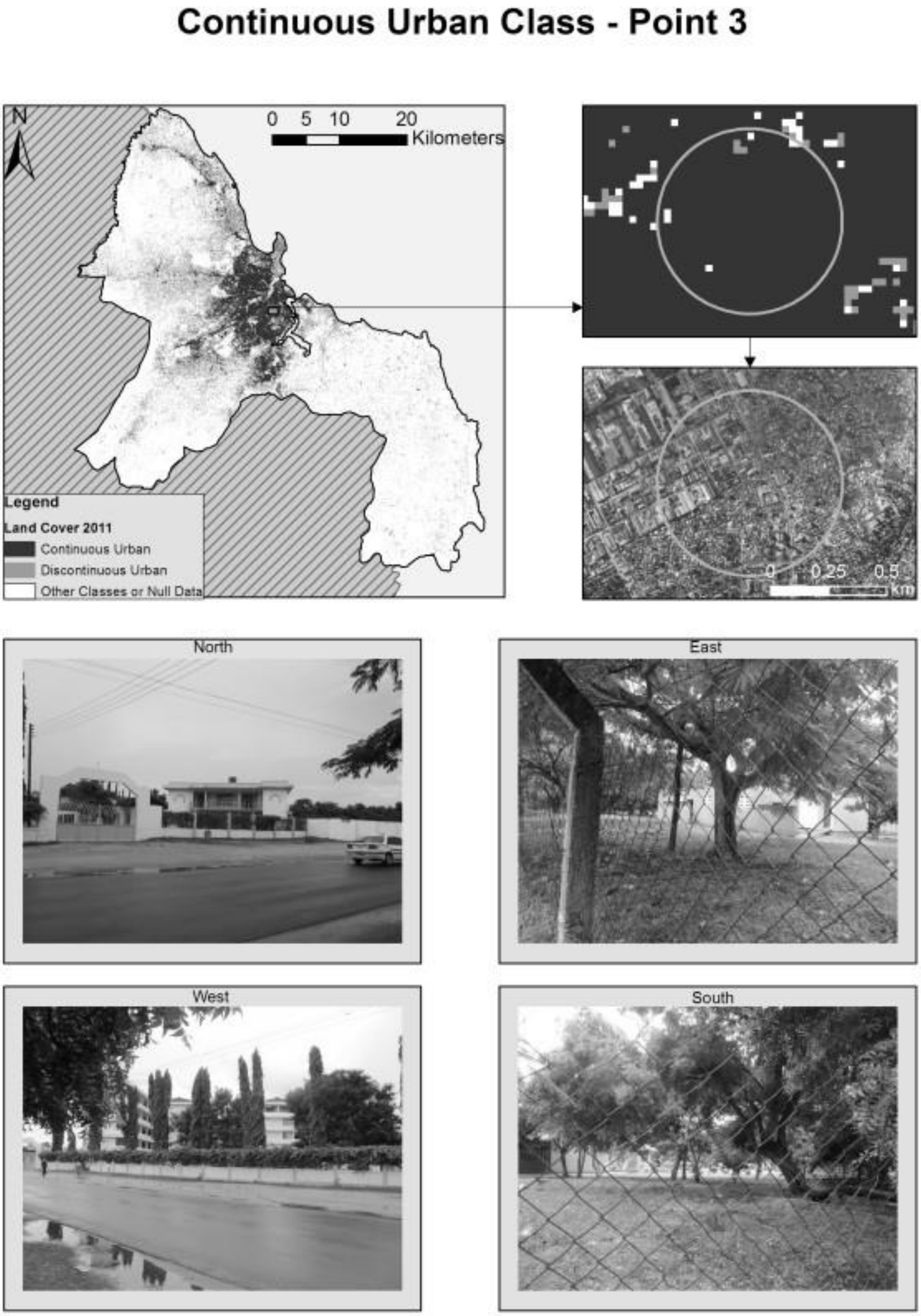

Figure 37: Continuous urban class, point 3

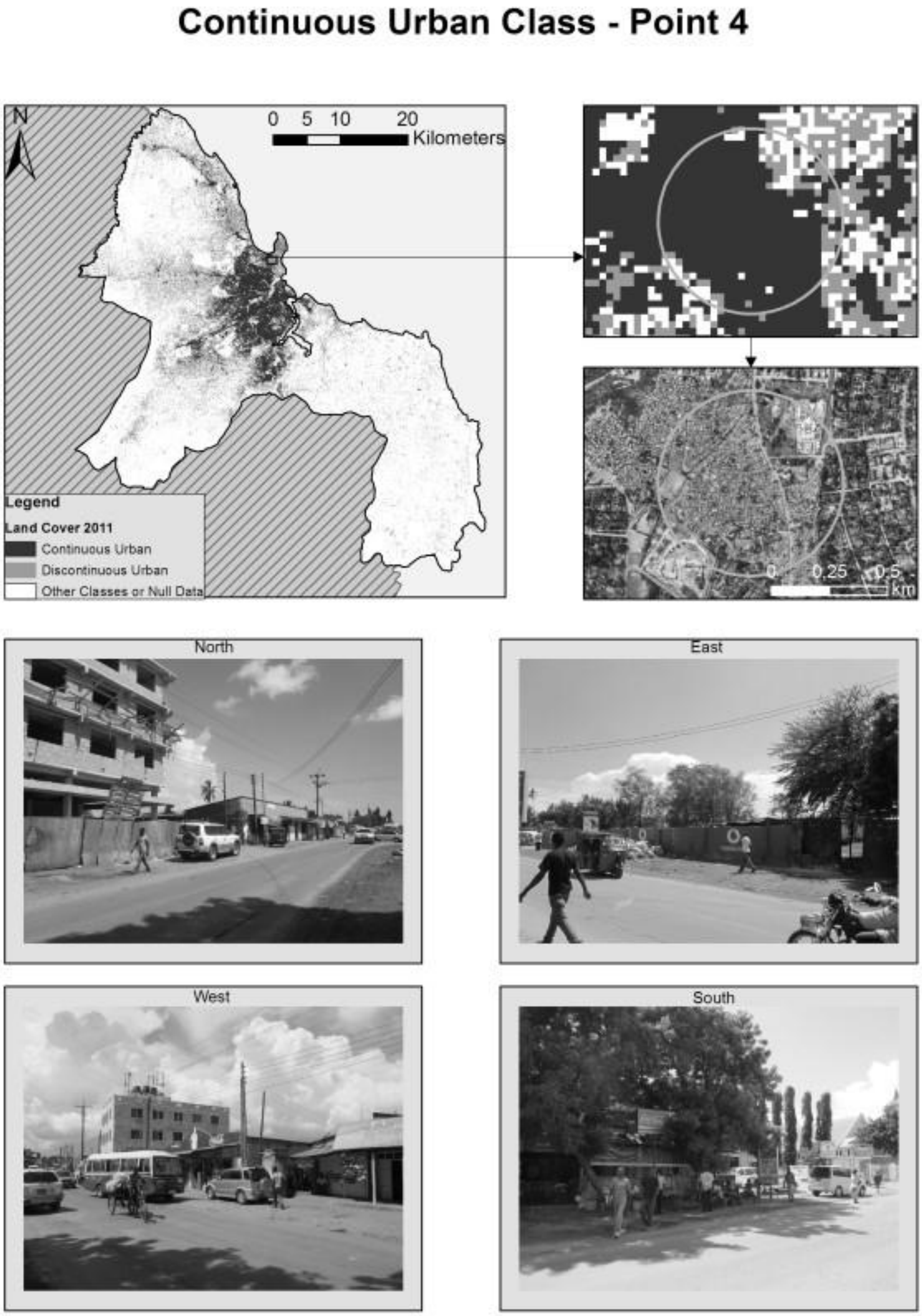

Figure 38: Continuous urban class, point 4

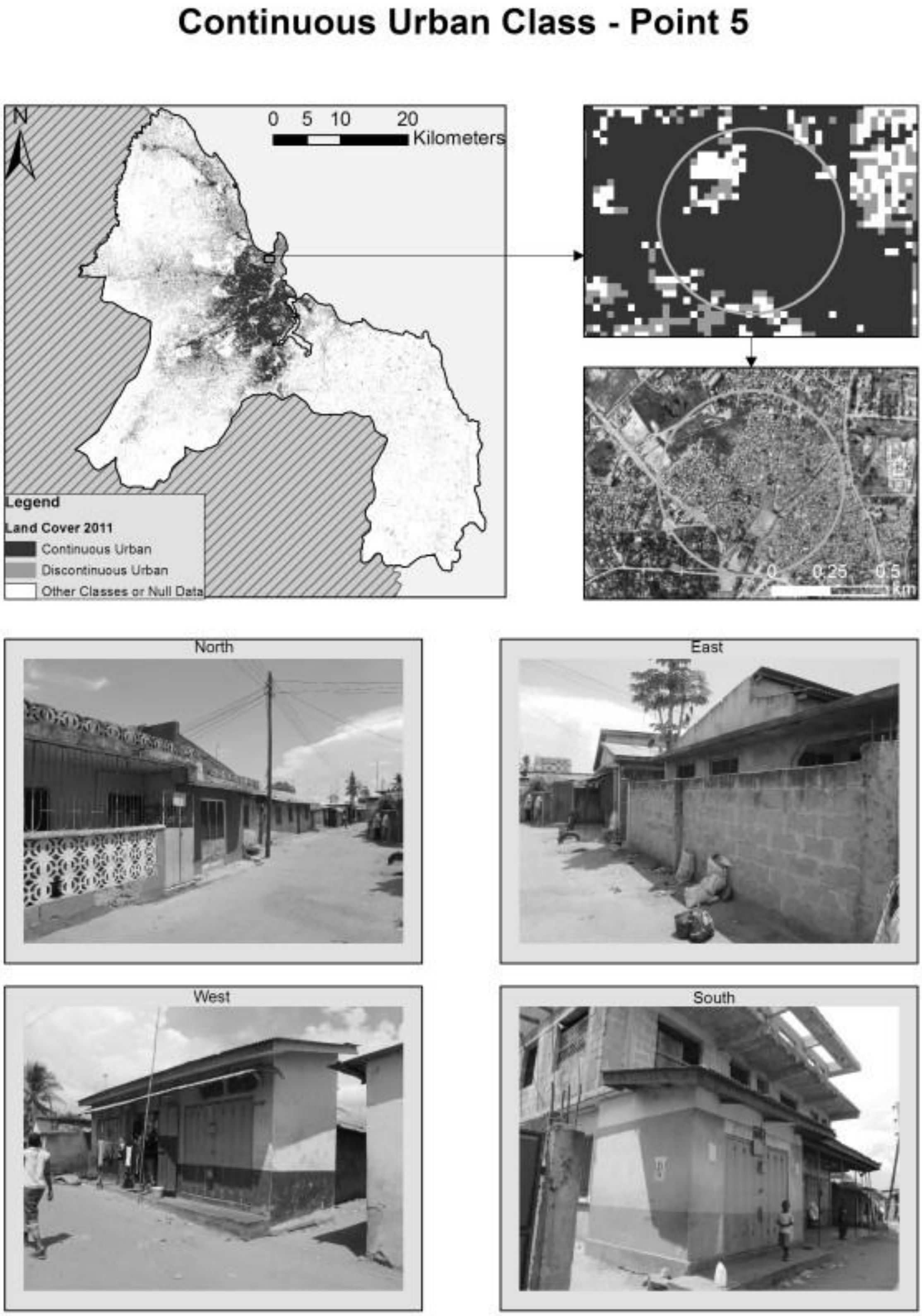

Figure 39: Continuous urban class, point 5

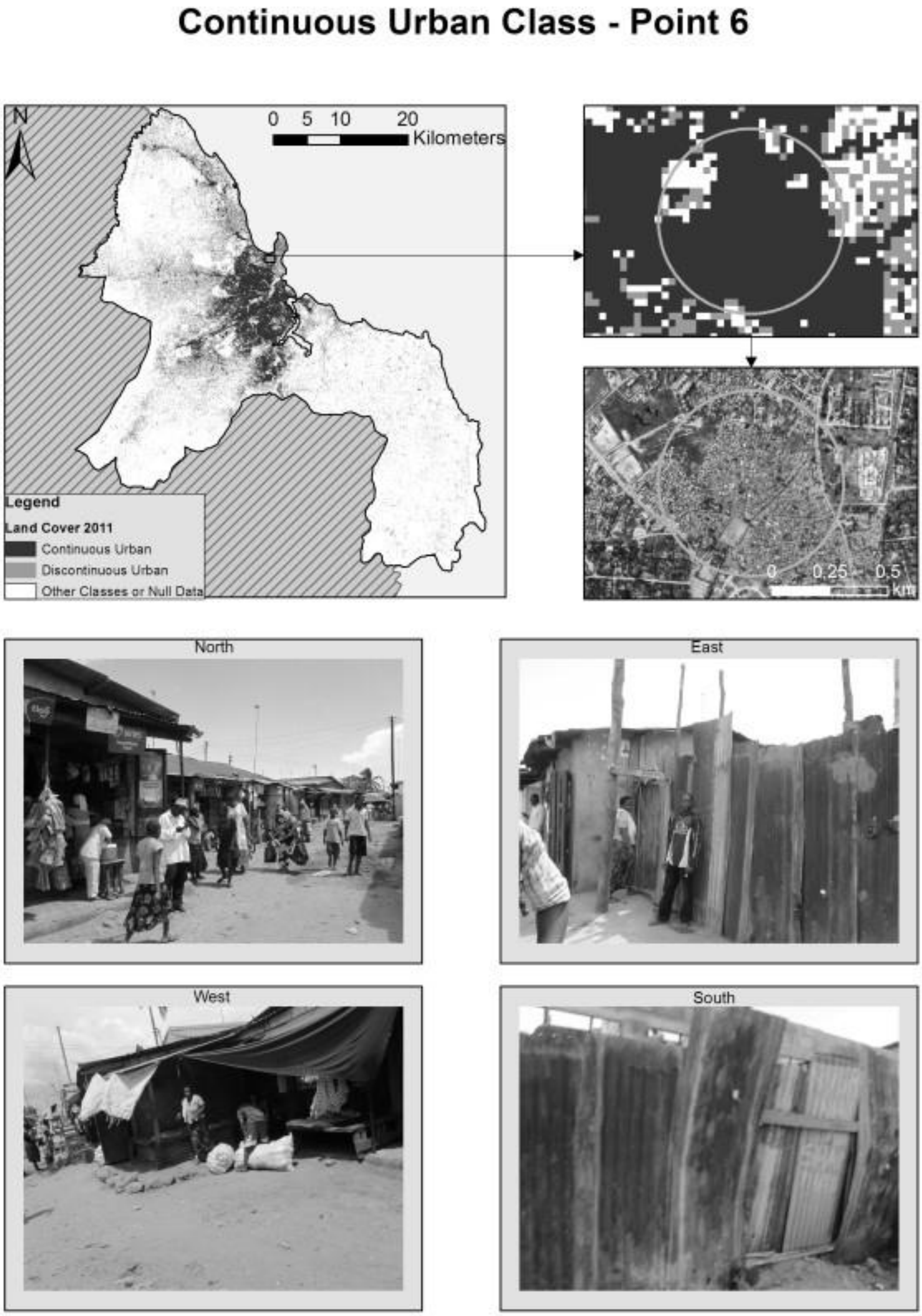

Figure 40: Continuous urban class, point 6

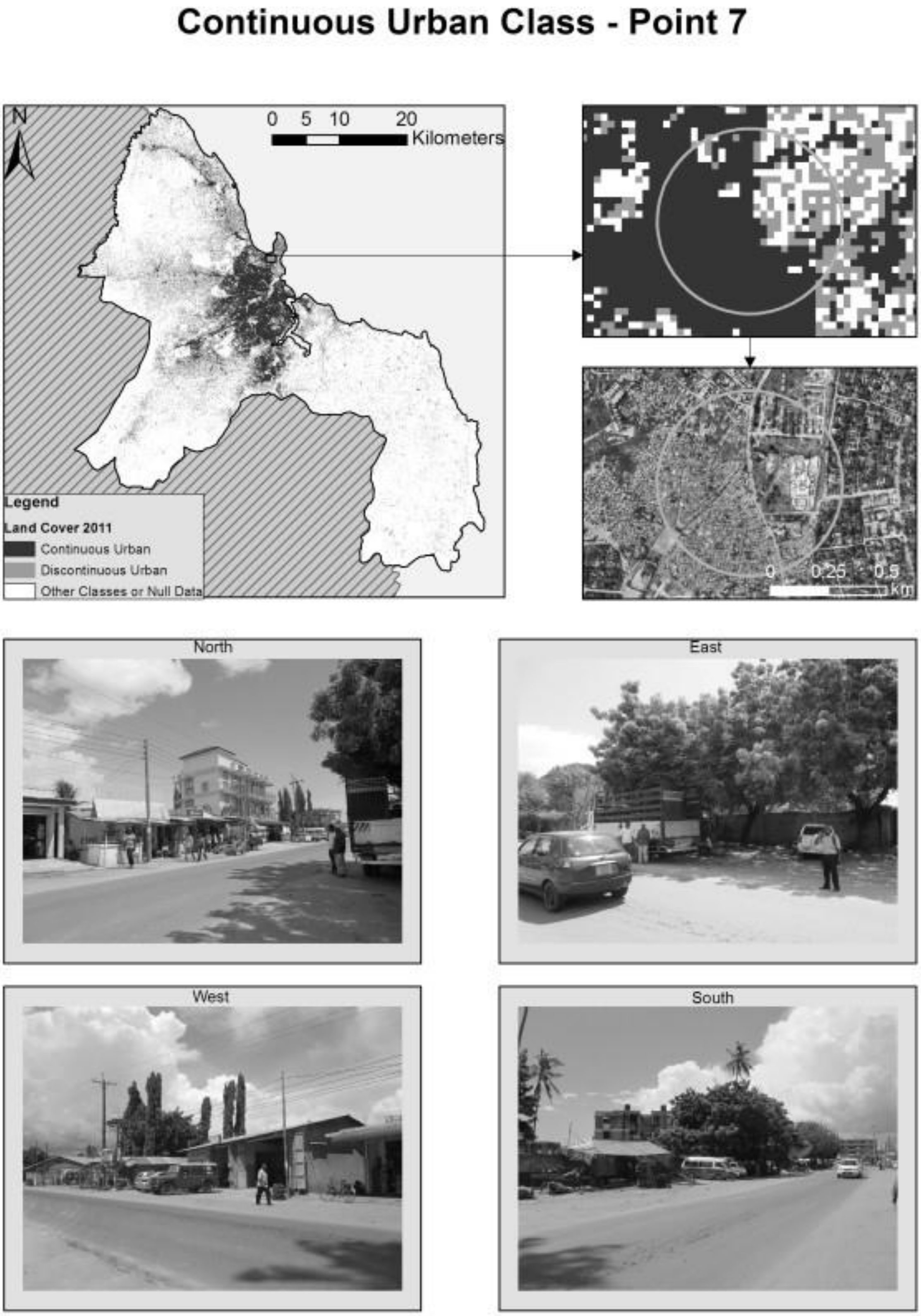

Figure 41: Continuous urban class, point 7

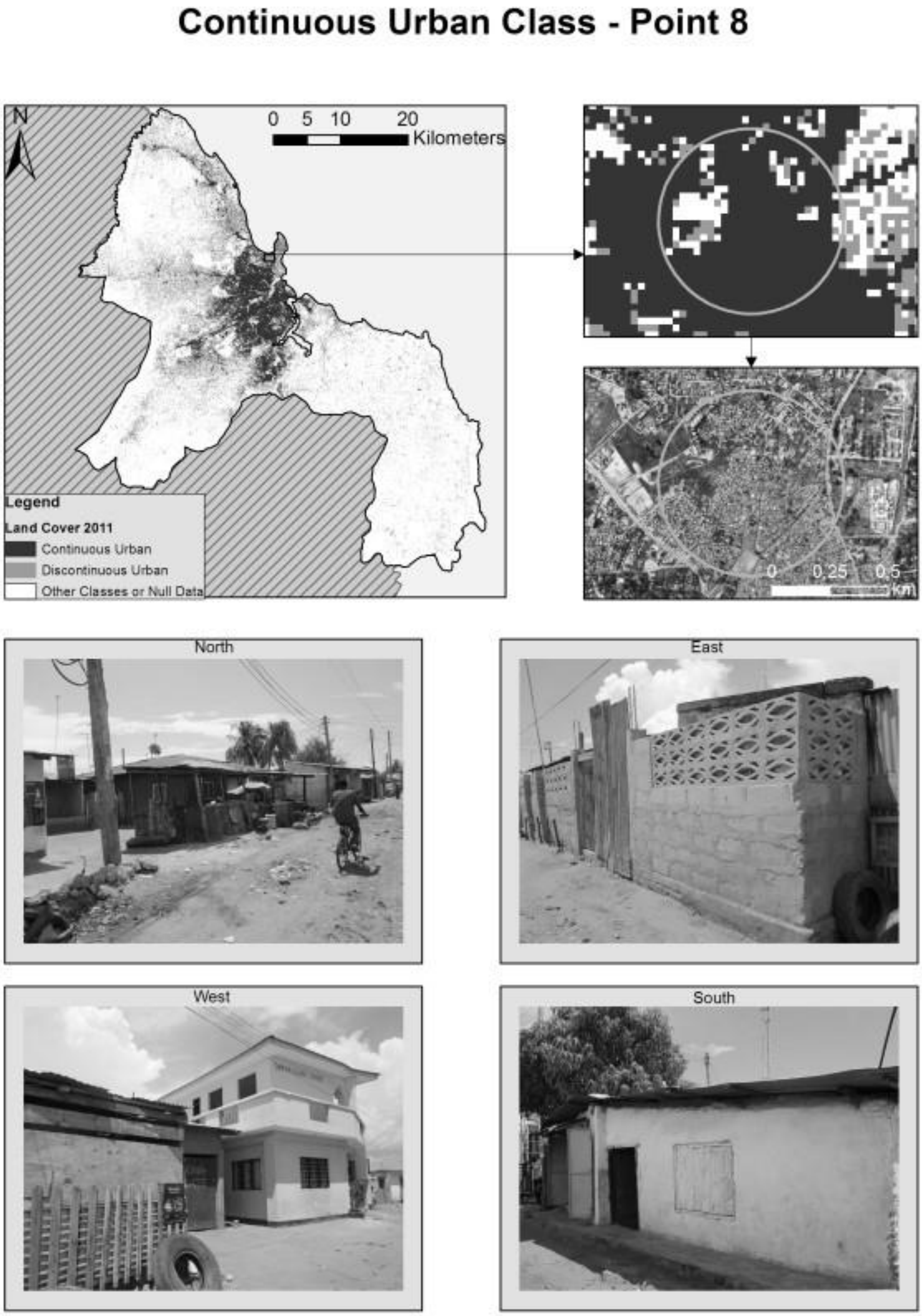

Figure 42: Continuous urban class, point 8

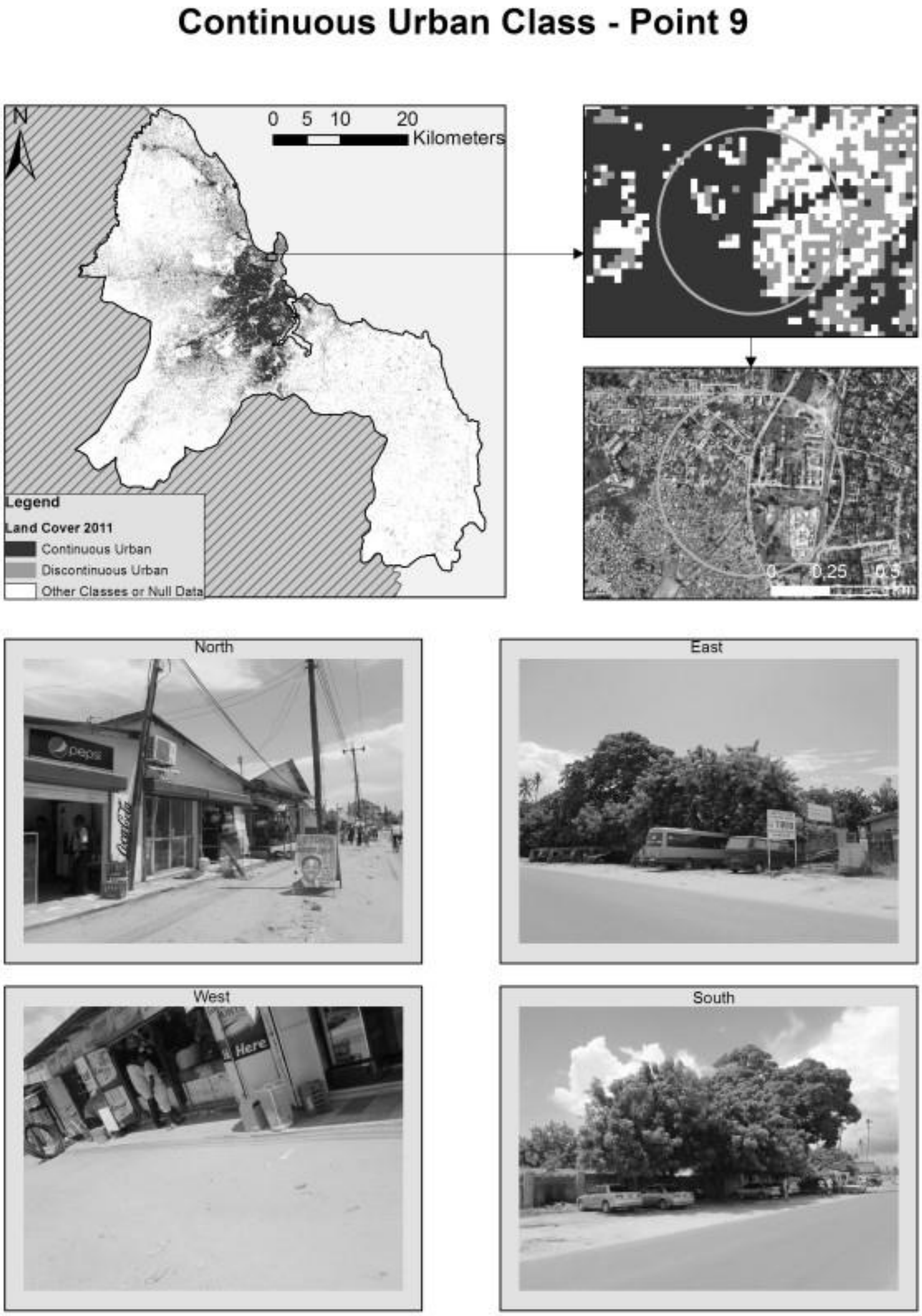

Figure 43: Continuous urban class, point 9

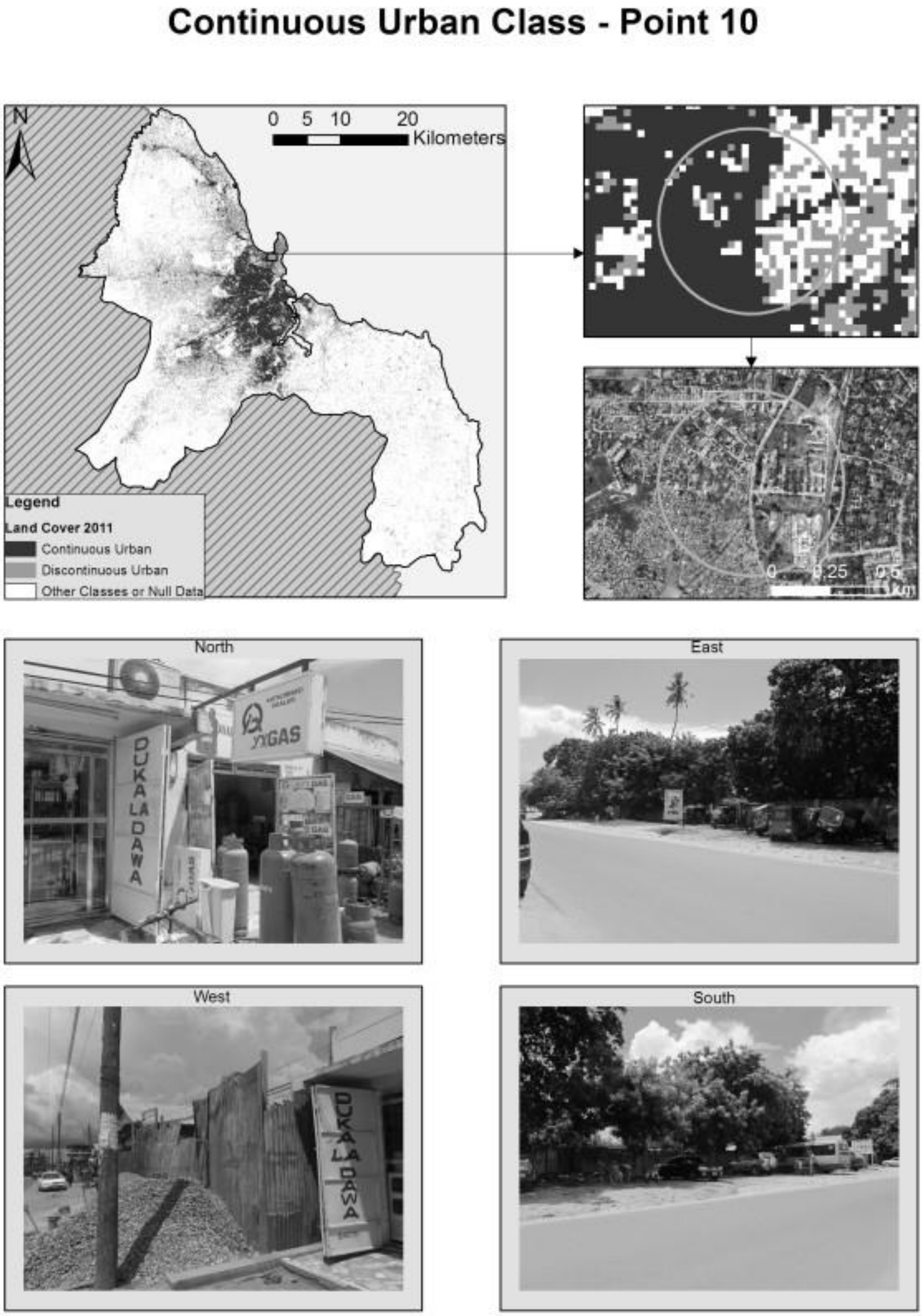

Figure 44: Continuous urban class, point 10

Continuous Urban Class - Point 11

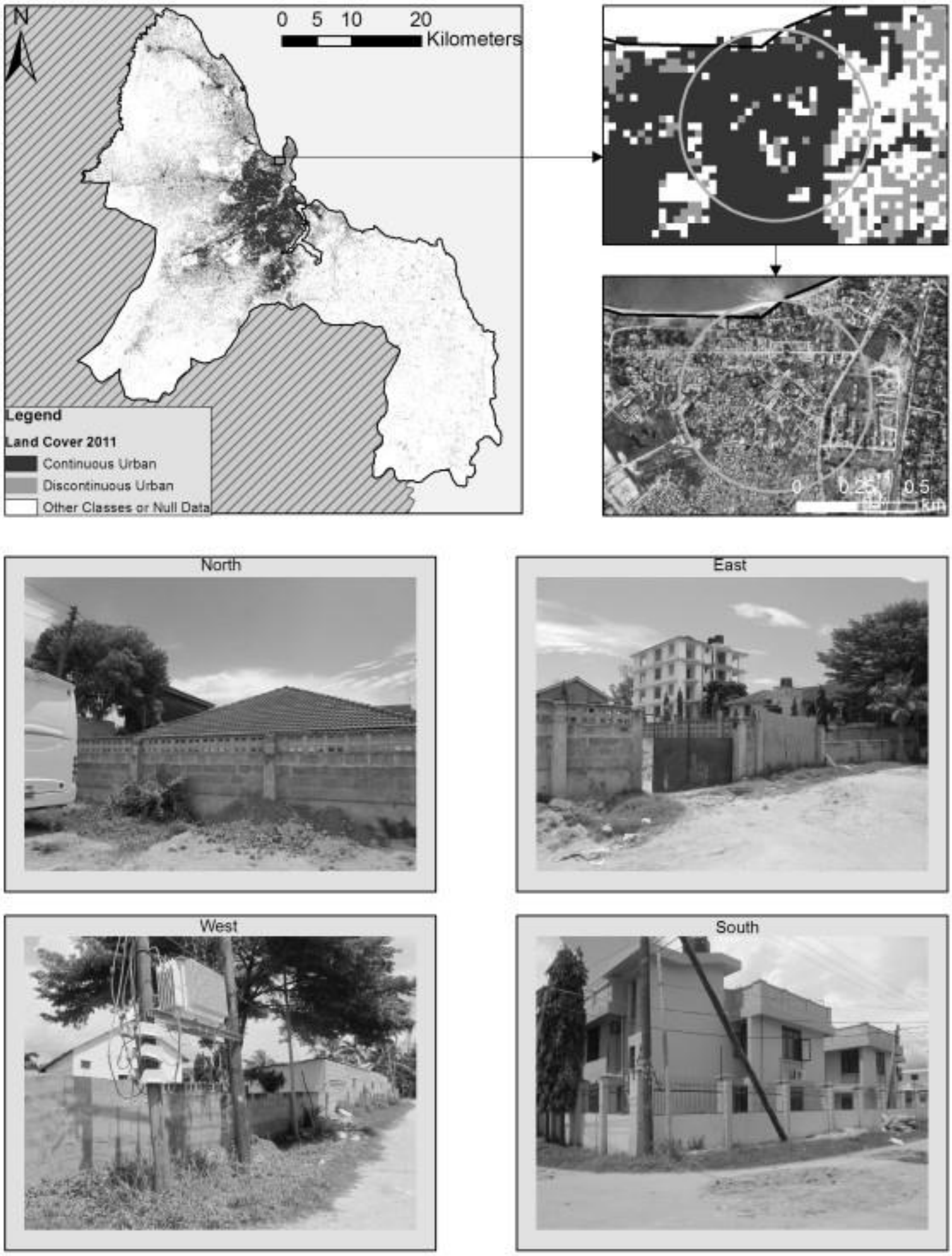

Figure 45: Continuous urban class, point 11

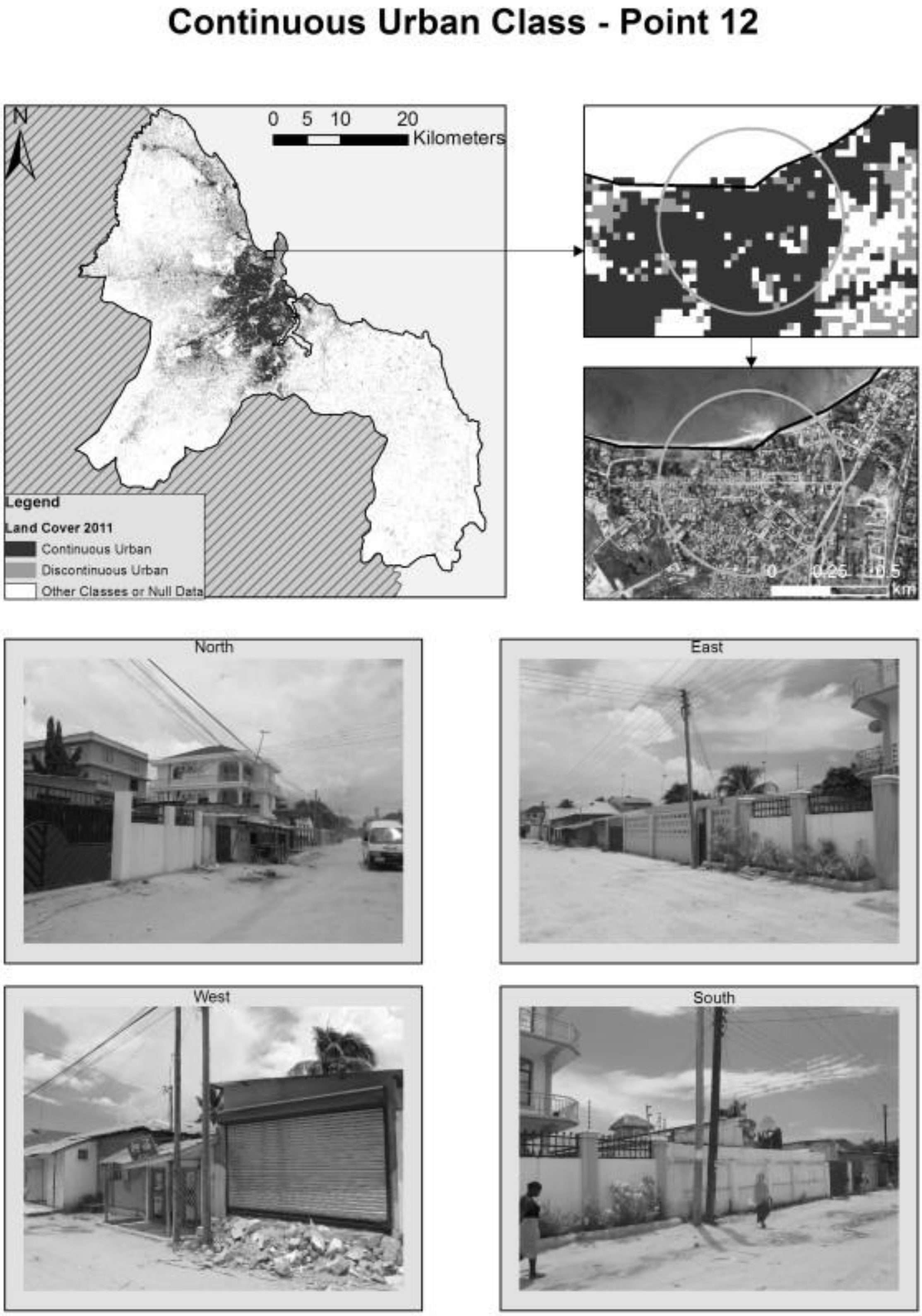

Figure 46: Continuous urban class, point 12

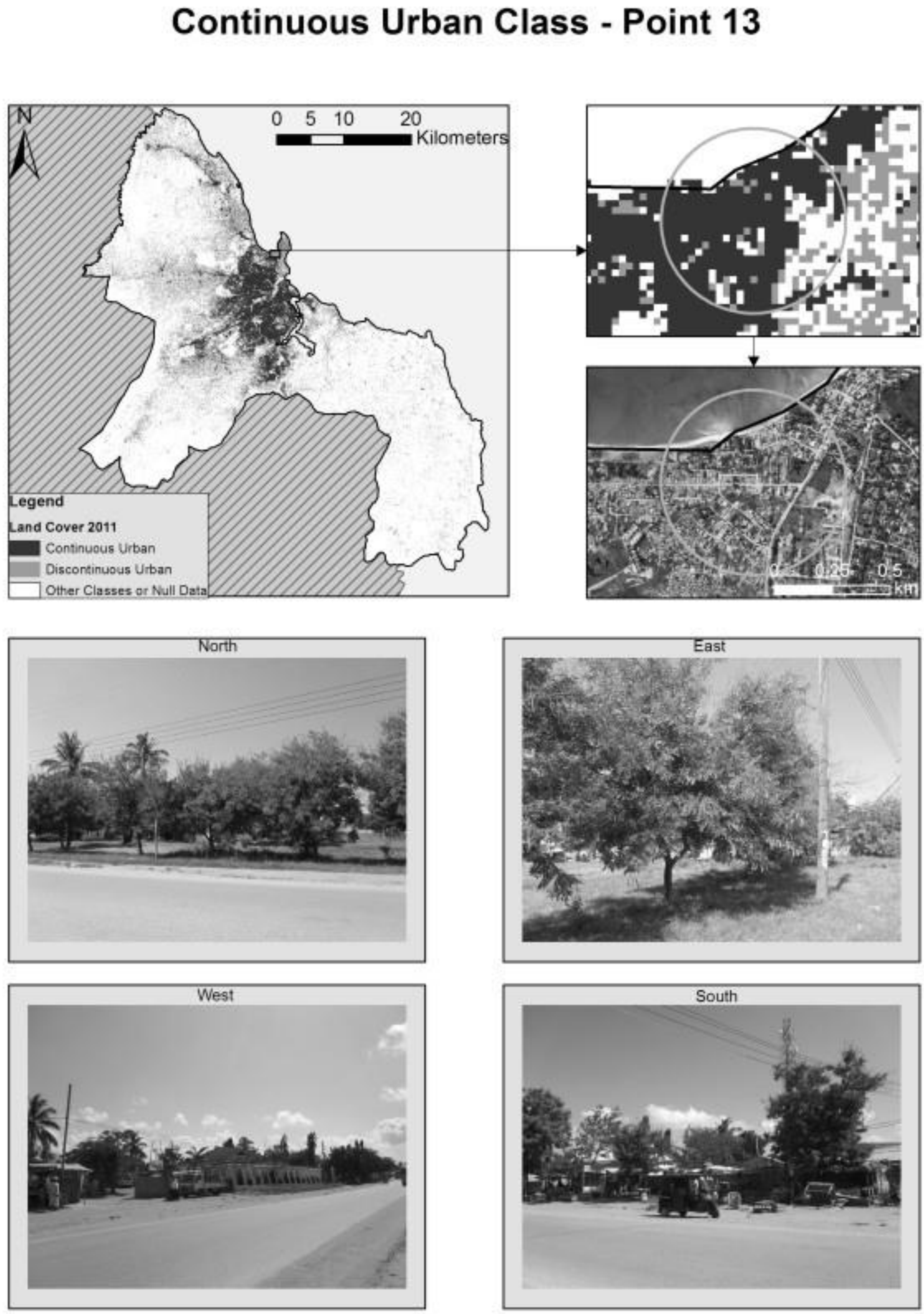

Figure 47: Continuous urban class, point 13

Continuous Urban Class - Point 14

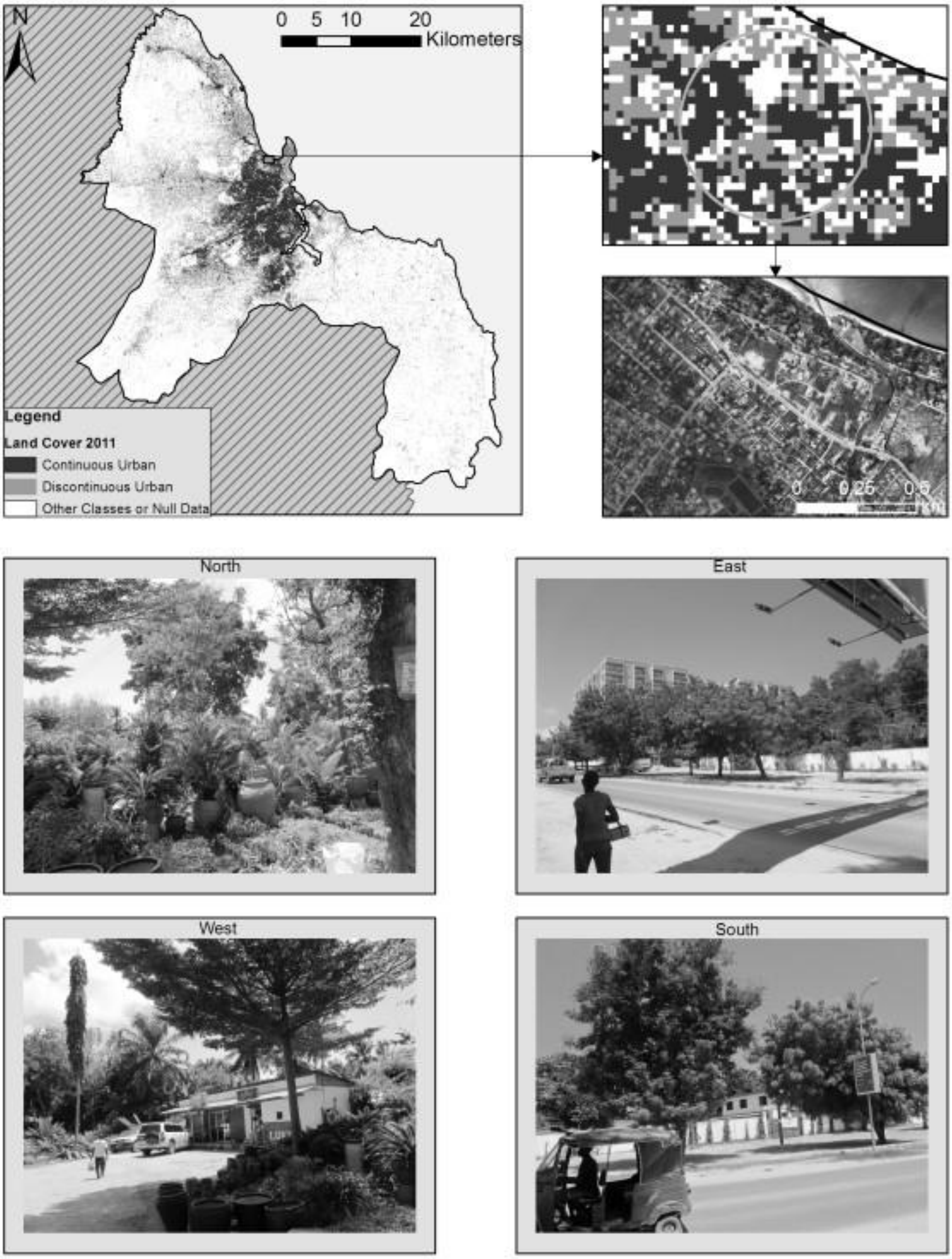

Figure 48: Continuous urban class, point 14

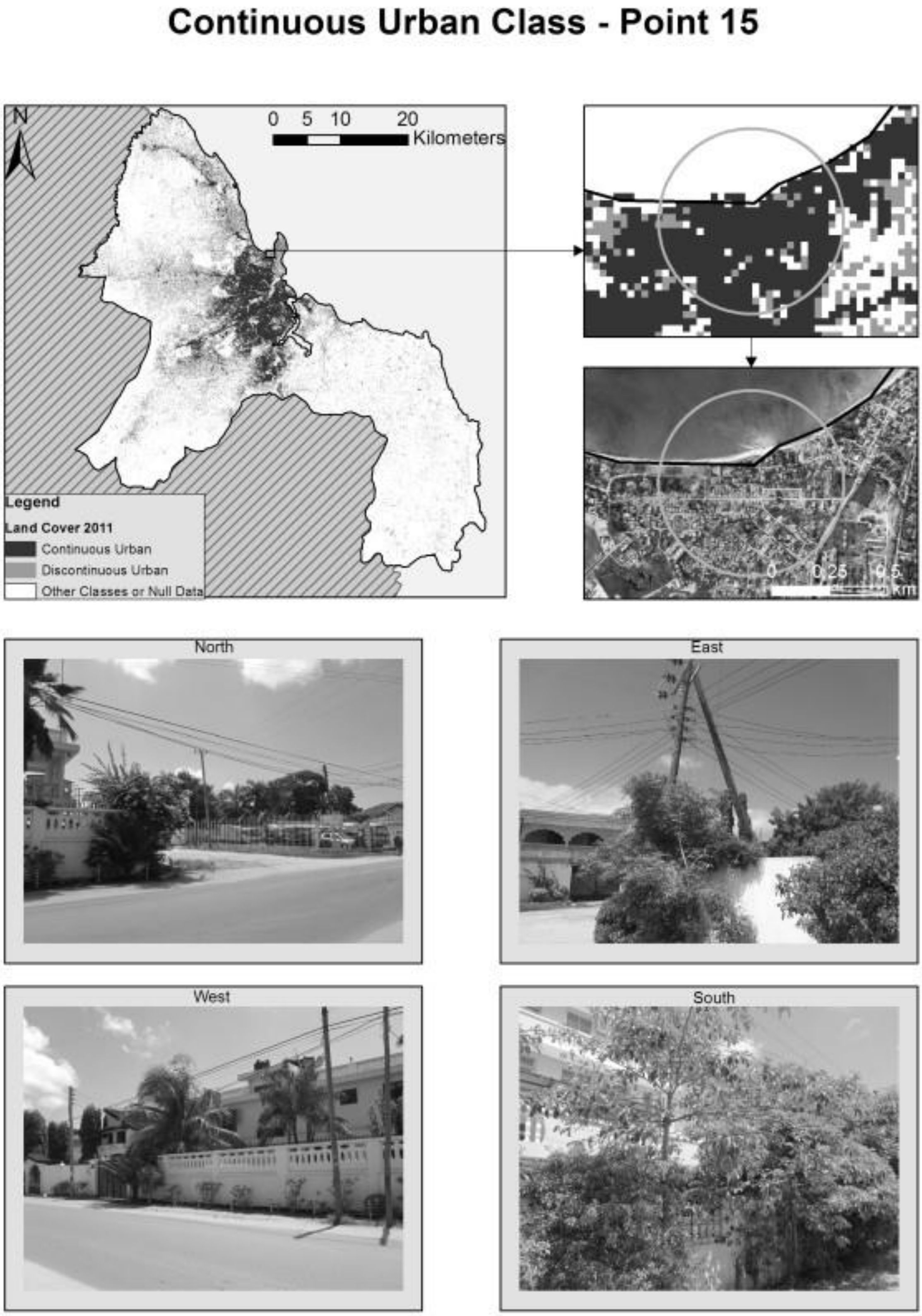

Figure 49: Continuous urban class, point 15

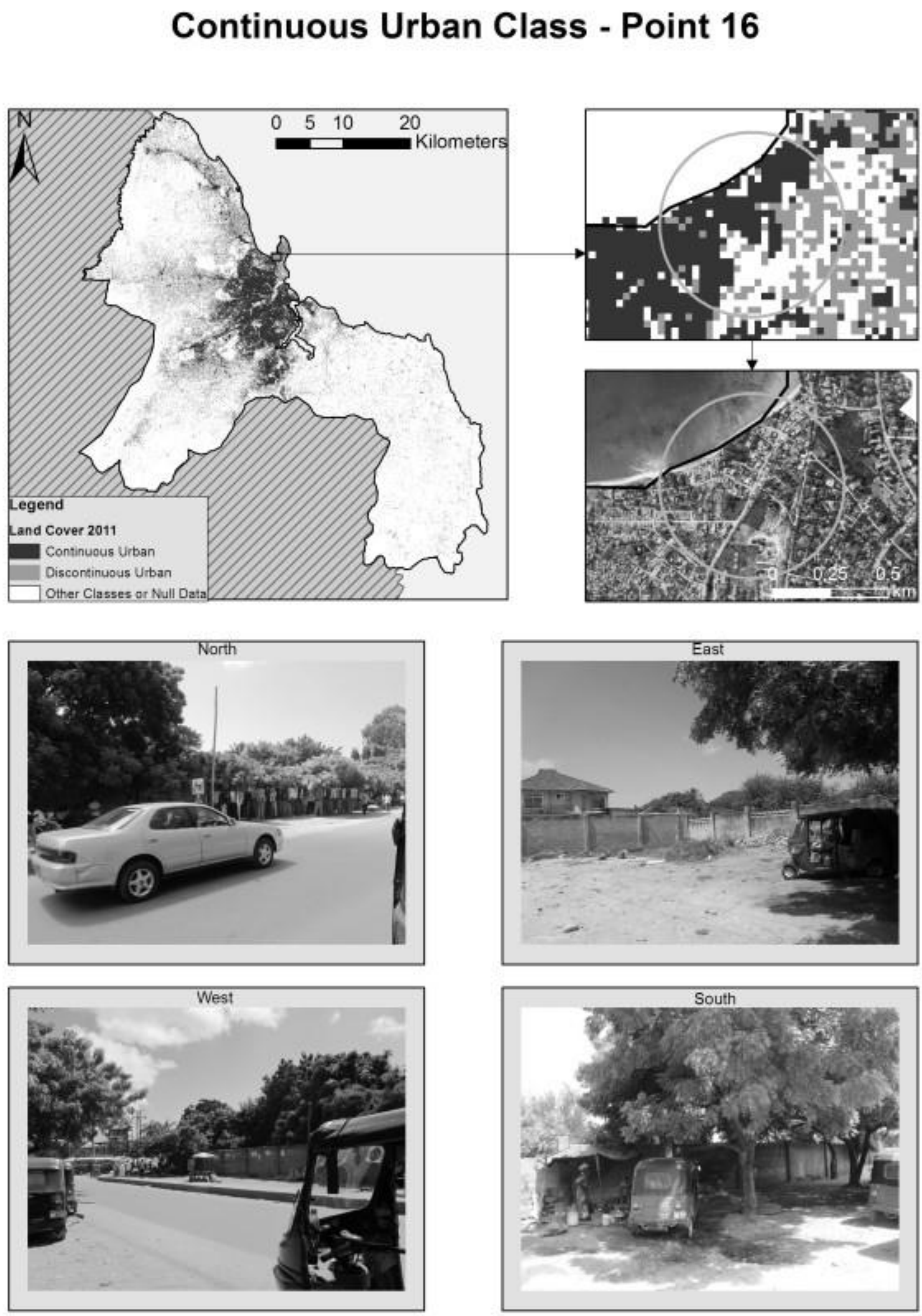

Figure 50: Continuous urban class, point 16

Continuous Urban Class - Point 17

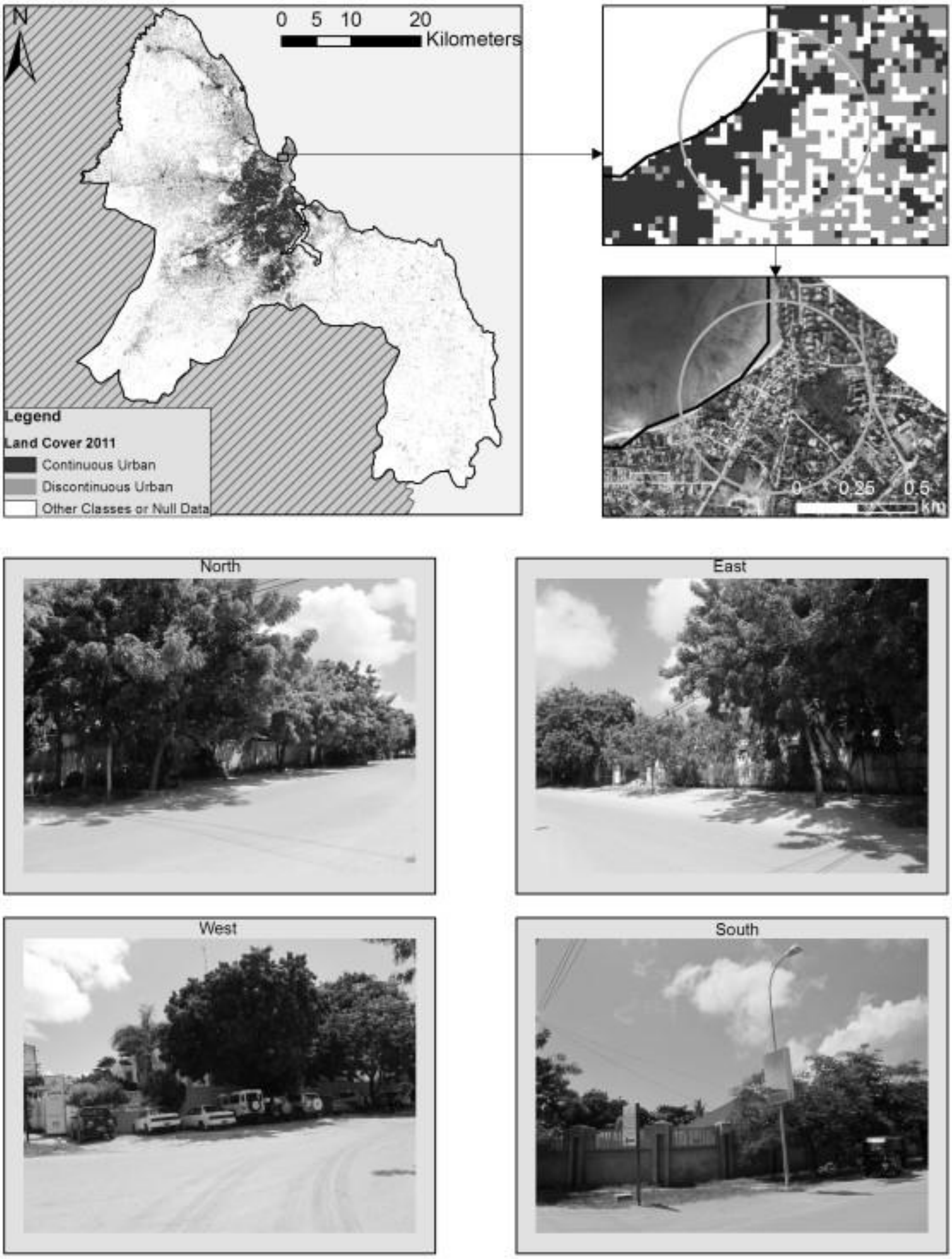

Figure 51: Continuous urban class, point 17

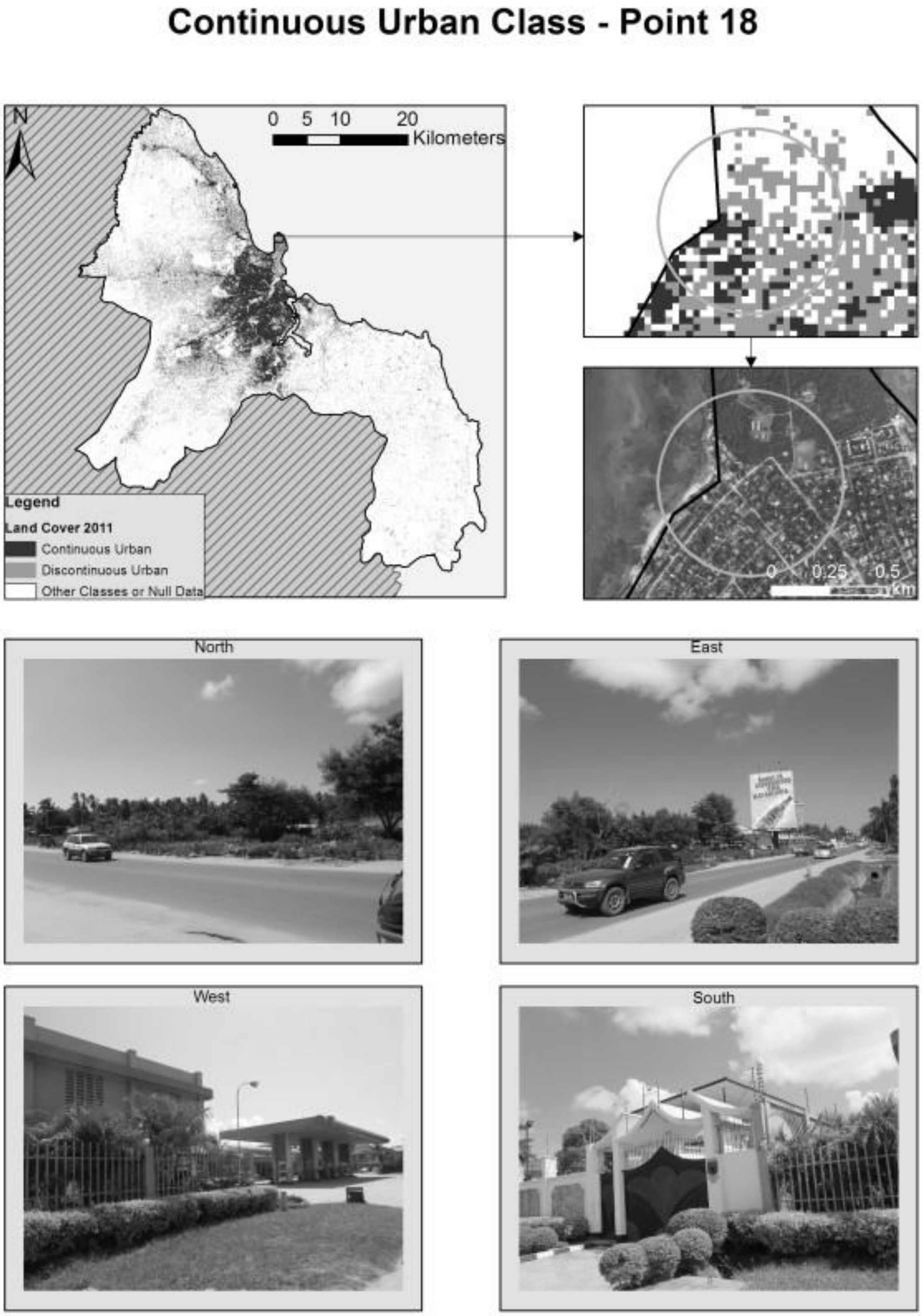

Figure 52: Continuous urban class, point 18

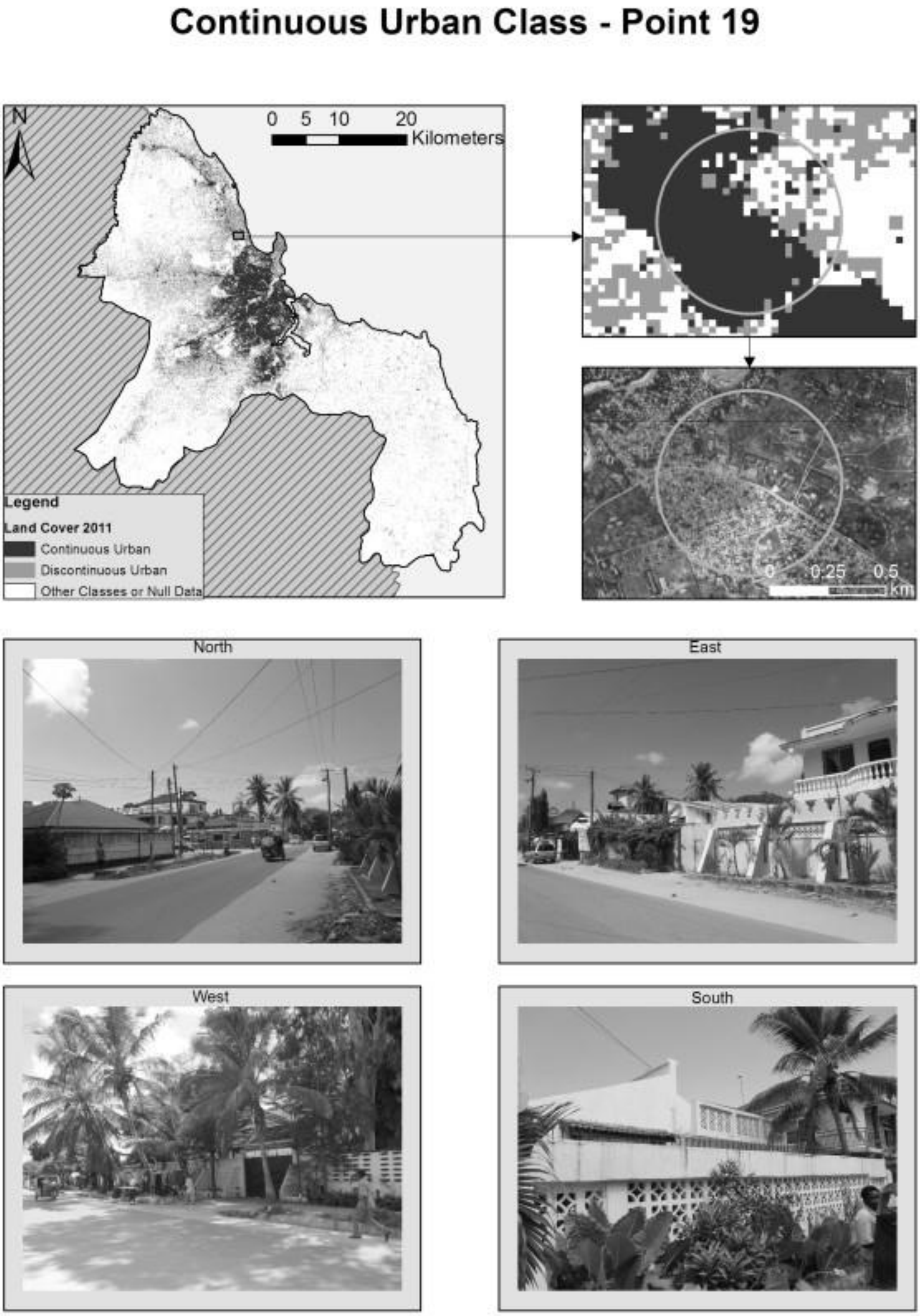

Figure 53: Continuous urban class, point 19

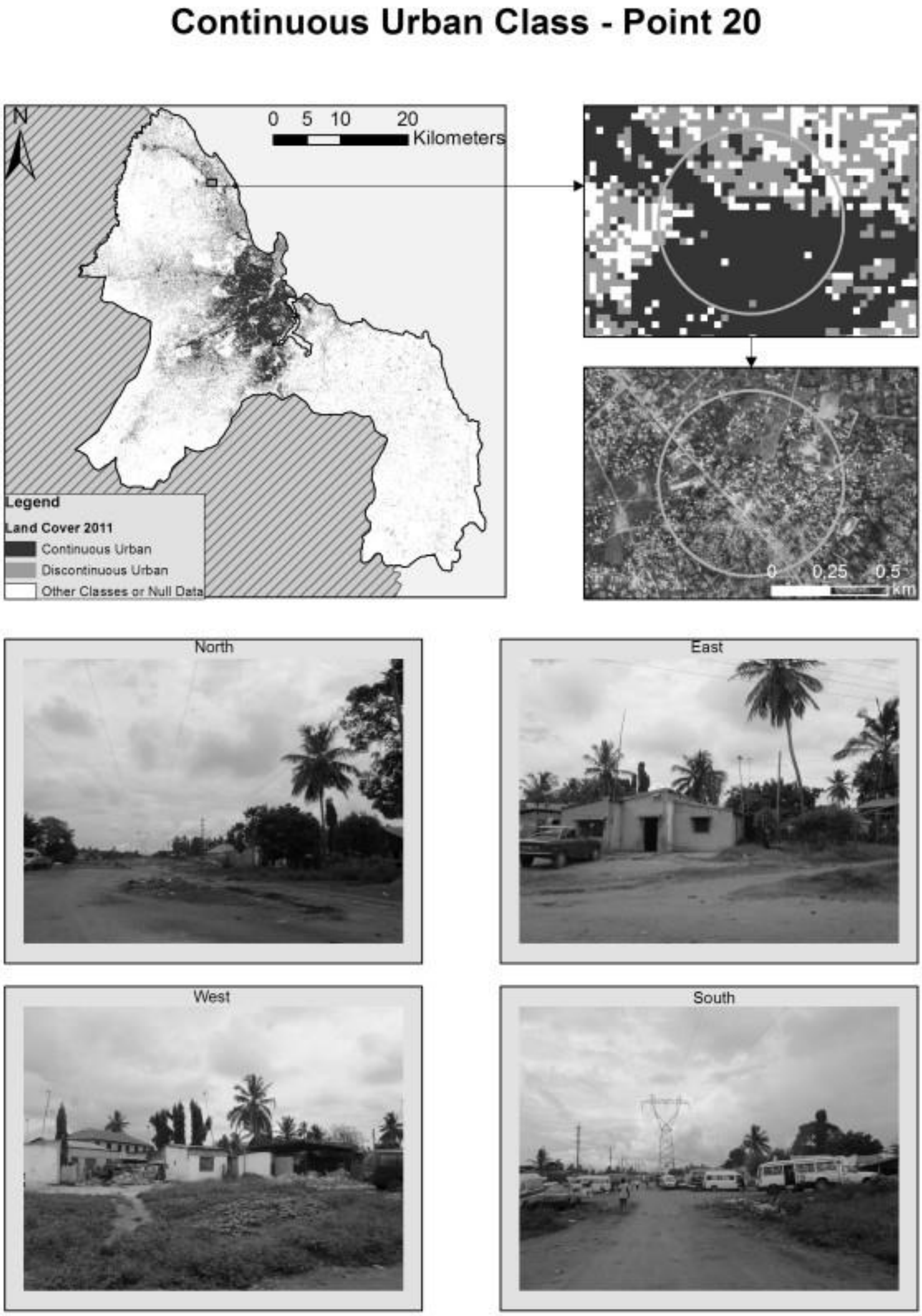

Figure 54: Continuous urban class, point 20