Potential of a multi seasonal spectral mixture analysis using Landsat imagery for detecting urbanization patterns in Ouagadougou, Burkina Faso

Bachelorarbeit

Humboldt-Universität zu Berlin

Geographisches Institut

eingereicht von:

[redacted]

Gutachter: Dr. Sebastian van der Linden

Prof. Dr. Jonas Ø. Nielsen

Berlin, den 10. November 2014

Abstract

Globally rising urbanization rates and population growth makes cities the most important future human living environment. Various remote sensing data sets and methods are already applied in a worldwide research on urbanization processes at different spatial scales. This study uses multi seasonal NASA Landsat satellite data from five time steps (1986 to 2011) in order to evaluate the potential of subpixel information using iterative spectral mixture analysis for historic urban monitoring in Ouagadougou, Burkina Faso. It places itself between studies using manual digitalization or conventional image classification on medium resolution data and those using high resolution imagery or supportive Radar data sets. The study region's high annual seasonality in precipitation and high rainfall dependency of vegetation recommend an approach considering multi seasonal data from both dry and rain season. This is supposed to reveal seasonal surface types and to minimize impacts from seasonal events like dust coverage in summer. In a first step, adequate reference surface types are identified and adapted to historic imagery. Secondly, comparative mixture analyses are conducted on 2011 mono and multi seasonal imagery and illustrate that mono seasonal unmixing produces high mathematic accuracy but lacks thematic consistency. Results of historic multi seasonal mixture analyses are validated with third party studies on a city level and in-situ observations and interviews on a neighborhood level. Important tendencies in city development can be traced easily in the first case. The applied method outmatches a conventional classification approach in that region. On a neighborhood level (1km²), analyses of historic pixel fractions show some implausibility, but are generally in line with interview information. Future data availabilities might enhance this approach to be alternative to more complex data combining and processing methods.

Thesis Structure

List of Figures

List of Tables

1. Introduction

In 1970, life environments in most parts of the world had a far more rural character than they have today. Whilst Europe and the Americas had already an urban population exceeding 50% of total inhabitant numbers, urbanization processes started later in Asia and Africa. Within the last four decades, African urbanization rates rose from 24% to 40%, being expected to reach 50% merely after 2013. Considering general population growth, the absolute number of urban population in Africa multiplied by five since the 1970s and is predicted to double again until 2030, then counting 870 million people (UNDESA 2012). In this context, understanding urban processes of growth and sprawl is crucial for several reasons. Historic urban monitoring on either scale (e.g. economic, demographic, structural) might enhance competences on future urban policies. In addition, urban sprawl implies the replacement of rural land cover types and although a city is very restricted in its spatial extent, urbanization affects the environment and ecosystem services in a global, regional and local dimension (Foley et al. 2005, Kelder 2011).

Since rapid urbanization, particularly in developing countries, is a rather young phenomenon, land cover and land use change sciences have the opportunity to monitor essential processes with remote sensing techniques, even if for remote sensing, urban environments stay one of the most challenging landscapes (Herold et al. 2004).

Urban sprawl takes place for manifold internal and external reasons. Its occurrence is very individual, but generally depends on the question if it is planned or unplanned. Either way, the determination of urban areas is difficult because of their dynamics. Therefore, (Bhatta 2010) brings together various methods of urban space identification(Bhatta 2010). It can, amongst others, be based on spectral surface characteristics or on their combination with urban metrics (Herold et al. 2005). Due to its degree of detail, high resolution airborne and satellite imagery (e.g. *QuickBird*, *RapidEye*) is appropriate and widely used for urban environments (Tigges et al. 2013, Lu et al. 2010, Shan & Hussain 2010). Nonetheless, open data archives since 2008 (USGS 2008) and approved preprocessing methods suggest the use of Landsat data from MSS, TM and ETM sensors. Landsat is a multispectral earth observation satellite, currently in its 8th generation. Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) are sensors characterizing Landsat generations 1 to 7 with a respective spatial resolution of 30m (USGS 2014). Studies show that medium spatial resolution data like Landsat can be reliably applicable in urban change mapping in combination with supplementary support data like Radar, census data or methods like object oriented classification based on object structure and texture (Taubenboeck et al. 2012, Griffiths et al. 2012, van de Voorde et al. 2009, Shan & Hussain 2010).

This study uses Landsat TM and ETM data to map historic urbanization processes in Ouagadougou, Burkina Faso. A preview of Landsat scenes set up in *Africa: Atlas of Our Changing Environment* (Fig. 1 (UNEP 2008)) and an ethnologic field research parallel to this study being able to provide in-situ observation data indicate research potential and opportunities of the study region. (de Jong et al. 2000) points out that medium resolution data alone using conventional classification methods do not produce sufficiently adequate results for Ouagadougou. Given the fact that historic supplementary data is rare for Ouagadougou, this study tries to compensate coarse spatial resolution with subpixel classifications using spectral mixture analyses (SMA), proven adequate and applied in urban environments in general (Small 2005, Michishita et al. 2012). SMA use equation systems to decompose a pixel's spectrum into fractions of given reference spectra allowing statements on a subpixel level (Hostert 2001, Small 2004). At the same time, regional climatic conditions featuring dry and rain seasons encouraged me to consider multi seasonal datasets for comparative analyses, since they may allow surface type detection with regard to seasonal variations. Several studies prove the benefit of multi seasonal data in urban environments (Yuan et al. 2005) and remote sensing in general (Reese et al. 2002, Griffiths et al. 2010).

The study's main objective is to use a comparative approach of mono and multi seasonal SMA in order to deduce quantitative and qualitative information about urban structures. My first research question is if combined data from two points in time offer advantages over data from only one moment of the year concerning SMA results. The second research question is if multi seasonal SMA results on Landsat data from different years allow to quantitatively or qualitatively retrace gradual urbanization processes based on different pixel surface fractions.

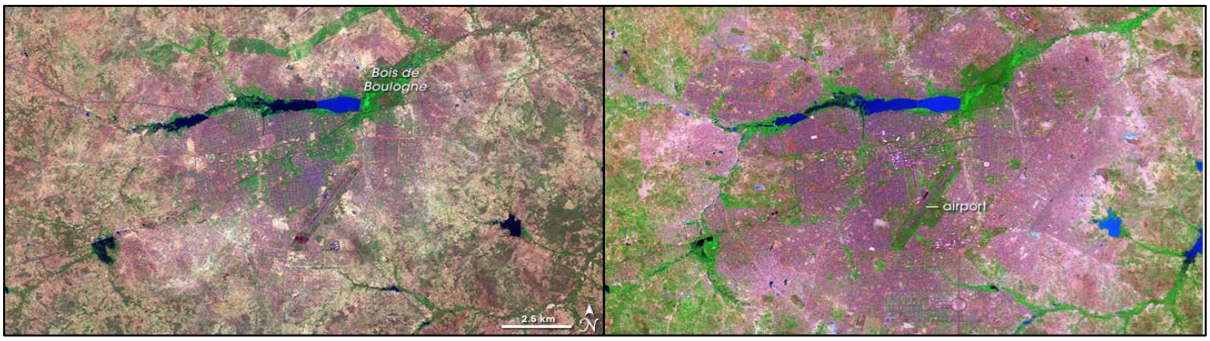


Fig. 1 NASA Landsat scenes of Ouagadougou, Burkina Faso, in 1986 and 2006.
Left: Landsat 5TM, 18 Nov 1986. Right: Landsat 7ETM+, 16 October 2006.

2. Study Area

The study region consists of an area of approximately 40 km width and 35 km height comprising the greater Ouagadougou metropolitan region and adjacent landscapes (Fig. 2). Capital of the west-African republic Burkina Faso, Ouagadougou is the largest city in a country counting 14 million inhabitants (51 inh./km²) after the 2006 census (INSD 2006).

2.1. Climate, water and vegetation

Burkina Faso is for its most part located on a plateau elevated about 300m above sea level (Fearon & Laitin 2006). As a result of the rather flat topography, the country's climate depends largely on geographic latitude and is affected by different climatic zones (Virmani et al. 1980, NCDC 2014). Despite of large regional variations in temperature and precipitation, Burkina Faso is in total characterized by tropical summer-humid climate under the influences of a trade wind driven dry season from October to April and an ITCZ driven wet season from May to September (Weischet & Endlicher 2012). Spectral surface features are, thus, supposed to differ considerably between the times of year.

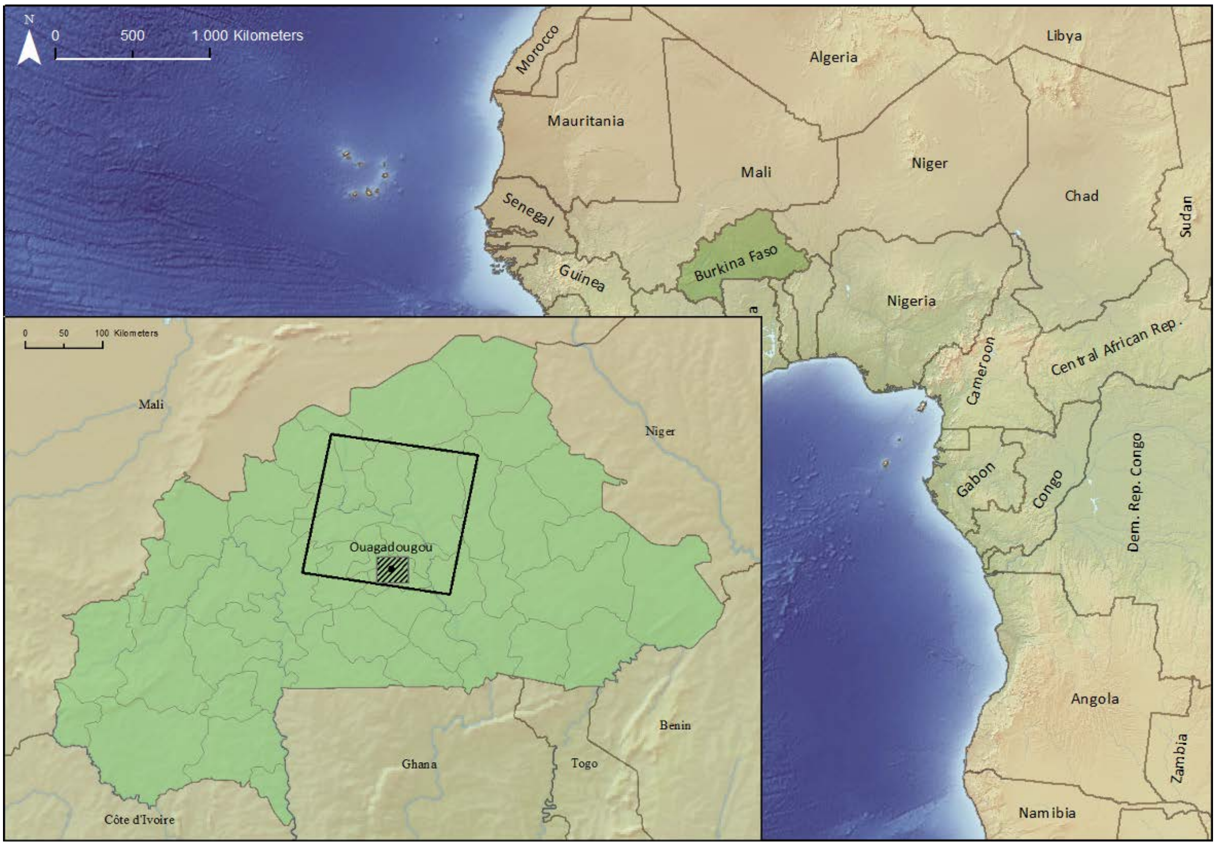


Fig. 2 Regional overview of the study site (shaded) including Landsat footprint (framed)
Background illustration data: www.naturalearthdata.com

Burkina Faso features annual water balance deficits and its total yearly water resources are limited (UNEP 2008). Offering one of the highest dam densities in Africa, most of them have rather small capacities and agricultural irrigation does not take place on a large scale (UNEP 2010, Sandwidi 2007). Phenology and, thereby, spectral features are in many areas exclusively rain dependent.

Ouagadougou is located in the Dry Sudan Savanna (UNEP 2010), which is naturally dominated by true grasses, legumes and sedges, but highly affected by human agricultural activities (Madsen et al. 2004). Predominant crops are cereals, cotton, groundnuts and sesame, dependent on seasonal rainfall. Decentralized rural development policies led to fragmented agricultural areas with tree and shrub populations (Ouédraogo 2002, UNEP 2008).[1]

2.2. Demography, land use and urban sprawl

Counting about 1.475.000 inhabitants in 2006, Ouagadougou has multiplied its population within the last decades (465.000 in 1985, 750.000 in 1996). With a current growth rate of 4 to 5% and prospective populations of 1.9 million in 2010 (no confirmed census) and 3.6 million in 2020 it has the potential for further future studies (Fournet et al. 2008, UNDESA 2012). Thus, Ouagadougou tends to even extend its hierarchical primacy in the country, which can be illustrated by several respective indices (Chatel et al. 2011).

Still a rather rural township in the mid 20th century, urban growth and structural modernization induced the necessity of a first urban development plan in 1984 going along with a nationalization of all territories (Fournet et al. 2008, Prat 1996). Since then, the reasons of rapid urbanization are diverse, reaching from rural-urban migration due to droughts and famines, the escape from traditional rural lifestyles (de Jong et al. 2000), elevated natural growth rates (Fournet et al. 2008) and the occupation of land for speculative reasons (Ouédraogo 2002) to external factors as political instability in the neighboring Ivory Coast in the 2000s (Beauchemin 2011). Some aspects not only lead to a rising urban extent of Ouagadougou, but also to an unplanned, unorganized and widely illegal settlement in the outskirt areas (Fournet et al. 2008).

[1] For more information on historical and current cultural and legislative aspects of land use and rural development in Burkina Faso consult Ouédraogo 2002.

3. Data and Methods

3.1.Data and preprocessing

Central Burkina Faso lies within the WRS-2 (Landsat Worldwide Reference System) scene path 195/row 051 (Fig. 2). Monitoring urbanization processes over time, a discrete time series including five time steps from 1986 to 2011 serves as a basic dataset. Each time step features one image taken just after the rain season in fall and one taken during the dry season in early spring (Table 1).

All ten images undergo automatic atmospheric correction using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS (Masek et al. 2006)) and are cloud masked by an object based Fmask algorithm (Zhu 2011). Water is masked using the Modified Normalized Difference Water Index (MDNWI) that generally offers a very high overall accuracy on inland waters (Xu 2006). Atmospheric correction adjusts spectral variation caused by atmospheric factors like aerosol concentration. Cloud and water masks are necessary to avoid unwanted statistical effects due to surfaces that this study doesn’t focus on.

Table 1 Analysed Landsat imagery

Landsat generation and sensor	Year	Images (DOY / Date)
5 TM	1986	021 / 21 jan 1987 322 / 18 nov 1986
7 ETM+	2002	022 / 22 jan 2002 246 / 03 sep 2002
5 TM	2007	044 / 13 feb 2007 268 / 25 sep 2007
5 TM	2009	052 / 21 feb 2010 273 / 30 sep 2009
5 TM	2011	039 / 08 feb 2011 247 / 04 sep 2011

All images are reduced to relevant spatial and spectral subsets containing six optical bands from TM and ETM sensors. An image stack of both spring and fall images containing twelve bands is provided for following analyses. It will further be referenced as *image stack*, whereas single imagery will be referenced as *spring imagery/fall imagery*.

3.2. Methods

The first step of this study consists in the choice of an adequate endmember set for the youngest year of observation, 2011. An endmember is a reference surface type that serves as input data for spectral mixture analyses. Endmember choices are made by visual pre-selection of different surface types and following statistical evaluation. Spectral libraries are then adapted to respective historic imagery. In a second step, comparative iterative spectral mixture analyses (ISMA) are conducted on mono and multi seasonal imagery of 2011. This contributes to the first research question leading to the interpretation of possible advantages of multi seasonal data. Finally, an image stack of all historic multi seasonal ISMA procedures is used to visually and quantitatively elaborate potentials of the method on a city and neighborhood level (Fig. 3).

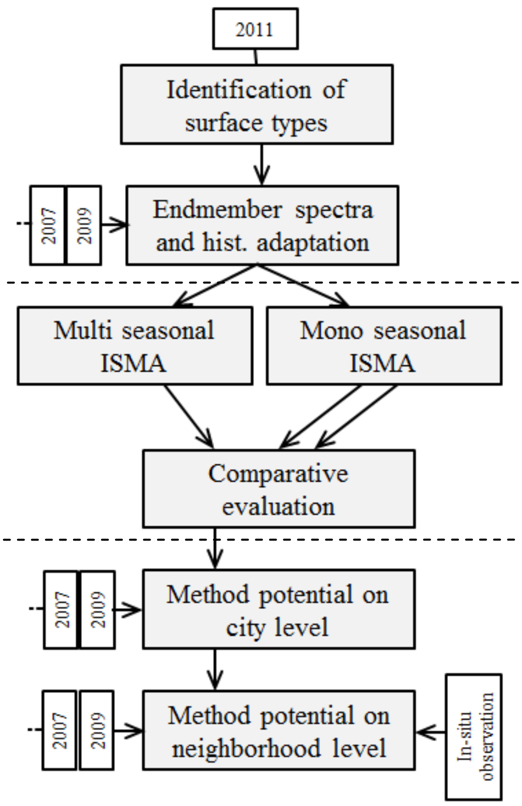


Fig. 3 Steps of analysis

3.2.1. Endmember selection

My approach aims at spectral endmembers originating from processes on the earth’s surface to ensure the SMA and its results to be driven by physical and not by thematic classes. Thematic classes would imply a precedent interpretation of processes already. Urbanization is understood here as a continuous process implying that there is no establishment of any discrete urban classification.

The selection of adequate endmember spectra that most likely represent pure physical surfaces of the imagery is important (Hostert 2001). However, the use of available database spectra seems too uncertain, because a same surface might differ largely depending on its location. In-situ measurements were not possible to do. Purely automated approaches (e.g. Pixel Purity Indices) turn out to identify rather extreme spectra (oversaturation, water, diff. tarmacs) at the expense of frequent surfaces. Finally, the study proceeds with a dual approach recommended by (Tompkins et al. 1997) based on a manual endmember selection considering high resolution aerial imagery from Google Earth, fine-tuned by statistical error analyses.

The endmember selection process is split into three steps: Initially, surface types applicable for the analyses are identified on a multi seasonal basis sampling multiple representative spectra per surface type. Secondly, test linear SMAs altering one of the input endmembers while keeping the others fixed are used to generate comparable error tables. This step is, however, done on mono seasonal data, because robust endmember spectra likewise fit to all three image types (*spring*, *fall* and *stack*). Spectra offering reasonable root mean square error (RMSE) values in five relevant regions of interest (ROI) are chosen as final endmember spectra.

In general, every historic image has an individually adapted endmember library. However, the amount and character of endmembers is supposed to be universally valid and the reference pixels stay at the same location. A reference pixel is replaced in the respective library if it is not considered suitable in the historic image for the surface it represents. A reason could be that, for example, forested area in 2011 did not contain trees yet in 2002. In this case example, the 2002 reference pixel for forest surfaces would be adapted.

3.2.2. Spectral mixture analysis

In order to allow a comparative approach both spring and fall imagery as well as the stacked image are unmixed using an iterative spectral mixture analysis (ISMA (Rogge et al. 2006)) tool embedded in the enMAP Box (Rabe et al. 2014). Linear SMA divides a pixel’s spectrum in fractions of all given image-wide input endmember spectra using a linear equation system (Small 2004). If the system is overdetermined (more equations than variables, i.e. more bands than endmembers), it uses approximation methods to minimize the additional error term. However, traditional SMA does not account for class variability within heterogeneous environments meaning that linear SMA considers every image endmember to be present in every image pixel (Somers et al. 2011). ISMA is a quantitative method for pixel based variable endmember analysis. It processes multiple linear SMAs per pixel reducing iteratively the number of input endmembers. By means of the resulting RMS errors an appropriate quantity and combination of endmembers per pixel can be designated whereas threshold criteria are manually set by the user (Rogge et al. 2006, Mehl & Hill 2014). In this study, numerous results from different parameter sets are compared considering the amount of shade fraction, a qualitative evaluation of the endmember choice and RMS-error statistics over selected ROIs. However, an automatic variable endmember choice led to important challenges like corrupt pixels where thresholds are never reached (up to 15% of all pixels per image). This effect multiplies to nearly 30% of all pixels that cannot be analyzed when stacking the images. Following SMAs are processed defining fixed amounts of endmembers (3-em and 4-em models) still allowing the automatized identification of endmember combinations.

At this point, the results of a multi temporal approach are expected to have important advantages for the study purpose for the following reasons:

- Seasonal Vegetation, like most agriculture, only emerges in multi seasonal spectra, since it is highly dependent on rainfall.
- Some surface types resemble in one season while they differ remarkably in the other one. So do crops and forest spectrally resemble in fall, while they differ in the dry season. Hence, a multi seasonal approach is assumed to be more robust.
- Since spectral mixture analyses are based on linear equation systems, mono seasonal SMA on Landsat imagery is limited to a maximum of six endmembers due to band limitations, whereas even less are recommended (Small 2004).

However, it is uncertain if the degree of overdetermination, which is significantly higher at multi seasonal mixture analysis, will finally have important impacts on error values and, thus, mathematical adequacy of used approximation algorithms.

3.2.3. Evaluation methods

The general potential of spectral mixture analyses on multi seasonal Landsat scenes over time is estimated on a city level, identifying trends and global patterns. It is qualitatively evaluated using multi seasonal spectral mixture results as well as (Prat 1996) and (Fournet et al. 2008). Both authors use the fact if a settlement is registered in cadastral surveys as a key categorization for urban mapping. (de Jong et al. 2000) relying on six socio-economic city sections predefined within a Ouagadougou city management program serve as evaluation data, too.

A more detailed and quantitative analysis is conducted on seven neighborhoods selected in accordance with the above mentioned field study (Appendix 1). Observing surface fractions over time reveals neighborhood characteristics like gradual densification or sudden urban development with temporal references allowing thematic interpretations. A neighborhood has a size of 1 km² and is supposed to have changed its urban character within the last 25 years. Results are finally illustrated using neighborhood mean spectra and showing each endmember fraction in each year of our analysis in one diagram that allows to trace a neighborhood's potentially complex development. Validation and evaluation of neighborhood results is based on in-situ surveys.

4. Results

4.1.Endmember selection

The manual endmember selection on 2011 imagery offers a first set of nine surface types including shade. For several reasons, the eventually applied endmember set only contains six different surface types (Table 2). The lack of areas that purely represent typical roof surfaces as concrete or corrugated iron suggests a spectral endmember accumulating all roof surfaces except brick as a mixture. Indeed, plastic sheets and canvas serve as rooftops of some small businesses and markets. Though, plastic surfaces in our Landsat scenes suffer from oversaturation and are not of central importance for the study's purposes. Tarmac as a typical urban land cover is not crucial for this study either. Roads will be overlaid by respective open street map information on final maps, since a tarmac endmember leads to severe and obvious misinterpretations. Error tables are used to

Table 2 Set of initial and finally applied surface endmembers

EM-Set 1	EM-Set 2	Remark
Vegetation	Vegetation	Includes forests, aquatic vegetation and permanent cultivations
Open Soil	Open Soil	Includes rural soils and urban waste land
Seasonal Vegetation	Seasonal Vegetation	Includes natural vegetation, grassland and periodic cultivation
Concrete		Includes concrete roofs and open urban spaces
Corrugated Iron		Includes iron roofs
	Mixed Urban Roofs	Includes corrugated iron, concrete and other rooftops. Mixture of soil and vegetative fractions cannot be denied.
Brick/Clay	Brick/Clay	Includes brick rooftops and clay pits
Plastic Roof		Includes canvas sheets and other plastic materials
Tarmac		Includes roads and airports
Shadow/Dark Fraction	Shadow/Dark Fraction	Zero value

find final reference spectra per surface (Table 3). Fig.5 illustrates all reference spectra for 2011 imagery.

Table 3 Example: Statistical comparison of potential reference spectra for one endmember.

Numbers imply maxima (above) and minima (below) RMSE values and their respective standard deviation out of ROIs. Seasonal vegetation has been a substitute for soil in the dry season and for vegetation in the rainy season. Values only have relative importance. Bold: Finally chosen references.

Altering endmember spectrum	Spectrum at location	Dry Season imagery		Rainy Season imagery	
		RMSE mean	Standard deviation	RMSE mean	Standard deviation
Seasonal Vegetation	4477/5663	76.8 134.0	38.3 33.7	80.0 106.5	23.2 91.6
	3758/6278	60.0 76.6	25.7 31.7	65.8 122.0	43.0 57.1
	3572/6327	**47.1** **83.8**	**18.1** **41.1**	**56.4** **113.7**	**54.0** **58.7**
	3648/5673	78.1 126.4	37.4 34.7	70.1 145.1	57.6 43.7
	4451/6062	62.6 80.3	26.7 31.4	49.8 127.7	23.9 54.9

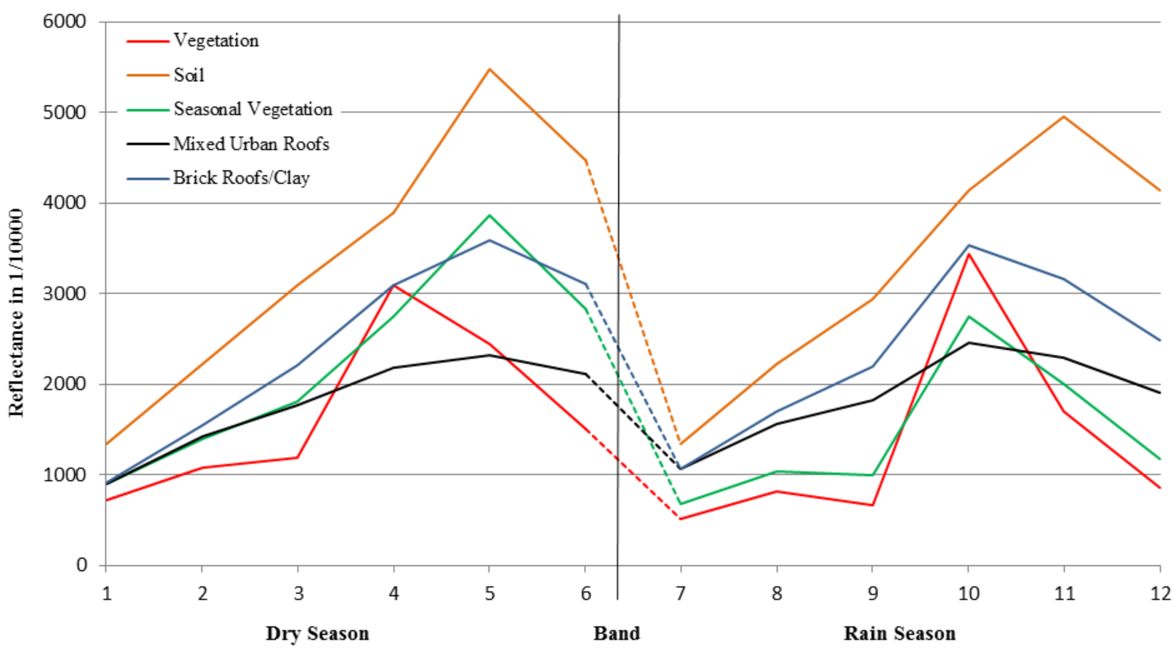


Fig. 4 Final reference endmember set for 2011 imagery.
Multi seasonal spectra consist of six bands that characterize the dry season and six bands that characterize the rain season

4.2. Spectral Mixture Analysis on mono and multi seasonal data

Spectral mixture analyses on 2011 images suggest that some of the previous assumptions on mono and multi seasonal data are correct. Due to climatic and atmospheric circumstances, every SMA result allows different perspectives and interpretations of the scene.

The SMA result of the dry season imagery is, as expected, largely dominated by soils (Fig. 5-1-C). Urban quarters are traceable and distinguishable visually considering roof fractions (Fig. 5-1-A & Fig. 5-1-B). Both 3-em and 4-em models suffer from negative surface fractions, particularly in brick roofs (Fig. 5-1-D). RMSE values are 0.8/100 in average and have a standard deviation of 0.4/100 (0.5/100 and 0.3/100 for the 4-em model) with lower values in urban environments.

Rain season's SMA result makes urban structures hard to detect. Roof fractions appear in areas that are obviously not urban in spite of very specific endmember spectra (> 50% fraction, Fig. 5-2-A). High inner-city vegetation fractions do not catch the character of a dry savanna city as it is on first sight (Fig. 5-2-B & Fig. 5-2-C). The 3-em model reveals nonetheless some plausible urban structures in recently built up areas (Fig. 5-2-C & Fig. 5-2-D). Again, the 4-em model clearly suffers from large negative fractions, whereas the 3-em model does not. RMSE values are 0.8/100 in average and have a standard deviation of 0.3/100 (0.7/100 and 0.4/100 for the 4-em model) with lower values in urban environments.

On first sight, the unmixed stack image allows to trace urban environments in a comprehensive way in a 3-em and 4-em model. Roof fractions are larger in established quarters than in those known to be built up after 2003 (Fig. 5-3-A & Fig. 5-3-B). Rural environments are dominated by seasonal vegetation including scattered spots of soil and permanent vegetation (Fig. 5-3-C). Vegetation patterns are similar to those from the dry season image, but at a higher fraction level. However, obvious misinterpretations of brick roofs occur in the city's surroundings on surfaces that are supposed to be of agricultural use (Fig. 5-3-D). The 4-em model differs by more frequent negative fractions and higher dark fractions in urban environments. Overall RMSE has an average of 1.0/100 and a standard deviation of 0.5/100 (1.0/100 and 0.4/100 for the 4-em model). The error image is regularly structured with slightly lower values in urban environments.

It can be stated that the extent of overdetermination of the mixture analysis' equation system does not have large impacts on the error term approximation result.

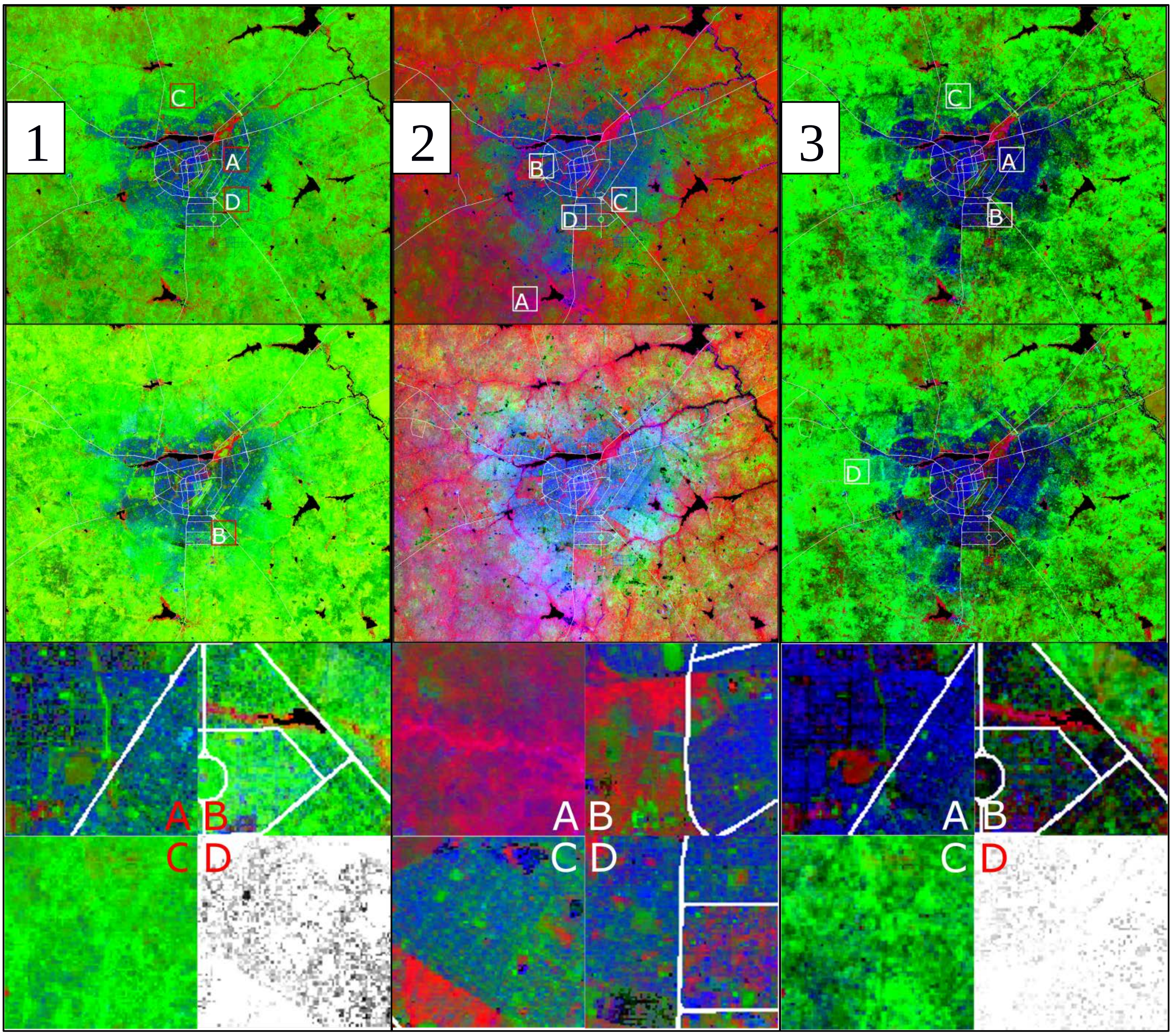


Fig. 5 Spectral mixture analysis results for dry season, rain season and multi seasonal data

Images visualize 3- (**above**) and 4-endmember (**center**) SMA models for dry (**1**), rain (**2**) and multi season (**3**) imagery.

Visualized endmembers for dry (**1**) and rain (**2**) season images are Vegetation (**red**), Soil (**green**) and Mixed Roof Surfaces (**blue**) scaled from 0 to 1. Visualized endmembers for stack imagery (**3**) are Vegetation (**red**), Seasonal Vegetation (**green**) and Roof surfaces (**blue**) scaled from 0 to 1.

1-D and 3-D show fractions of Brick Roofs scaled from -1 to 0 (black = negative fractions)!

4.3. City level analysis

On a city level, the unmixed multi seasonal images of each time step allow to identify global patterns of development since 1986. Results are based on an integral observation of spectrally unmixed multi seasonal images (Fig. 6).

In 1986, the city of Ouagadougou has a rather small dimension. Built up areas characterized by rooftop surfaces are concentrated around a city center comprising the districts of *Paspanga*, *Koulouba* and *Zangouettin* (Appendix 3c). The spectral mixture results reveal decreasing roof fractions towards the city's periphery (Appendix 2a-1). Scattered rooftop fractions also appear in the city's south western outskirts. The Ouagadougou green belt as well as a forest east of the inner-city dam are easily detectable through its large fractions of permanent vegetation (Appendix 2a-2). The rural areas are dominated by soils containing fractions of seasonal vegetation besides watercourses and lakes.

From 1986 to 2002, Ouagadougou experiences urban growth towards all directions. *Wogodogo-Nossin*, not yet parceled out in 1983 (Appendix 3b), is now dense built up area. Large urban expansion can be observed between the basin and the green belt (Appendix 2b-1) as well as around the military base (Appendix 2b-2). New districts emerge in the south of the city and loose constructions with high soil fractions appear in the east (Appendix 2b-3 and 4). Considering the overall area, seasonal vegetation is dominant over soil and permanent vegetation. Soil surfaces stay frequent in the periphery.

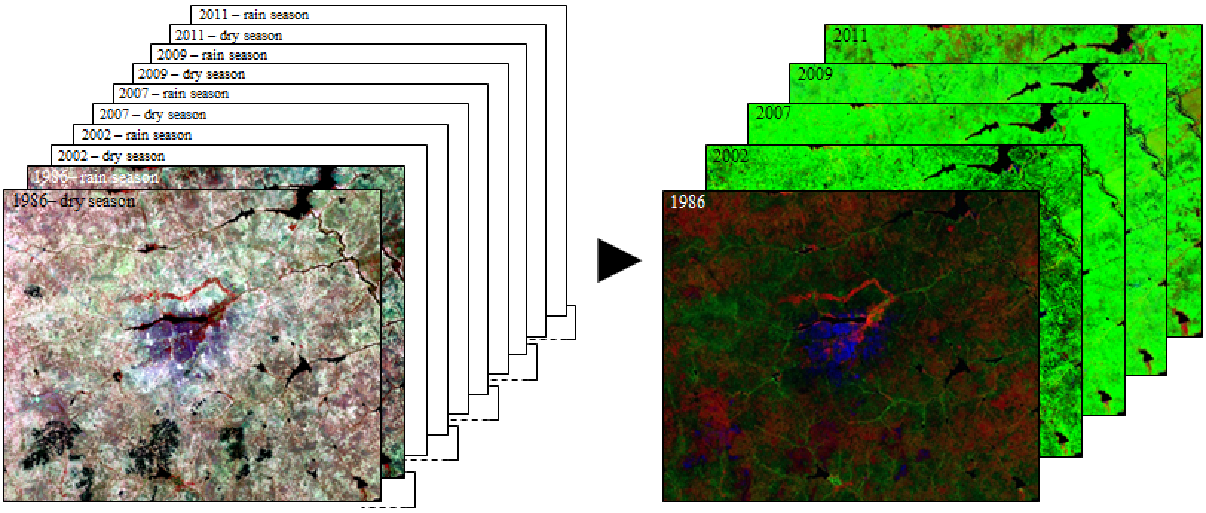


Fig. 6 Initial seasonal data (left) and multi seasonal SMA data for city level observations (right)

In 2007, fractions of roof and seasonal vegetation seem to become more dominant. First comprehensive constructions north of the green belt can be identified and the southern quarters of *Pissy* and *Ouaga 2000* (Appendix 3c & Appendix 2c-1) finally seem to have established. In the eastern part of the agglomeration, roof fractions increased and replaced predominant open soils. Clusters of larger rooftop surfaces also show up in the very south of the study area.

Those roof fractions disappear again in 2009 imagery, which again features rising soil fractions in the city. Besides very slight land cover changes, a neighborhood next to the airport disappeared (Appendix 2d-1).

In 2011, that airport neighborhood is about to be reconstructed (Appendix 2e-1). Further expansions in the south and densifications in the north east are remarkable for this point in time. In general, soils and permanent vegetation on lakes are again more important in the city's surroundings.

4.4. Neighborhood level analysis

Analysis of urbanization processes on the neighborhood level are presented for each neighborhood including a short description from in-situ observations, one representative photo, one selected fraction combination of historic multi seasonal SMA results and one diagram illustrating historic development of endmember fractions (Fig. 7). Fractions are based on neighborhood mean spectra.

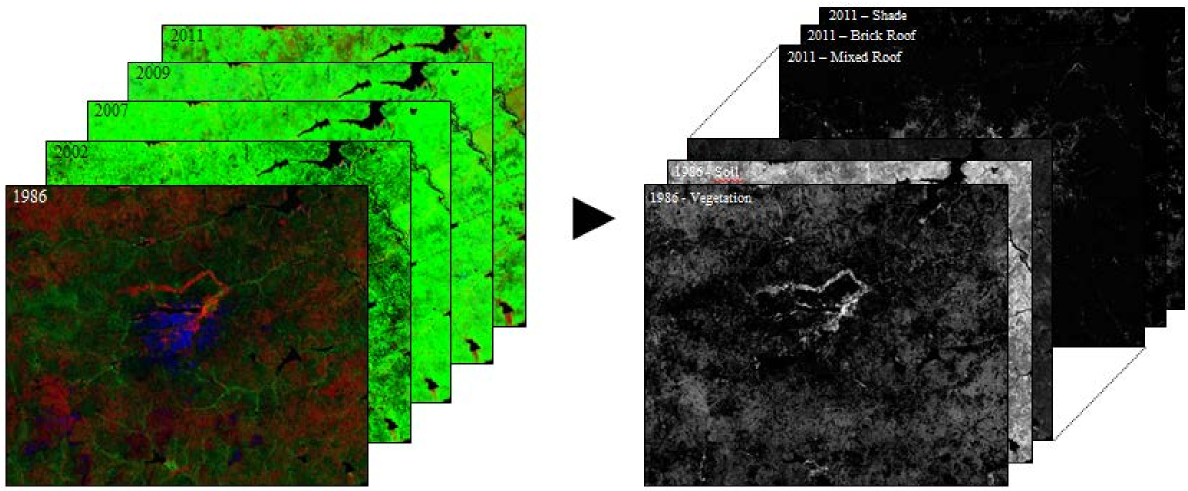


Fig. 7 Multi seasonal SMA data on a city level (left), 30 band stack of historic SMAs (right)

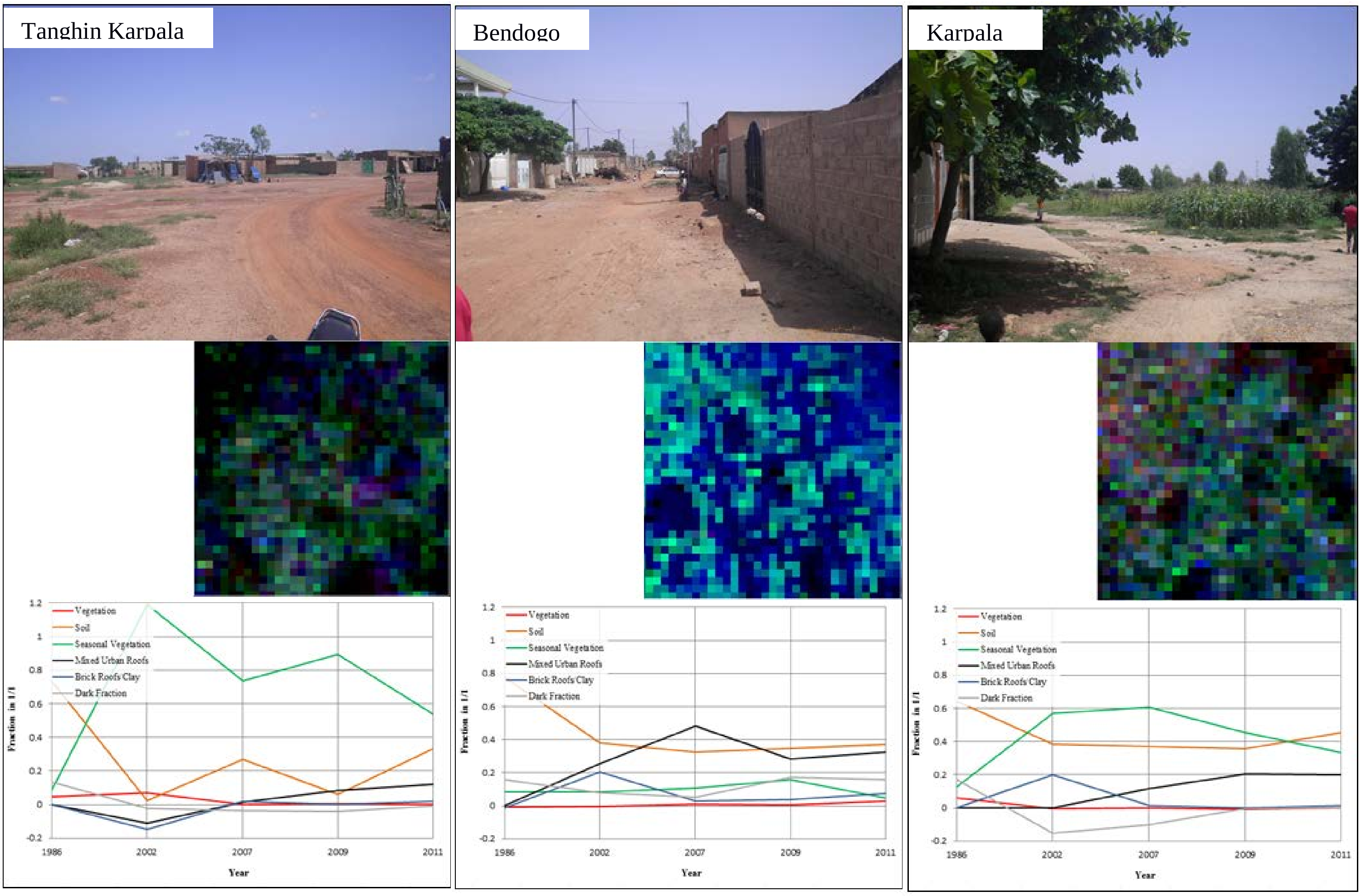


Fig. 8 Results Tanghin Karpala (left), Bendogo (center), Karpala (right)
Photo (above), Historic endmember fractions (below), RGB roof 2007/2009/2011 (left +right), RGB roof 1986/2002/2007 (center)

N1: Tanghin Karpala (Fig. 8)

The *Tanghin Karpala* neighborhood is described as a residential area under construction. It is lotted but very loosely built up with many free spaces (including reserve zones for administrative infrastructure). The quarter seems to be young, since there is no supply of electricity or water. The vegetation is very sparse with scattered trees and shrubs. The historic endmember fractions show an increase in rooftops since 2007 up to 15-20%. Seasonal Vegetation and Soil are predominant altering in reverse proportion. Negative fractions occur in 2002.

N2: Bendogo (Fig. 8)

Bendogo is also a lotted residential area featuring more built up parcels than *Tanghin Karpala*. The neighborhood gives the impression to be established for a longer time. More rooftops consist in robust materials and are fixed. There is supply of electricity and water.

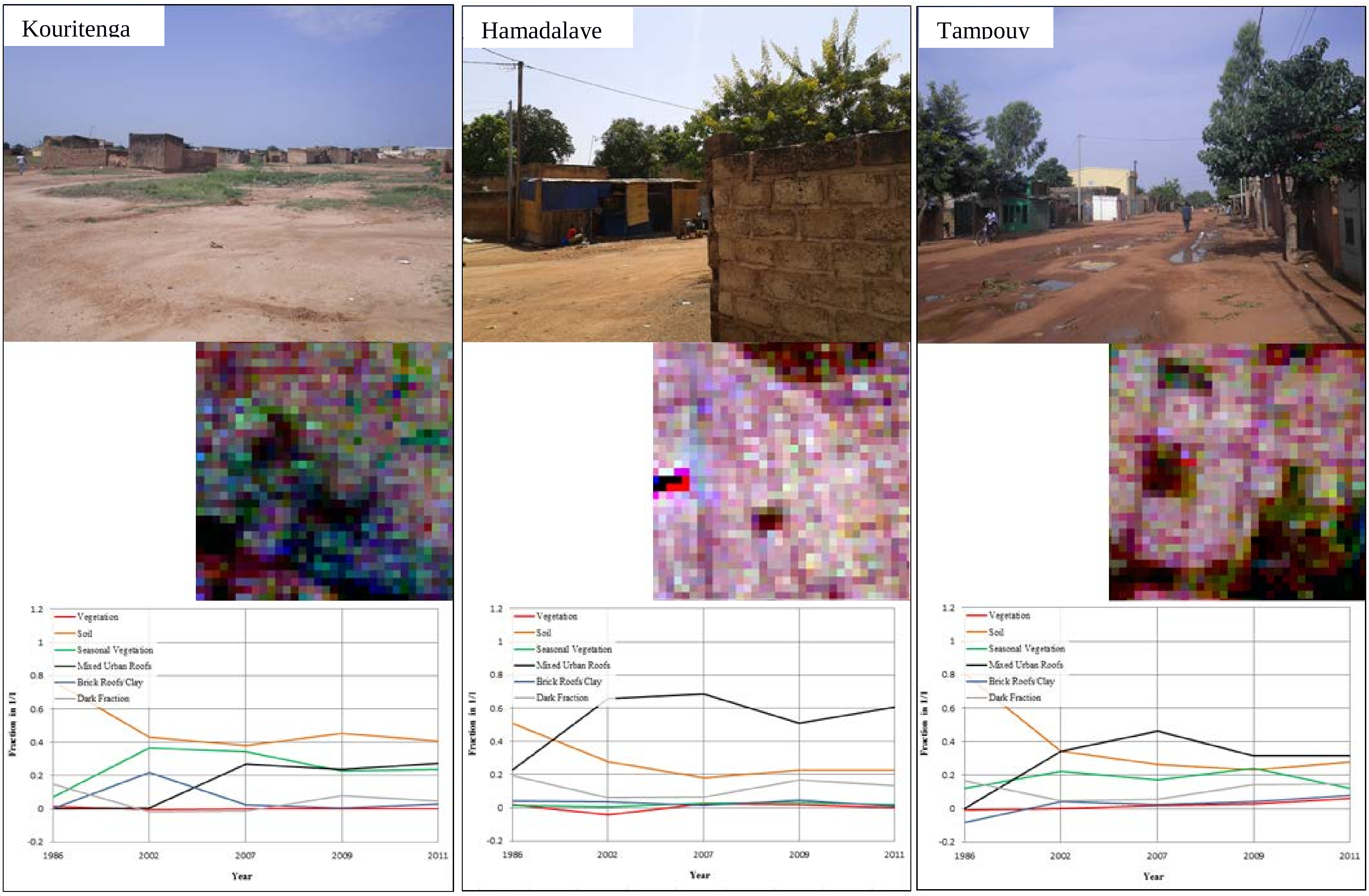


Fig. 9 Results Kouritenga (left), Hamadalaye (center), Tampouy (right)
Photo (above), Historic endmember fractions (below), RGB roof 2007/2009/2011

Interviews indicate that the quarter has not changed significantly since 2009. Vegetation is sparse, too, but the overall impression is that there are less green spaces than in *Tanghin* due to less free spaces in general. Fraction history shows that Soils decreased significantly since 1986. Rooftop covers about 40% of the area from 2002 to 2011, with a slight break in 2009.

N3: Karpala (Fig. 8)

Karpala (= *new quarter* in Mooré language) is a loosely built up residential area with many free spaces. Roads are of a bad quality and the neighborhood is characterized by urban corn fields. The quarter seems to be very young and because of a flood in 2009 many people are about to move away again. An important number of houses is abandoned. Agricultural use makes it a green neighborhood at the beginning of the rain season. Fractions show rising roof coverage since 2002, varying Seasonal Vegetation and no permanent vegetation underlining crops’ rain dependency.

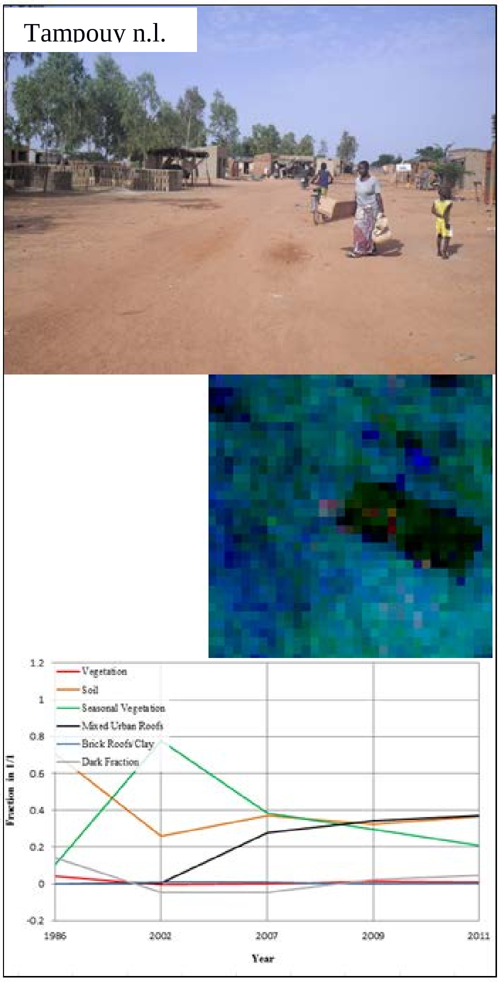


Fig. 10 Results Tampouy non loti
Photo (above), Historic endmember fractions (below), RGB roof 2007/2009/2011

N4: Kouritenga (Fig. 9)

Interviews reveal that *Kouritenga* has been lotted in 2009. Small huts are about to be replaced by larger buildings. The building density within the neighborhood varies. Construction materials and vegetation are similar to *Bendogo*. So is the historic fraction map.

N5: Hamadalaye (Fig. 9)

Hamadalaye is an established inner-city neighborhood lotted since 1985. There are no free lots. The quarter is well organized, provides electricity, water as well as house numbers. Some houses have more than one floor. Vegetation is rare, but if trees exists, they have obviously been planted regularly and a long time ago. Fraction history shows roof fractions increasing from 1986 to 2011, then staying on a 60%-level with a break in 2009.

N6: Tampouy (Fig. 9)

Tampouy is an established neighborhood lotted since 1986 and located north of the western basin. There are no free lots, whereas half of a built up lot is estimated to be impervious. The neighborhood's character seems similar to *Hamadalaye*. Rooftop coverage developed similarly, but on a lower level with respectively higher Seasonal Vegetation fractions.

N7: Tampouy non loti (Fig. 10)

This quarter is characterized by a nearby stone pit. Apparently, the neighborhood is currently about to be lotted, but huts are still constructed in an unorganized way, stand very close to each other and are partly uninhabited. Vegetation is very rare. Again, roof coverage rises since 2002 with a decreasing speed. Cumulated Seasonal Vegetation and Soil surfaces drop accordingly.

5. Discussion

Ouagadougou obviously experienced severe changes in urban structure between 1986 and 2011. Even in the 2000s urbanization processes can be recognized within periods of not longer than two years. This chapter will interpret and discuss the methods and results presented above.

Mono and multi seasonal spectral mixture analysis

Spectral mixture analysis results confirm the advantage of a multi seasonal unmixing approach. Although error values are very low in both processes, they only indicate a mathematic accuracy of how good the parameter set is for the respective image. Difficulties of mono seasonal approaches have, though, a thematic character.

This thesis confirms that studies in the dry savanna zone should consider data from both dry and rain season. Multi seasonal data allow to take into account surfaces that are only identifiable when being observed over time. Mono seasonal approaches lead to misinterpretations due to negative fractions and lower endmember diversity. This might be caused by the fact that in a fixed endmember amount model, the method is forced to determine more variables than mathematically accurate for mono seasonal SMA equation systems for some pixels. In addition, mono seasonal data are very sensitive to natural circumstances like dusty rooftops and a surface's moisture content. Improvements are in particular possible in the choice of reference endmembers. A more detailed distinction of urban surfaces would require in-situ measurements or multispectral high resolution imagery. Additional use of land cover maps would facilitate the process of validation and a variable amount of endmembers would probably enhance the quality of SMA results. As ISMA turns out to be not adequate for multispectral imagery (as it is also recommended for hyperspectral imagery), the use of a Multiple Endmember Spectral Mixture Analysis (MESMA) to Landsat scenes could be an alternative, as it worked fine in (Michishita et al. 2012). MESMA, however, does not support variable endmember combinations at all.

City level analysis

Cross-validation with (Prat 1996) and (Fournet et al. 2008) emphasizes that on a city level, spectral mixture analyses using multi seasonal Landsat data works fine to trace global trends of urbanization in Ouagadougou.

In 1986, the spatial extent of rooftop surface fractions more or less corresponds to the city extent Prat found out for the year 1987 (Appendix 3a). Parceled zones in Prat's study tend to have higher roof fractions in the SMA image than non-parceled zones. However, Fournet's map of urbanization in 1983 shows a slightly larger city extent (Appendix 3b). Those discrepancies might find their reason in the fact that both authors consider if an area is parceled, i.e. it does not necessarily have to be built up. Examples are the districts of *Cissin* and *Patte d'Oie*. The SMA image represents a result that seems adequate for describing the city's extent at that time. Roof fractions in the south west of the study region could be interpreted as villages, even if large villages are improbable in the rural outskirts. Low fractions of seasonal vegetation might be due to the fact that the 1986 rain season image originates from November, whereas rain season images of other image pairs are taken in September. Important rain dependent vegetation might have disappeared already.

Soil surfaces within the city in 2002 and their development to built up areas in 2007, especially in the eastern part of Ouagadougou, show that inner city soil surfaces might be an indicator for future construction works. Yet, it has to be considered that roof coverage in 2007 is extremely dense compared to other images and it cannot be excluded that they are overestimated. Compared with Fournet's map of parceled area in 2003, results of the 2002 SMA again seem to be well interpretable (Appendix 3c, beige colored & Appendix 2b).

Comparing 2011 SMA results with a prediction of city expansion from 2010 to 2015 by Fournet (Appendix 2e and Appendix 3d), it can be stated that some tendencies seem to be confirmed in this study's SMA results, like further expansion west of the military camp. Others are not traceable yet, like expansions east of *Ouaga 2000*.

The method of subpixel fraction analysis applied here outmatches de Jong's results using conventional and contextual classification methods using SPOT-XS images (de Jong et al. 2000). De Jong chose a maximum likelihood approach using discrete thematic classes and showed that new and old peripheral quarters, squatter settlements and industrial areas are very difficult to distinguish in his study (Appendix 4). Indeed, this study and (de Jong et al. 2000) are not comparable in detail. However, there are important advantages of subpixel analysis on a city level. General tendencies of city expansion are easily traceable over time. In addition, fractions of different surface types, particularly rooftops, are an indicator for gradual and continuous processes without the necessity for discrete classes that require previous determination of thresholds. It also underlines that medium resolution imagery like

Landsat is generally applicable in urban environments without supplementary data. Quantitative validation of results might nonetheless turn out to be complicated, since it is easier proceeding previous discretization.

Neighborhood level analysis

The combination of historic urban monitoring using a spectral mixture analysis approach on Landsat data with in-situ interviews and observations already allows to draw precise and plausible conclusions referring to urban processes on a neighborhood level.

Substantial statements can especially made about the temporal development of rooftop coverages within each neighborhood. The overall tendencies correspond widely to in-situ survey results. The fraction value is a plausible indicator for settlement density. Seasonal Vegetation and Soils are a sign for open spaces, even if climatic circumstances recommend to add up both classes in order to avoid misinterpretations due to varying precipitation. Vegetation fractions are authentic. Single particular events are explicable, e.g.:

- The beginning of residential constructions often coincides in interviews and the SMA images. So did housing in *Tanghin Karpala* begin “a few years ago” according to interviews. First rooftop fractions in that quarter emerge in 2009.
- *Kouritenga* has been parceled in 2009. At the same time, rooftop coverage decreases. This might indicate the demolition of illegally built huts.
- *Karpala* suffered from floods in 2009 making a lot of people move away. Roof coverage stagnates since then after experiencing a constant increase before.
- Settlements in most cases replace soils or season vegetation.

Nevertheless, some events leave questions unanswered:

- In many neighborhoods, roof fractions drop in 2009. This is also the case in those quarters, where no change occurred when relying on interviews (e.g. *Hamadalaye*).
- The endmember representing brick roofs seems to be less confidential, since unexplainable peak values emerge in 2002. 2002 is also characterized by negative fractions in some classes.

Those inconsistencies might have various reasons. A revision of the 2002 spectral library might already improve the results. It is in addition possible that automatic atmospheric correction led to irregular unmixing preconditions.

Method restrictions

In spite of the overall promising results of the study, the applied methods still suffer some limitations. The evaluation of results on a city level is rather subjective due to a lack of historic documentation. It is moreover not certain if the quality of neighborhood results is reproducible in other city areas featuring different earth and urban processes. The evaluation is based on in-situ interviews that contain inconclusive statements and inconsistent thematic focus. Furthermore, the study accepts the impurity of some spectral references. The example of *Hamadalaye*, a district with regular tree appearance but no vegetative fractions after the unmixing process, underlines that the mixed rooftop endmember already contains vegetation.

6. Conclusion

In a first step, this study states that in the observed study region of the African dry savanna, multi seasonal data is advantageous for thematic interpretations due to the region's climatic features. It is, thus, in line with (Reese et al. 2002) and (Griffiths et al. 2010) who, indeed, applied the principle of multi seasonal data in a slightly different approach. The comparison with approaches using single point of time imagery in the same region of interest (de Jong et al. 2000) underlines the potential of multi seasonal data sets. Future analyses might be enhanced due to more regular data availability allowing to select and combine multi seasonal images on a more criteria oriented basis.

Results on a city level allow a fairly adequate overall trend detection of urban development. This work places itself between mapping approaches using cadastral or survey information and individual digitalization (Fournet et al. 2008, Prat 1996, Chatel et al. 2011) and those using combined or enhanced data sets to monitor urban expansion globally and locally in high resolution (Lu et al. 2010, Taubenboeck et al. 2012, Marconcini et al. 2013). It adds a dense historic component to the former and can reveal disparities between city cadasters and actual extents of a settlement. The latter are numerous and well validated which makes this study a less complicated approach in case of some central enhancements.

Apart from resolution issues, remote sensing methods suffer from severe limitations in urban areas in general, because they can not measure essential factors to draw conclusions on neither real urban features nor processes considering population, culture, policy or economy (Miller & Small 2003). (Michishita et al. 2012) proved that enhancements in the set-up of spectral libraries and validation methods can make spectral mixture analysis a reliable alternative in urban areas. That study also managed to correlate fractions of built-up areas to some of the above named factors, knowing that it used a slightly different approach (MESMA) within a different study area.

Following steps could also include a concept of change map. (Griffiths et al. 2010) and (Schneider 2012) established discrete change maps presuming thresholds, whereas (Michishita et al. 2012) developed gradual change maps. In the study region, it might complement a project by (Kelder et al. 2013) observing vegetation trends based on iNDVI values at selected spots in Ouagadougou using MODIS data for a 2002 to 2009 period.

On a neighborhood level, SMA results correspond well with in-situ observations. However, a quantitative evaluation and validation is difficult, since reference fraction data is not available. A following study could adopt the approach from (Michishita et al. 2012) only considering the dominant fraction endmember for validation or using high resolution imagery for validation of the youngest imagery.

Future potential of the methods presented in this study is based on future data availabilities. Since they are highly dependent on adequate data selection, the emergence of Landsat 8 and Sentinel II data might allow to compare corresponding points in time and phenology more reliably. In addition, higher spatial resolution provided by Sentinel II could make unmixing approaches more performant and complex data combination techniques redundant (ESA 2013).

7. Acknowledgements

This study is the final thesis of the Geography bachelor’s program at Humboldt University of Berlin. It has been made possible by Dr. Sebastian van der Linden who supervised it supporting regular discussions and giving important advice. Without the help of Andreas Rabe and Patrick Griffiths concerning software debugging and data preprocessing, many parts of the thesis would have turned out to be far more difficult. A special thanks is to Janine Hauer for discussions about the study area and, in particular, for providing in-situ information as a basis for a detailed validation of analyses on a neighborhood level.

References

Beauchemin, C. 2011. Rural–Urban Migration in West Africa: Towards a Reversal? Migration Trends and Economic Situation in Burkina Faso and Côte d'Ivoire. *Population, Space and Place,* 17**,** 26.

Bhatta, B. 2010. *Analysis of Urban Growth and Sprawl from Remote Sensing Data,* Springer.

Chatel, C., Denis, E., Herre, D., Moriconi-Ebrard, F., Séjourné, M. & Thiam, O. 2011. Africapolis. Urbanization Trends 1950-2020: A Geo-statistical Approach. West Africa. *In:* Agence Française de Développement (ed.),

de Jong, S. M., Bagre, A., van Teeffelen, P. B. M. & van Deursen, W. P. A. 2000. Monitoring Trends in Urban Growth and Surveying City Quarters in Ouagadougou, Burkina Faso Using SPOT-XS. *Geocarto International,* 15**,** 8.

ESA. 2013. *The operational Copernicus optical high resolution land mission* [Online]. European Space Agency. Available: http://esamultimedia.esa.int/docs/S2-Data_Sheet.pdf [Accessed 24 October 2014].

Fearon, J. & Laitin, D. 2006. Burkina Faso. *In:* Stanford University (ed.) *Random Narrative.*

Foley, J. A., DeFried, R., Asner, G., Barford, C., Bonan, G., Carpenter, S. R., Stuart Chapin, F., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Colin Prentice, I., Ramankutty, N. & Snyder, P. K. 2005. Global Consequences of Land Use. *Science,* 309**,** 5.

Fournet, F., Meunier-Nikiema, A., Salem, G., Harang, M., Kafando, Y., Meyer, P.-E., Rican, S. & Varenne, B. 2008. *Ouagadougou (1850-2004) - Une urbanisation différenciée,* IRD Orstom.

Griffiths, P., Hostert, P., Gruebner, O. & van der Linden, S. 2010. Mapping megacity growth with multi-sensor data. *Remote Sensing of Environment,* 114**,** 14.

Griffiths, P., Kuemmerle, T., Kennedy, R. E., Abrudan, I. V., Knorn, J. & Hostert, P. 2012. Using annual time-series of Landsat images to assess the effects of forest restitution in post-socialist Romania. *Remote Sensing of Environment,* 118 (2012)**,** 16.

Herold, M., Couclelis, H. & Clarke, K. C. 2005. The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems,* 29**,** 31.

Herold, M., Roberts, D. A., Gardner, M. E. & Dennison, P. E. 2004. Spectrometry for urban area remote sensing - Development and analysis of a spectral library from 350 to 2400 nm. *Remote Sensing of Environment,* 91**,** 16.

Hostert, P. 2001. *Monitoring von Degradationserscheinungen im europäisch-mediterranen Raum mit Methoden der Fernerkundung und GIS. Untersuchungen am Beispiel der Weidegebiete Zentralkretas.*

INSD. 2006. *http://www.insd.bf/fr/* [Online]. Institut National de la Statistique et de la Démographie. [Accessed July 16 2014].

Kelder, Y. 2011. *Ecology of Urbanization: The case of Ouagadougou, Burkina Faso.*

Kelder, Y., Nielsen, T. T. & Fensholt, R. 2013. The Role of Methodology and Spatiotemporal Scale in Understanding Environmental Change in Peri-Urban Ouagadougou, Burkina Faso. *Remote Sensing,* 5**,** 19.

Lu, D., Hetrick, S. & Moran, E. 2010. Land Cover Classification in a Complex Urban-Rural Landscape with QuickBird Imagery. *Photogrammetric Engineering & Remote Sensing,* 76**,** 10.

Madsen, J. E., Lykke, A. M., Boussim, J. & Guinko, S. 2004. Floristic composition of two 100 km² reference sites in West African cultural landscapes *Nrodic Journal of Botany,* 23**,** 16.

Marconcini, M., Esch, T., Felbier, A. & Heldens, W. High-Resolution Global Monitoring of Urban Settlements. *In:* M. Schrenk, V. Popvich, P. Zeile & P. Elisei, eds. REAL CORP 2013, 2013.
Masek, J., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., Gao, F., Kutler, K. & Lim, T.-K. 2006. A Landsat Surface Reflectance Dataset for North America, 1990-2000. *IEEE Geoscience and Remote Sensing Letters,* 3**,** 7.
Mehl, W. & Hill, J. 2014. Iterative Spectral Mixture Analysis. 1.0 ed, University of Trier.
Michishita, R., Jiang, Z. & Xu, B. 2012. Monitoring two decades of urbanization in the Poyang Lake area, China through spectral unmixing. *Remote Sensing of Environment,* 117**,** 16.
Miller, R. A. & Small, C. 2003. Cities from space: potential applications of remote sensing in urban environmental research and policy. *Environmental Science and Policy,* 6**,** 9.
NCDC. 2014. *Cliamtic Data Online. Find a Station.* [Online]. National Oceanic and Atmospheric Administration - National Climatic Data Center. Available: http://www.ncdc.noaa.gov/cdo-web/datatools/findstation [Accessed August 18 2014].
Ouédraogo, M. 2002. Land tenure and rural development in Burkina faso: Issues and strategies. *Drylands Issue Paper E112, International Institute for Environment and Development (IIED)***,** 28.
Prat, A. 1996. Ouagadougou, Capitale Sehélienne: Croissance Urbaine et Enjeu Foncier. *Mappemonde,* 1**,** 7.
Rabe, A., Jakimow, B., Held, M., van der Linden, S. & Hostert, P. 2014. EnMAP-Box. 2.0 ed,
Reese, H. M., Lillesand, T. M., Nagel, D. E., Stewart, J. S., Goldmann, R. A., Simmons, T. E., Chipman, J. W. & Tessar, P. A. 2002. Statewide land cover derived from multiseasonal Landsat TM data: A retrospective of the WISCLAND project. *Remote Sensing of Environment,* 82**,** 14.
Rogge, D. M., Rivard, B., Zhang, J. & Feng, J. 2006. Iterative spectral unmixing for optimizing per-pixel endmember sets. *IEEE Transactions on Geoscience and Remote Sensing,* 44**,** 12.
Sandwidi, J. P. 2007. *Groundwater potential to supply population demand within the Kompienga dam basin in Burkina Faso.* Rheinische Friedrich-Wilhelms-Universität zu Bonn.
Schneider, A. 2012. Monitoring land cover change in urban and peri-urban areas using dense time stacks of Landsat satellite data and a data mining approach. *Remote Sensing of Environment*, 124**,** 16.
Shan, J. & Hussain, E. 2010. Very High Resolution Remote Sensing Data: Processing Capabilities and Limitations in Urban Area. *In:* Purdue University School of Civil Engineering (ed.),
Small, C. 2004. The Landsat ETM+ spectral mixing space. *Remote Sensing of Environment,* 93**,** 17.
Small, C. 2005. A global analysis of urban reflectance. *International Journal of Remote Sensing,* 26**,** 21.
Somers, B., Asner, G., Tits, L. & Coppin, P. 2011. Endmember variability in Spectral Mixture Analysis: A review. *Remote Sensing of Environment,* 115**,** 14.
Taubenboeck, H., Esch, T., Felbier, A., Wiesner, M., Roth, A. & Dech, S. 2012. Monitoring urbanization in mega cities from space. *Remote Sensing of Environment,* 117 (2012)**,** 15.
Tigges, J., Lakes, T. & Hostert, P. 2013. Urban vegetation classification: Benefits of multitemporal RapidEye satellite data. *Remote Sensing of Environment,* 136**,** 10.
Tompkins, S., Mustard, J. F., Pieters, C. M. & Forsyth, D. W. 1997. Optimization of Endmembers for Spectral Mixture Analysis. *Remote Sensing of Environment,* 59**,** 18.

UNDESA 2012. World Urbanization Prospects: The 2011 Revision., United Nations - Department of Economic and Social Affairs - Population Division.

UNEP (ed.) 2008. *Africa Atlas of our Changing Environment,* Nairobi, Kenya: United Nations Environment Programme.

UNEP (ed.) 2010. *Africa Water Atlas,* Nairobi, Kenya: United Nations Environment Programme.

USGS 2008. Imagery for Everyone. U.S. Department of the Interior - U. S. Geological Survey.

USGS. 2014. *Satellite and Sensor Information* [Online]. U.S. Department of the Interior - U. S. Geological Survey. Available: http://landsat.usgs.gov/Satellite_and_Sensor_Information.php [Accessed 21 September 2014].

van de Voorde, T., Demarchi, L. & Canters, F. 2009. Multi-temporal spectral unmixing to characterise change in the urban spatial structure of the greater Dublin area. *In:* European Association of Remote Sensing Laboratories (ed.) *Remote Sensing for a Changing Europe.*

Virmani, S. M., Reddy, S. J. & Bose, M. N. S. 1980. *A Handbook on the Rainfall Climatology of West Africa : Data for Selected Locations*, Patancheru, Andhra Pradesh, India.

Weischet, W. & Endlicher, W. 2012. *Einführung in die allgemeine Klimatologie,* Stuttgart, Germany.

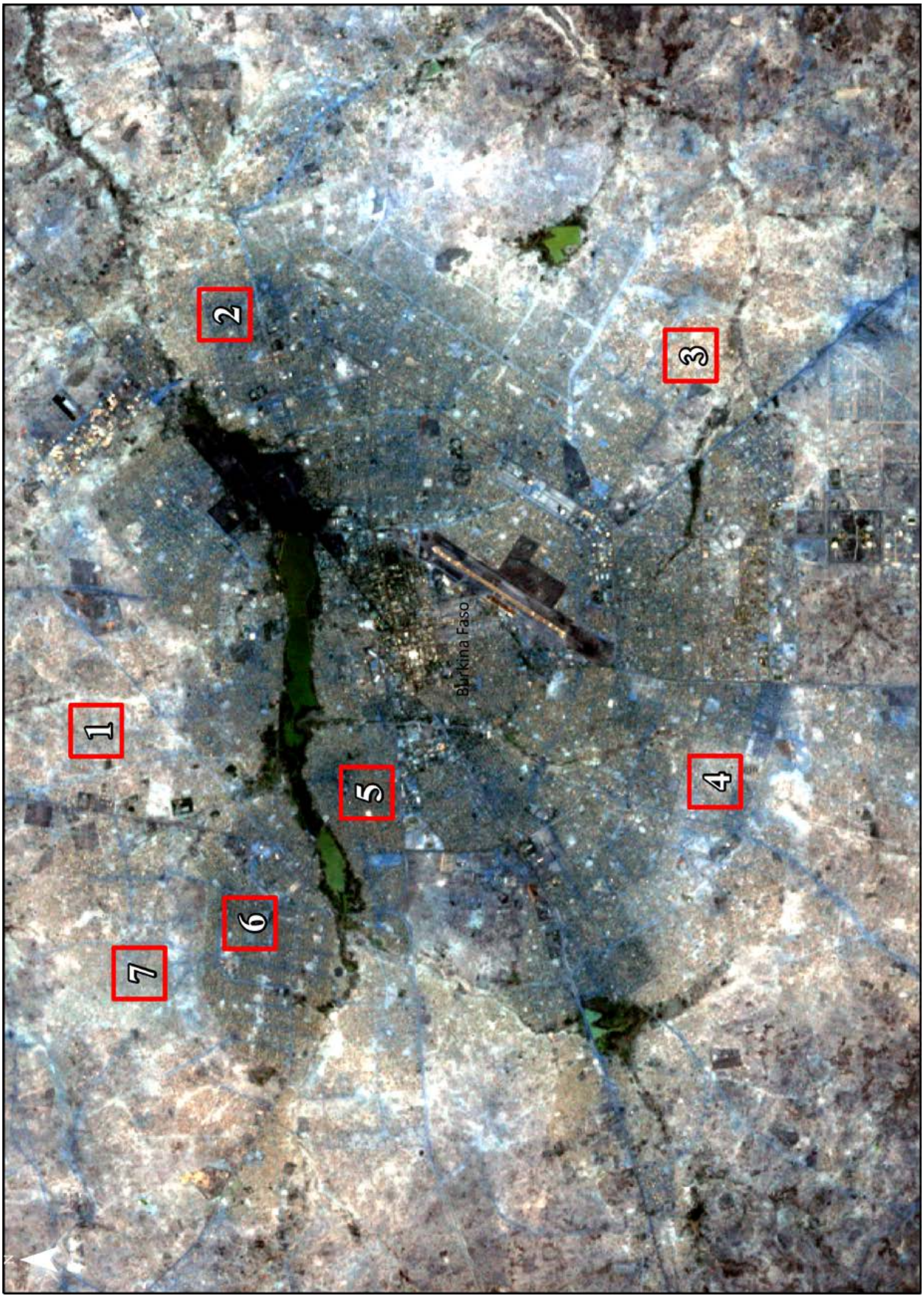
Xu, H. 2006. Modification of normalised difference water index (NDWI) to enhance openwater features in remotely sensed imagery. *International Journal of Remote Sensing,* 27/14**,** 9.

Yuan, F., Bauer, M. E., Heinert, N. J. & Holden, G. 2005. Multi-level land cover mapping of the Twin Cities (Minnesota) metropolitan area with multi-seasonal Landsat TM/ETM+ data. *Geocarto International,* 20**,** 10.

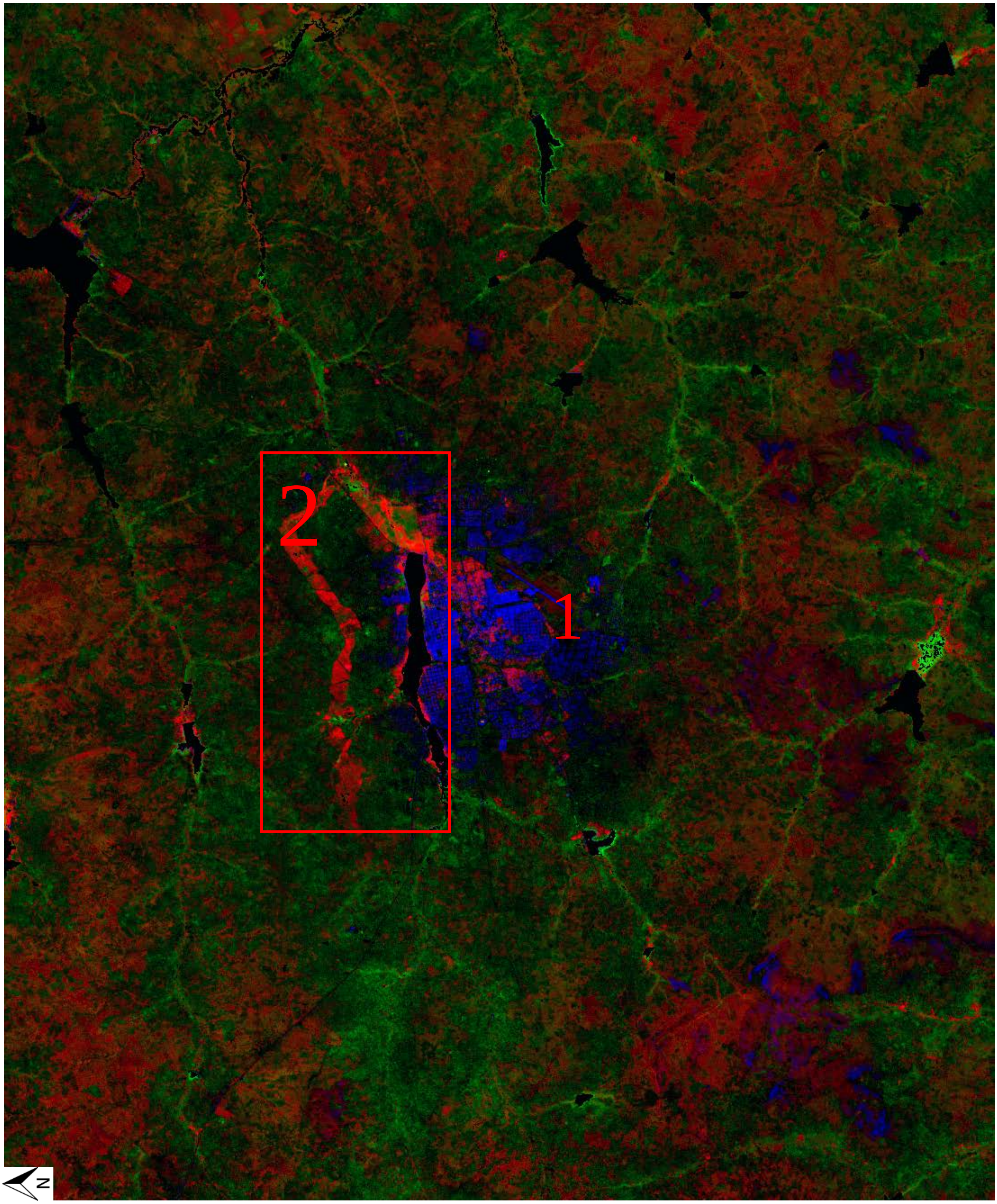
Zhu, Z. W., C.E. 2011. Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment,* 118**,** 12.

Appendix

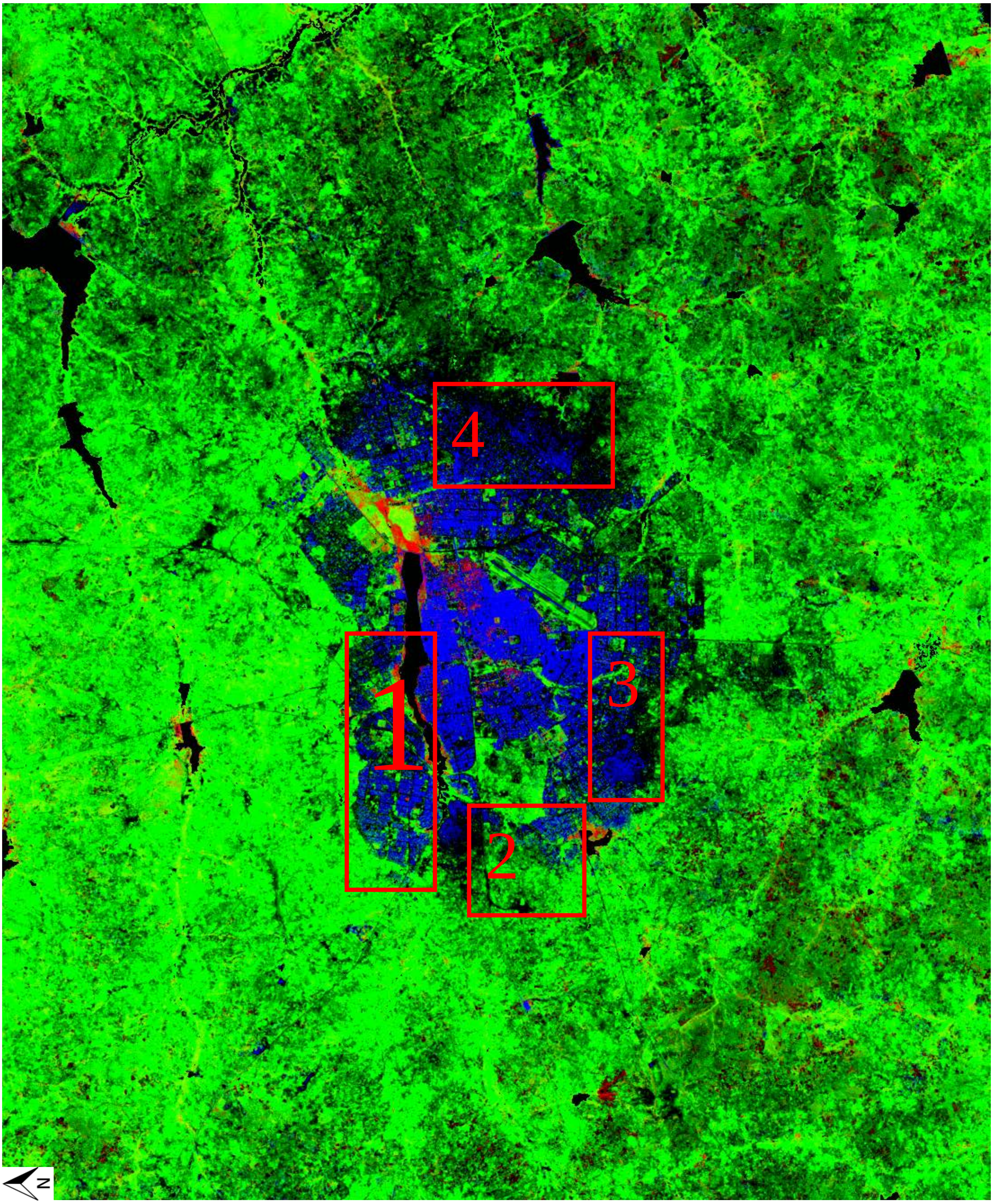
Appendix 1: Neighborhoods for neighborhood analysis



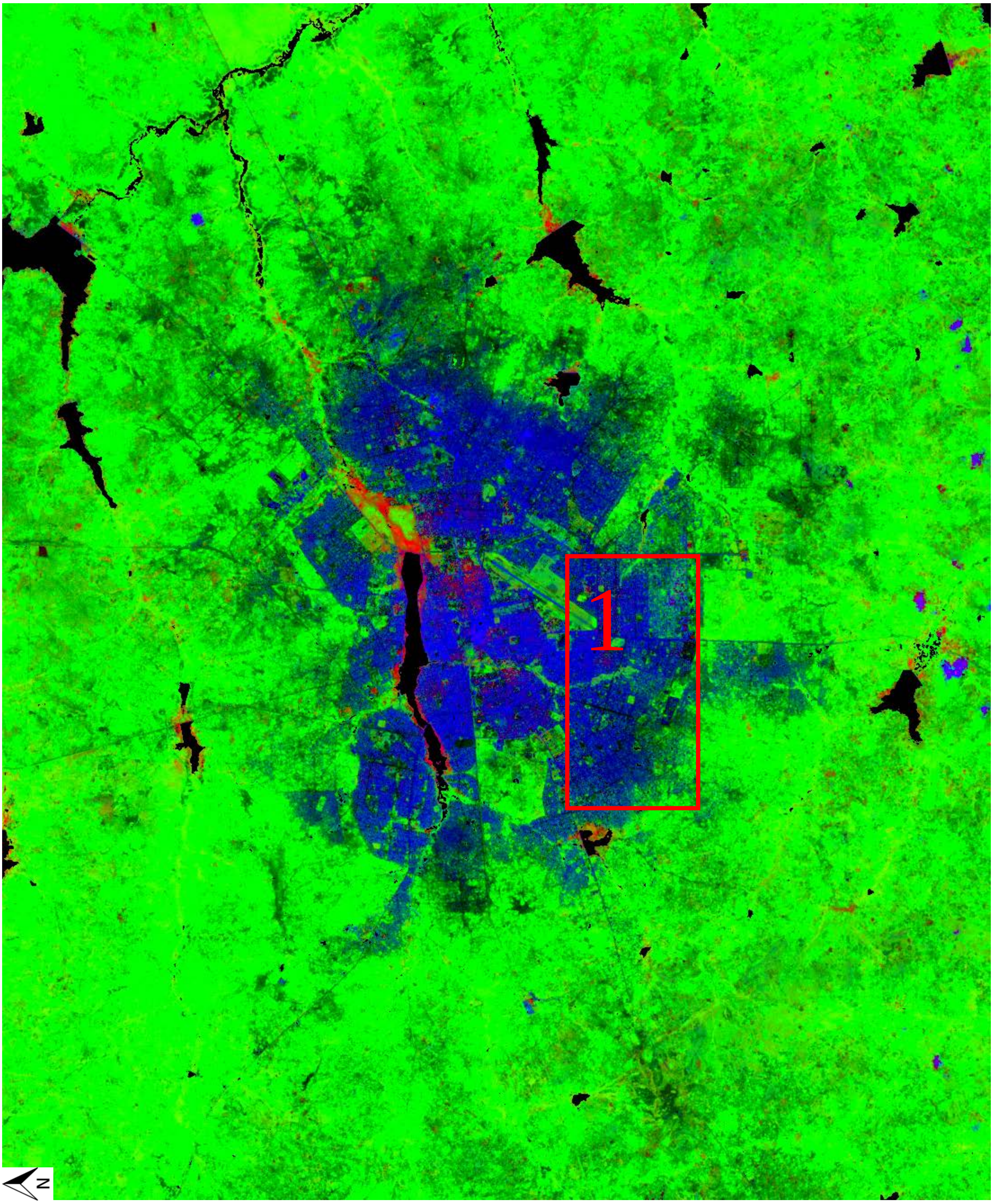
Appendix 2a: Spectral mixture analysis result for image stack 1986
RGB = Vegetation, Seasonal Vegetation, Mixed Rooftop



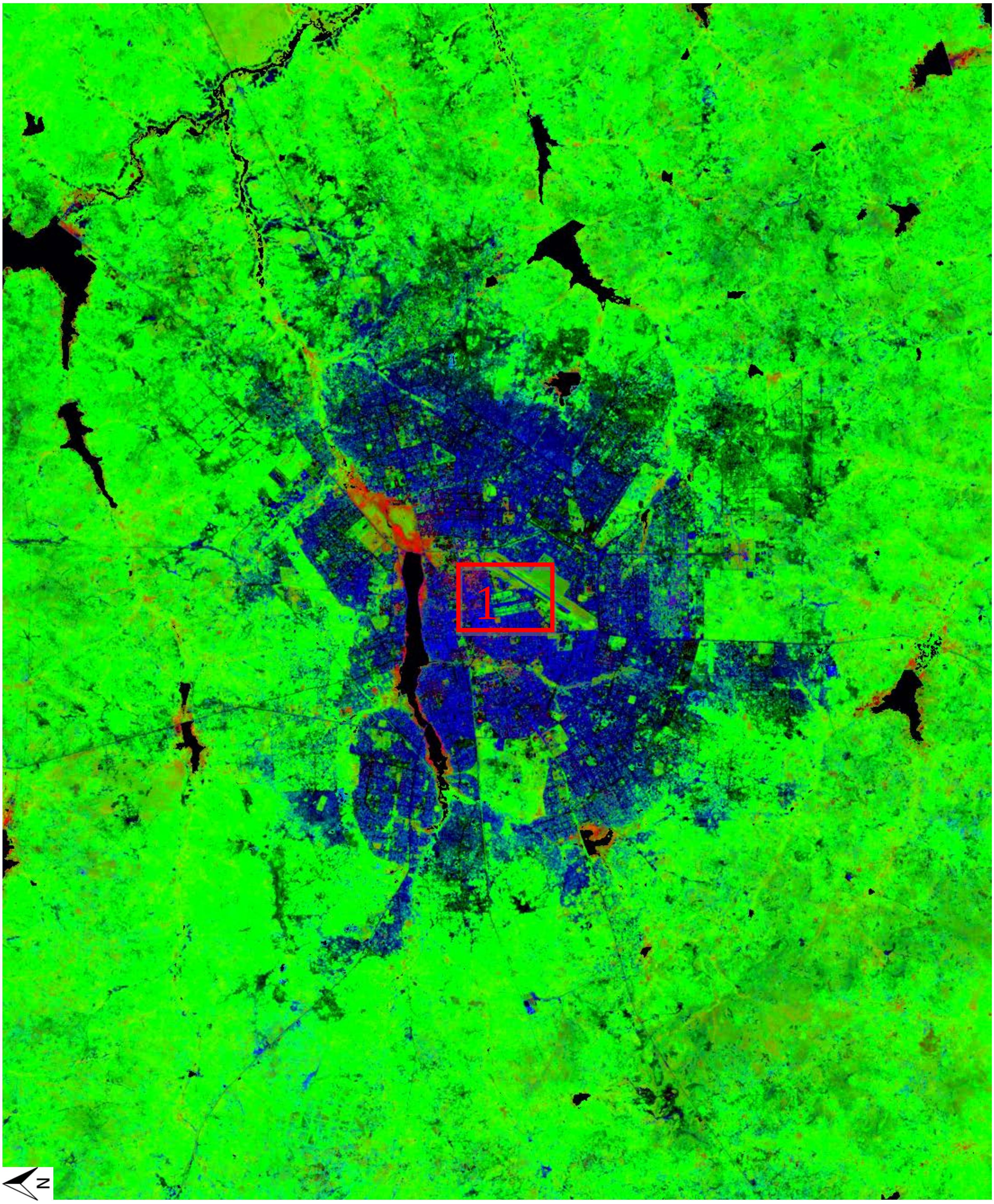
Appendix 2b: Spectral mixture analysis result for image stack 2002
RGB = Vegetation, Seasonal Vegetation, Mixed Rooftop



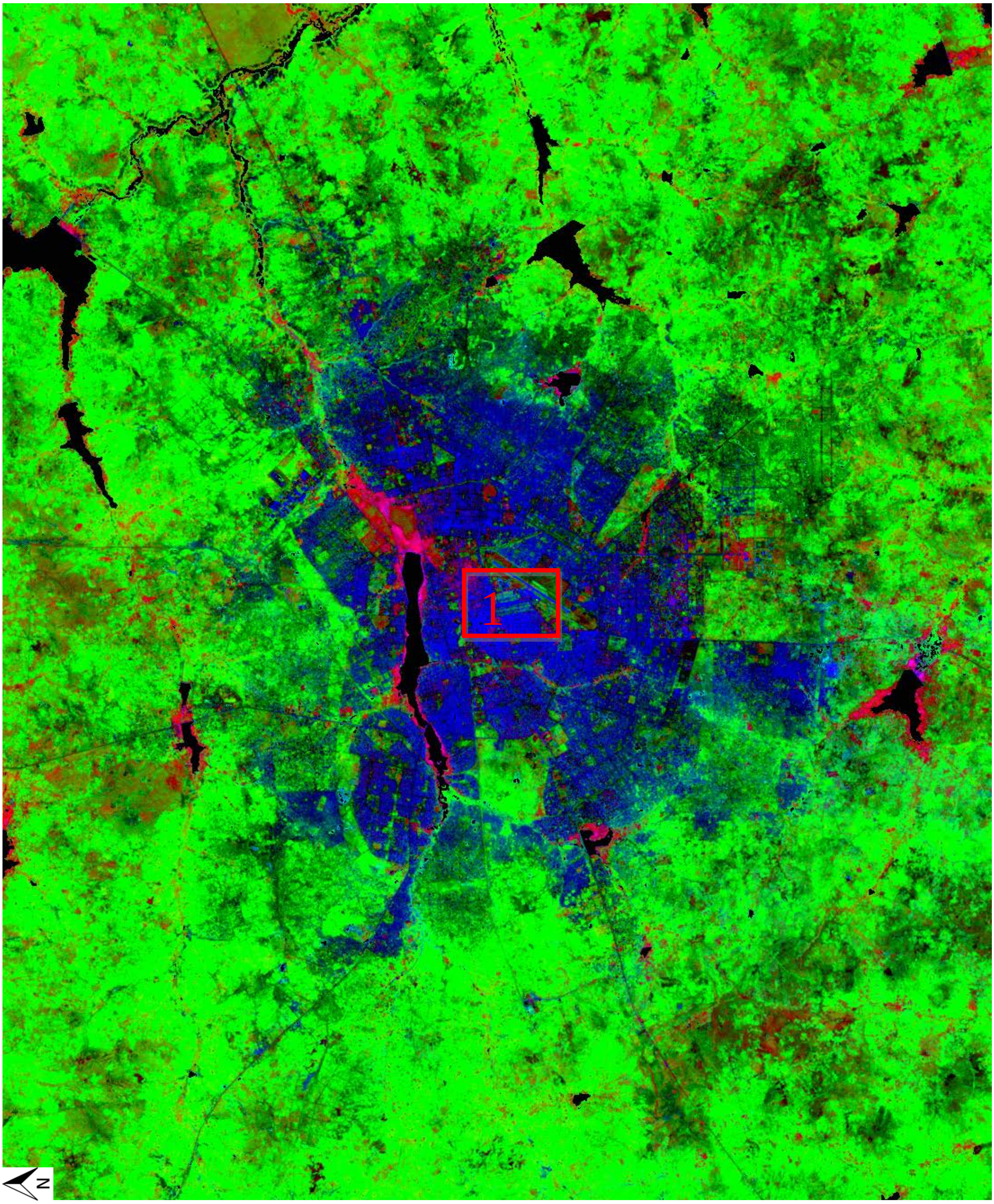
Appendix 2c: Spectral mixture analysis result for image stack 2007
RGB = Vegetation, Seasonal Vegetation, Mixed Rooftop



Appendix 2d: Spectral mixture analysis result for image stack 2009
RGB = Vegetation, Seasonal Vegetation, Mixed Rooftop

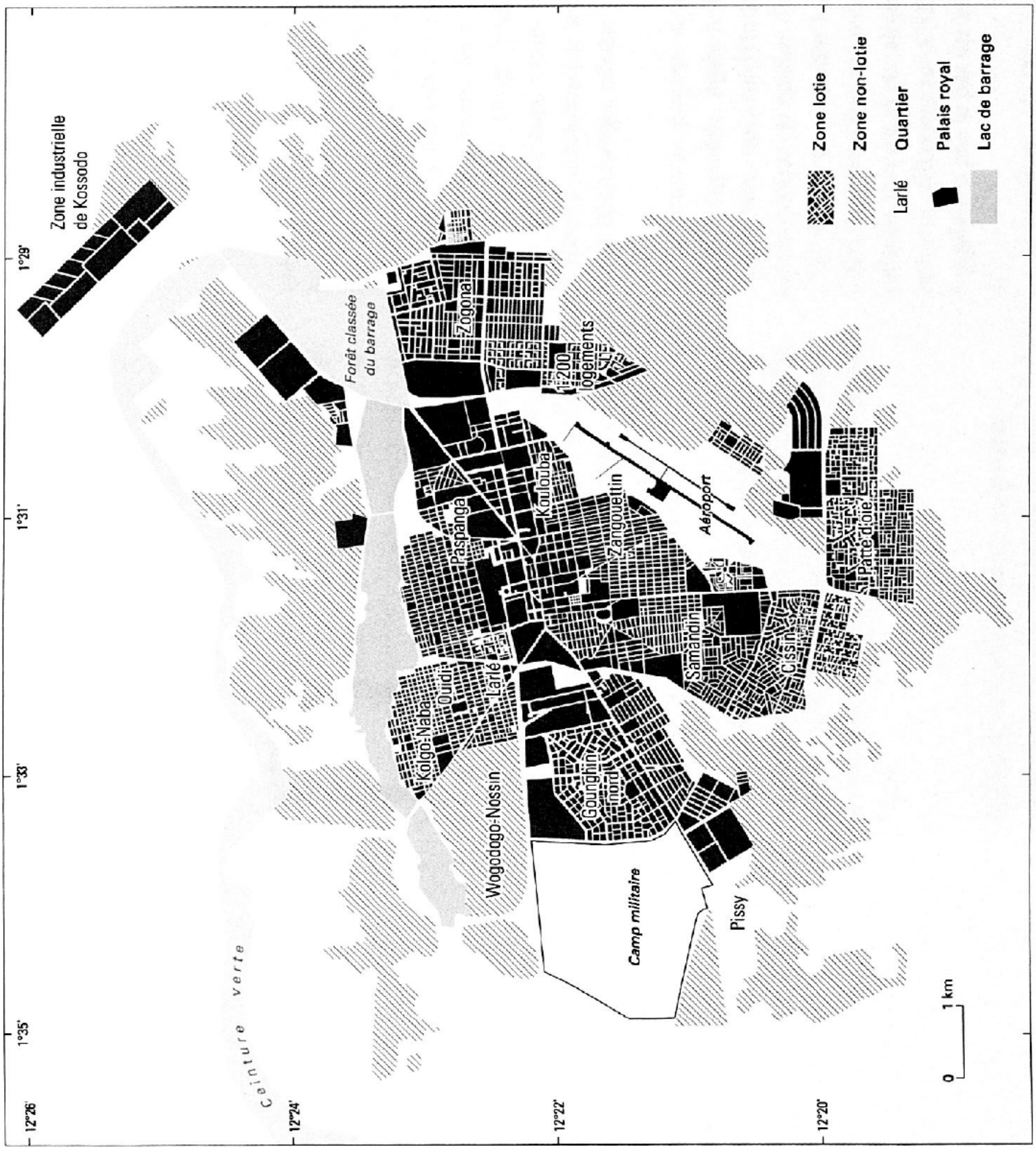


Appendix 2e: Spectral mixture analysis result for image stack 2011
RGB = Vegetation, Seasonal Vegetation, Mixed Rooftop

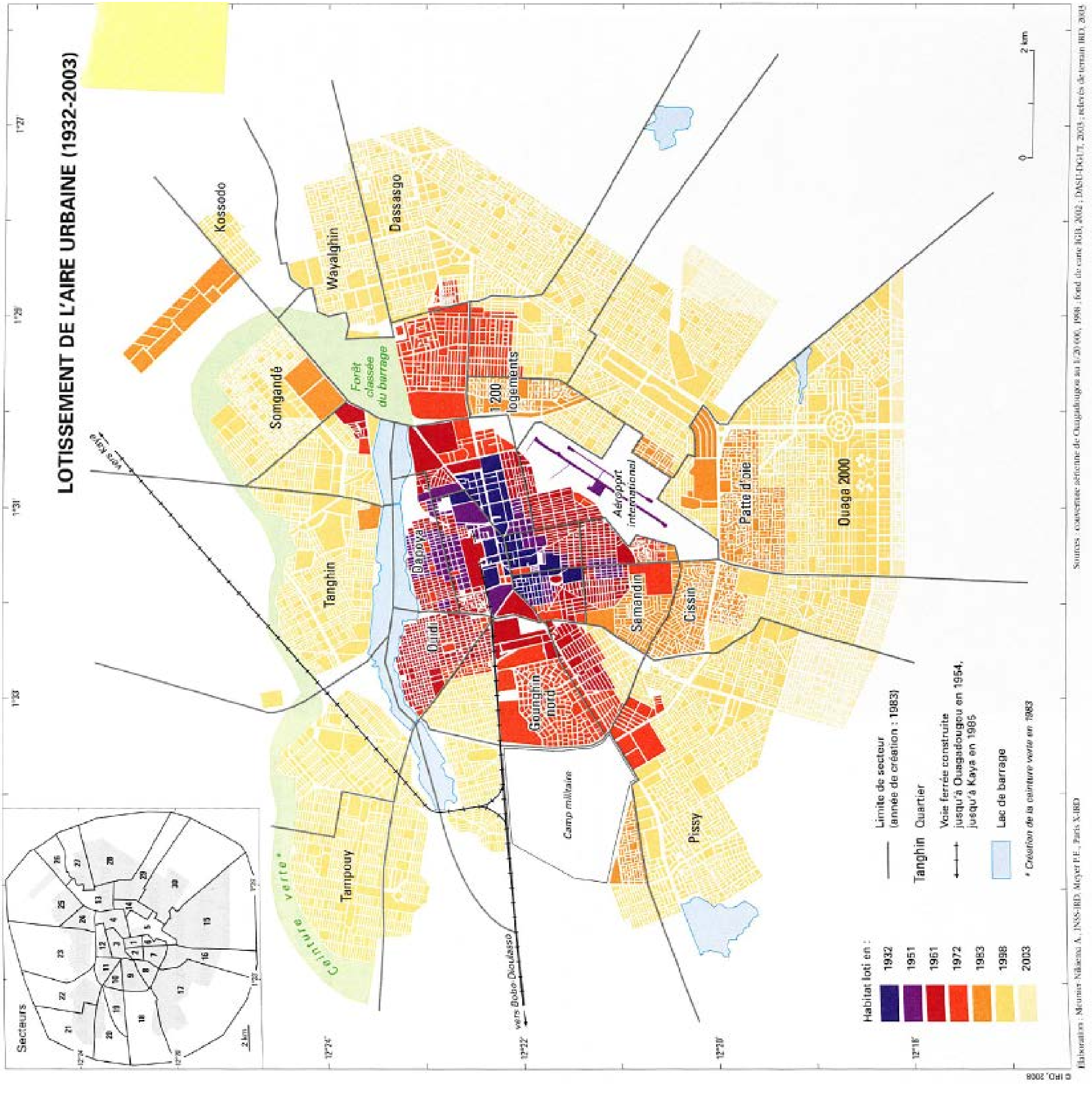


Appendix 3a: City extent Ouagadougou 1975 - 1993 (Prat 1996)

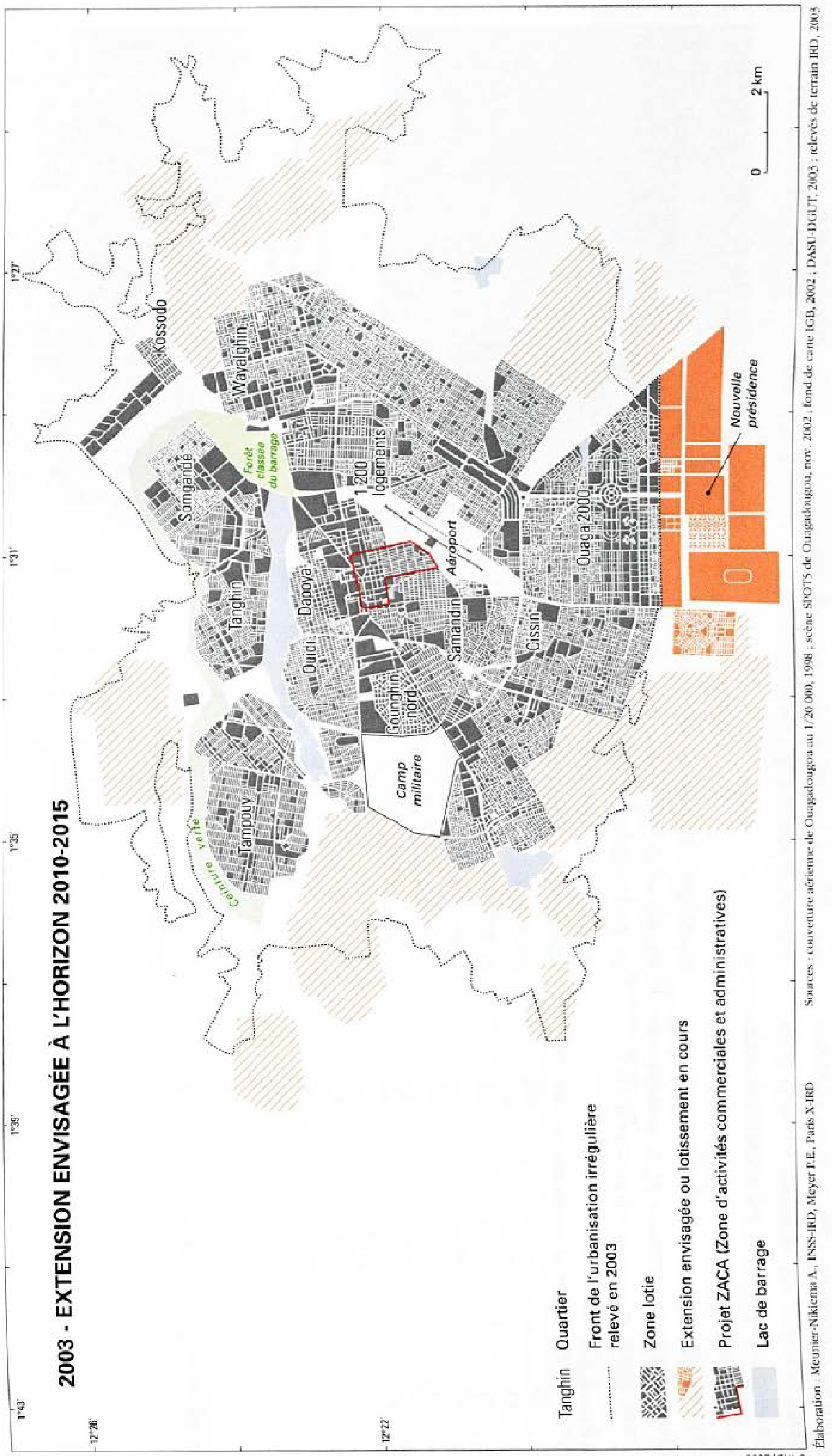
Appendix 3b: City extent Ouagadougou in 1983 (Fournet et al. 2008)



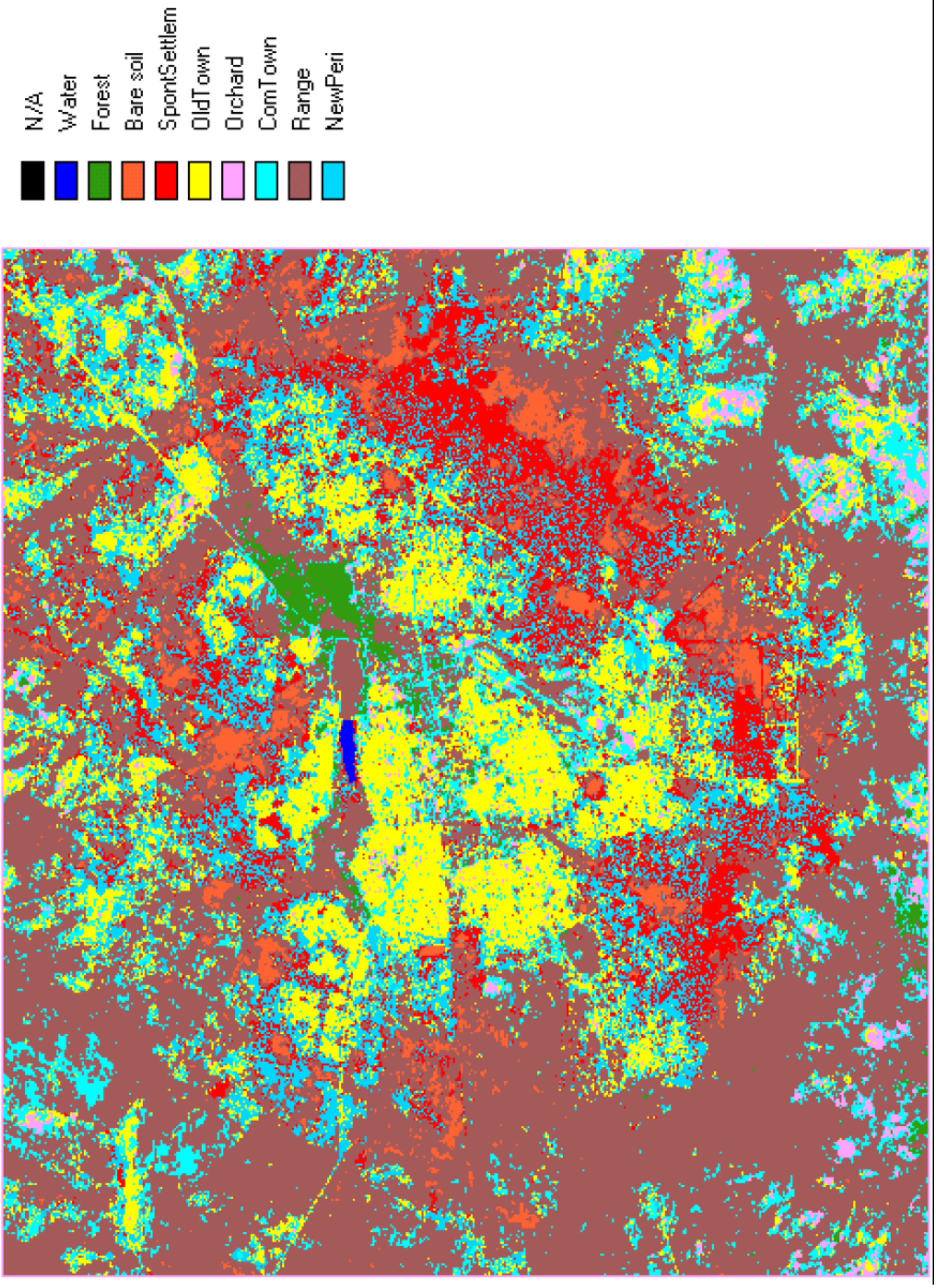
Appendix 3c: City extent Ouagadougou in 2003 (Fournet et al. 2008)



Appendix 3d: Estimated city extent Ouagadougou 2010 – 2015 (Fournet et al. 2008)



Appendix 4: Classification (Maximum likelihood + SPARK (contextual enhancement) on SPOT data for Ouagadougou in 1997 (de Jong et al. 2000)



Erklärung

Ich erkläre, dass ich die vorliegende Arbeit nicht für andere Prüfungen eingereicht, selbständig und nur unter Verwendung der angegebenen Literatur und Hilfsmittel angefertigt habe. Sämtliche fremde Quellen inklusive Internetquellen, Grafiken, Tabellen und Bilder, die ich unverändert oder abgewandelt wiedergegeben habe, habe ich als solche kenntlich gemacht.

Mir ist bekannt, dass Verstöße gegen diese Grundsätze als Täuschungsversuch bzw. Täuschung geahndet werden.

Berlin, den

Unterschrift