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Detection of favelas in Brazil using texture parameters and machine learning

MASTER'S THESIS

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Abstract

According to the United Nations, almost a third of the world's urban population lives in slums. As a result of increasing urbanization, the number will increase significantly in the future. Up to 2 billion people may live in slums in 2030.

With a total number of 11 million dwellers, Favelas are a major urban policy issue in Brazil. Therefore, this thesis investigates, whether it is possible to detect Favelas in Brazil using machine learning and texture parameters. Further research issues focus on the influence of the kernel size on the accuracy. Moreover, investigations analyze the influence of different sensors and the morphology of the areas of interest Rio de Janeiro and Sao Paulo on the classification results. The classification approach uses Random Forest Classifier and Haralick’s texture parameter calculated from Sentinel 2, CBERS 2B HRC and Orbview 3 data. The results show that the approach is capable to detect favelas with a characteristic slum morphology as well as to map differences in morphology of different settlement forms. However, the high diversity of different favelas types and frequently occurring mixed forms between regular settlements and favelas represent a challenge. They lower both, the classification accuracies as well the explanatory power of the results. Moreover, the work shows that the classification accuracies increase with increasing kernel sizes due to a smoothing effect. The obtained significant differences depending on the city and the sensor underline that it is important to select sensors that can represent the morphology of a city in sufficient form for the classification approach.

Zusammenfassung

Laut Zahlen der Vereinten Nationen lebt knapp ein Drittel der weltweiten urbanen Bevölkerung in Slums. Durch zunehmende Verstädterung wird sich die Zahl in Zukunft drastisch erhöhen, 2030 könnten bis zu 2 Milliarden Menschen in Slums leben.

Am Beispiel von Brasilien, in dem Favelas ein bedeutendes stadtpolitisches Thema sind, wird in dieser Masterarbeit untersucht, ob es möglich ist mittels maschineller Lernverfahren und Textur-Parametern Favelas auf Satellitenbildern zu erfassen. Die weiteren Forschungsschwerpunkte dieser Arbeit befassen sich mit dem Einfluss der Kernelgröße auf die Genauigkeit und ferner dem Einfluss unterschiedlicher Sensoren und der Morphologie der Untersuchungsgebiete Rio de Janeiro und Sao Paulo auf die Klassifikationsergebnisse. Der Klassifikationsansatz verwendet dabei den Random Forest Classifier und aus Sentinel 2, CBERS 2B HRC als auch Orbview 3 abgeleitete Textur Parameter nach Haralick.

Die Ergebnisse zeigen, dass sowohl Favelas mit einer charakteristischen Slum-Morphologie, als auch Unterschiede in der Morphologie der unterschiedlichen Siedlungsstrukturen der Untersuchungsgebiete erfasst werden könne. Jedoch stellt die hohe Diversität an unterschiedlichen Favelas und häufig auftretende Mischformen zwischen regulären Siedlungsformen und Favelas eine Herausforderung sowohl für die Klassifikation, als auch für eine objektive Auswertung der Ergebnisse dar. Die Arbeit zeigt darüber hinaus, dass die Klassifikationsgenauigkeiten mit zunehmender Kernelgröße steigen, was auf einen Glättungseffekt zurückzuführen ist. Signifikante Unterschiede in Abhängigkeit von der Stadt und dem Sensor unterstreichen außerdem, dass es wichtig ist, Sensoren zu wählen, die die Morphologie einer Stadt in für den Klassifikationsansatz ausreichender Form darstellen können.

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List of Abbreviations

AA	Accuracy Assessment
AOI	Area of interest
CART	Classification and Regression Trees
DMP	Differential morphological profile
GE	Google Earth
GLCM	Gray level co-occurrence matrix
GSO	Generic Slum Ontology
GUF	Global Urban Footprint
IBGE	Instituto Brasileiro de Geografia e Estatística (Brazilian Institute of Geography and Statistics)
K	Kappa
LBP	Local Binary Pattern
LU/LC	Land use / land cover
ML	Machine learning
OA	Overall Accuracy
OBIA	Object Based Image Analysis
OSM	Open Street Map
PPV	Positive Predictive Value
RF	Random Forest
SVM	Support vector machine
SEN	Sensitivity
UN	United Nations
VHR	Very high resolution

1. Introduction

1.1. Background

2009 was the first year in human history where more people lived in urban areas compared to rural ones (United Nations 2017). While urban growth is stagnating in the more developed countries, it will continue in the third world. According to estimates by the UN, an increase of 2.8 billion people (as of 2015) living in cities to 4 billion in the year of 2030 is possible. That would comply with an increase of 1.2 billion urban residents in just 15 years (United Nations 2003).

The reasons for this extreme urbanization process in developing countries are manifold. On the one hand, they include the push factors such as famine, unemployment and a lack of public services which 'push' people to rural exodus. On the other hand, there are other 'pull factors' that pull people into the cities. These include jobs, better medical care and education and thus better overall chances of success (Bronger 2007).

However, city authorities often cannot adequately handle the pressure of migration. Social housing for people is often insufficient or does not even exists. The consequences of these grievances are similar all over the world even though they differ in their genesis. The poorer strata of the population occupies land illegally and erects improvised housing. Their appearance varies from stilts in the sea to occupied skyscrapers or improvised dwellings at cemeteries. This form of settlement is often referred to as a 'slum'. In relevant literature, the terms 'informal settlement' or 'squatter settlement' are used more often but describe similar settlement structures. UN Habitat (2003) estimates that according to their definition 924 million people lived in slums in 2001, mounting to 32% of the world's urban population. Due to the persistent urbanization progress the number of slum dwellers is likely to significantly increase in the next decades to up to 2 billion in 2030 (United Nations 2003).

A country where this settlement problem has always been a much-respected topic is Brazil. According to the latest census (2010) about 11 million people are living in favelas, the local form of informal settlements. Similar to the whole continent Latin America, this country has experienced a rapid process of urbanization since the middle of the 20th century, already exceeding the 50% value in 1961 (*see figure 1*). Here again, favelas resulted from a planning policy that failed to provide affordable housing to a frequently growing city population. Today about 20% of Rio's population (equalizing 1.7 Mio people) lives in favelas and around 10 percent of Sao Paulo's equalizing 1.2 million people (Saraiva 2016; Lavalle et al. 2013).

However, those numbers are only rough estimates and the real number could strongly deviate, as it is difficult to get detailed and reliable data about favelas and slums for multiple reasons. Firstly, there is a lack of a unified definition of what is a slum. Second, measuring slums from the ground is challenging for authorities: Drummod (1996, p. 125, cited by König, translated from German by the author) described the phenomenon as follows: 'Are there 200, or are there 300 favelas in Rio de Janeiro? In the time when they are counted, others are created ... Where there is an empty place, where no hut was built yet (but will be built) out of thin cement, scraps and pots emerge, Smoke appears from the hearth for an improvised dinner...'. In addition to the high expenditure of time, authorities would face the problem that they cannot ensure to receive reliable information from slum dwellers while recording census data.

However, detailed information about size and the spatial distribution is important for city administration and authorities, not only in Brazil but all over the world. City authorities need reliable population estimates and built-up area maps to enable appropriate city planning to face those problems. A key role in this process can be remote sensing, which nowadays provides high-resolution image data in a timely manner covering huge areas and can also modify urban structures by means of complex analysis methods. It allows new approaches such as change detection or population estimates to support urban decision-makers in their planning processes. Therefore, this thesis will present an approach based on remote sensing and geotechnologies to detect favelas in Rio de Janeiro and Sao Paulo in Brazil.

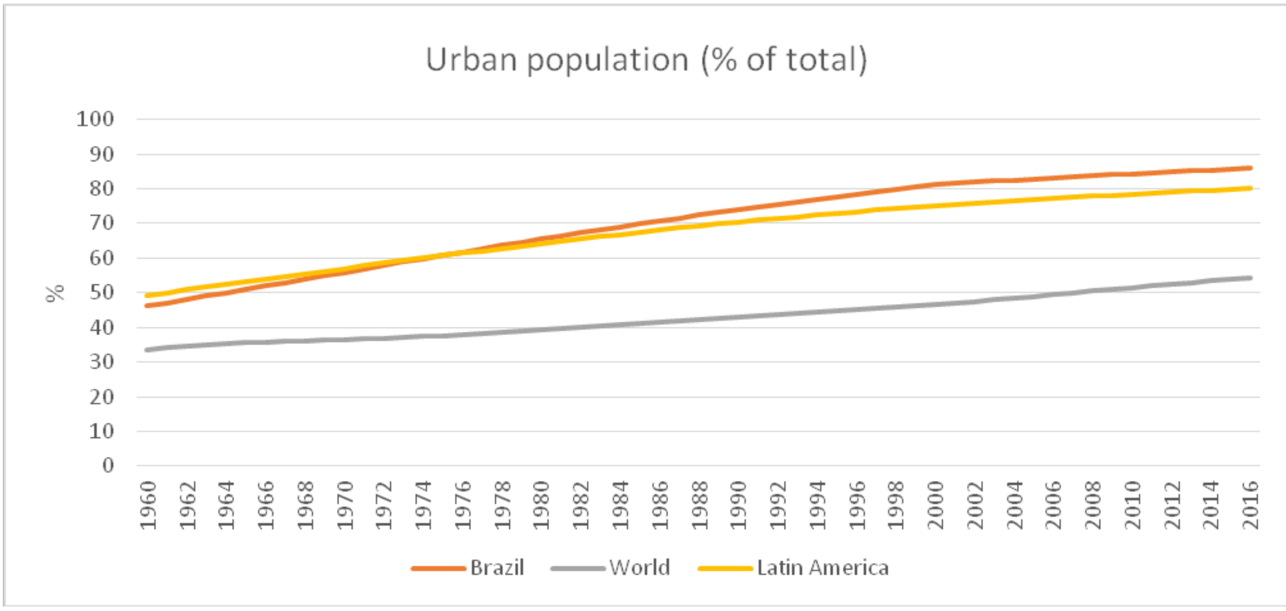

Figure 1. Development of the urban population in the world, Brazil and Latin America (Source: World Bank 2016)

1.2. Scope of this study

In doing so, this work deals with the geographical background of informal settlements as well as with its morphology, which is important for their detection from space. As the research into the field of slum mapping is relatively new, unified approaches of detecting slums from space do not exist. Hence it is necessary to investigate which data and approaches are suitable to detect slums in specific areas. Hereby the goal of this thesis is not to gain new information about the location of favelas in Brazil, but to explore remote sensing approaches with regard to suitability to detecting slums. In addition to a theoretical discourse about favelas in Brazil and 'slum mapping', this thesis will deal with the following research issues:

'Is it possible to detect favelas in Rio de Janeiro and Sao Paulo using texture parameters and machine learning'

Moreover, it will be investigated:

'Which kernel size leads to the highest accuracy?'

'How do the accuracies vary using different satellite data?'

'How does the city's morphology influence the accuracy?'

In order to answer the research issues, the master thesis uses a literature research to derivate a methodical approach and gain a knowledge base in terms of 'Slum mapping' and Favelas in Brazil. In the further process, remote sensing technologies are used for preprocessing satellite and reference data. Image classification is subsequently used to detect Favelas in the cities Sao Paulo and Rio de Janeiro and is evaluated using an accuracy assessment.

By addressing above mentioned questions, new knowledge in remote sensing in the topic of slum mapping will be gained and a more precise characterization and differentiation of the informal settlements in Brazil will take place. The resulting information can be used for further research, e.g. by transferring the applied approach to other Brazil cities or other countries. Moreover, there is a wide range of further research possibilities on those topics. Other satellite images, features sets or machine learning algorithms can be tested to improve the results as well as characteristics of the slums that impede the classification process. Hence, this work is relevant for researchers, as well as authorities and city planners.

1.3. Content of the thesis

The remainder of this thesis is organized as follows.

The 1st chapter serves to approach the topics and to explain the necessity for further research into this field. Subsequently, the research questions are defined and the scope of the work presented.

In chapter 2, the essential theoretical background will be introduced by explaining the challenge in defining the term ‘favela’ and related terms such as ‘slum’ or ‘informal settlement’. Moreover, an overview of different types of slums and their morphological characteristics will be introduced. Finally, the state of research will be outlined by giving an overview of different approaches of slum mapping. This results in the deriving of an approach used in this thesis and the adoption to the area of investigation (AOI).

In chapter 3, the data basis used in this thesis will be outlined. General information about the used satellite images as well as the source of the reference data will be provided. In addition, the AOI will be introduced by showing statistical information helping to identify challenges for the following classification step. In a final step the chapter will explain the used Haralick’s texture parameters derived from a Gray level co-occurrence matrix (GLCM).

The chapter 4 is the main part of the thesis, as it includes the application of the chosen method and its implementation. Starting with a short definition of machine learning and an overview of different algorithms, the functioning of the chosen Random Forest Classifier will be explained. Additionally, fundamentals of Data Sampling and the chosen technique will be provided followed by explanation of the process of the implementation of an accuracy assessment (AA). Last points in this chapter include the workflow and realization of the classification.

In chapter 5, subsequently, the obtained results will be evaluated. Hence this chapter will answer all the research issues. Firstly, classification results will be discussed by evaluating the AA parameters. Hereby accuracies of the different kernel sizes will be compared and afterward accuracies in respect to the different satellite sensors will be investigated. With these findings, the research issues will be answered.

The chapter 6 will complete the work by summarizing the findings and drawing a conclusion. Moreover, an outlook on possible further research is presented.

2. Slums (favelas) in Brazil

The aim of this chapter is to introduce the theoretical background about slums in general and favelas in Brazil in particular. Firstly, the meaning of the term ‘slum’ and related expressions will be discussed as they will be used in the subsequent chapters. In this context, it will be distinguished between definitions used in the scientific context and the explicit usage of the term in this thesis. Afterwards, an overview of different types of slums and their characteristics in the area of interest (AOI) is provided. This information will be necessary to understand the challenges and outcome of the chosen methological approach. The chapter closes with an analysis of the state of research and the derivation of an approach.

2.1. Definitions

In a first step, the following part will provide an overview of frequently used terms in the context of slums. First, it has to be outlined, that there is no commonly applied definition of this expression. Herby the goal of this chapter is not to discuss which of those definitions is right. Instead, the aim is to outline the difficulties of finding a general understanding of this term and to be aware of the different thematic backgrounds of those terms. Therefore in the following the terms ‘informal settlements’, ‘squatter settlements’, ‘slum’ and ‘favela’ are explained as they are the most frequently used terms (Kuffer et al. 2016). Afterwards, it will be determined how specific terms are used in following chapters of this thesis.

The most common term in scientific papers dealing with slum mapping is ‘informal settlements’ as Kuffer et al. (2016) investigated. Clearly, it focuses on the land rights and hence on the legal aspects of housing. The United Nations (1997) define informal settlement with the following characteristics:

- areas where groups of housing units have been constructed on land that the occupants have no legal claim to, or occupy illegally;
- unplanned settlements and areas where housing is not in compliance with current planning and building regulations (unauthorized housing).

An almost equal concept is described by ‘squatter settlements’. They are defined as residential areas in peripheral locations having inadequate infrastructure and services, similar to informal settlements, their land- and building rights vary from illegal, semi-legal to legal (Bronger 2007, Srinivas 1991). However, those settlements are not only found in developing countries, but also in the ‘Developed world’ in form of protest camps or illegal housing occupation.

In contrast to those terms referring to the ownership, **'slums'** refer to the environmental aspects. A highly ciliated definition was released in the 'Global Report On Human Settlements' (2003) by the United Nations. This scientific report can be seen as the first approach of defining universal guidelines of measuring slums. To understand why it is problematic to establish a unified definition, UN Habitat mentions several features:

- Slums are too complex to define according to one single parameter.
- Slums are a relative concept and what is considered as a slum in one city will be regarded as adequate in another city – even in the same country.
- Local variations among slums are too wide to define universally applicable criteria.
- Slums change too fast to render any criterion valid for a reasonably long period of time.
- The spatial nature of slums means that the size of particular slum areas is vulnerable to changes in jurisdiction or spatial aggregation.

Subsequently, the heterogeneous and dynamic nature of slum communities limits the use of rigid slum definitions (Hacker et al. 2013). To face this problem UN Habitat summarized instead inherent features of slums such as: *A Lack of basic services, substandard housing or illegal and inadequate building structures, overcrowding and high density, unhealthy living conditions and hazardous locations, insecure tenure (irregular or informal settlements), poverty and social exclusion and finally minimum settlement size*.
Out of these features, they based an operational definition which defines an area as a slum that combines to various extents the following characteristics:
Inadequate access to safe water, inadequate access to sanitation and other infrastructure, poor structural quality of housing, overcrowding, insecure residential status.
Though this definition is widely used in science, it has also caused criticism by several authors such as Hacker et al. (2013) and Bronger (2007). They find fault with the operational definition is not including infrastructure deficiencies and the deprivation between and within slum communities.

Additionally, other local terms are used in Latin America and Brazil such as 'favela'. UN Habitats (2003) and other sources refer to this term as a synonym. This view is, however, also sporadically recounted in the literature, since it does not adequately describe their political-historical genesis (Wilhelmy & Bodersdorf 1984). However, this complex issue will not be discussed at this point. Instead it will be referred to the definition by the Brazilian geographic institute. The term 'favela' was first officially defined for the Brazil census in 1993 as 'A substandard settlement (aglomerado subnormal), of at least 51 housing units, with a haphazard layout, on illegally occupied private or public land, and lacking essential services. In 2000 the definition has changed to the effect, that the decisive factor is the originally illegal occupation of land and no longer the current property relations (Dupont et al. 2015). Hence favelas have rather to be seen as a type of squatter settlements as the definition refers to the land rights more than it refers to the poor living conditions of the dwellers (Xavier & Magalhães 2003). Further facts that outline that favelas are not settlements of poverty (anymore) were published by Data favela, a Brazil research institute, in 2013. Referring to this report, in the last 10 years alone, the proportion of middle-class residents in the favelas has risen from 33% to 65% of their population. Indeed, the residents of favelas have a combined annual income of R$63.2 billion, the equivalent of the total consumption of countries such as Paraguay and Bolivia. Here, similar to the dynamic slums, favelas are '… a dynamic phenomenon that is constantly changing both within itself and in its relationship to the specific character of Rio's urban structure.' (O'Hare & Barke 2002, p. 1)

By this, it is obvious that the use of relevant terms needs to be defined in regards with this thesis. As nearly all of the above mentioned characteristics are either social-economic or judicial ones, they are not suitable for describing slums from space. Hence it is necessary to determine morphological features describing the spatial appearance of slums and define what is considered a slum in this thesis (cf. chapter 2.2). In the theoretical part of this thesis, however, always the same conceptual term will be used as in the source. To avoid ambiguities, the term favela is not used as a synonym, and will only be used if it was used in the respective source. The use of the term as a special slum type in Rio is explained in more detail in chapter 2.3

In short, this chapter has shown, that slums are a dynamic and heterogeneous phenomenon that cannot be defined unambiguously and unified. Hence the definition of a slum must be adapted to the local context of each city to represent the specific characteristics of each city such as the political background, history and local construction methods.
Furthermore, a remote sensing based detection of the slums requires a morphological definition. So, in this thesis from chapter 3 on the term is only used in a morphological context.

2.2. Characteristics of slums

As discussed in the previous chapter, it is necessary to determine physical characteristics to describe and map slums from space. Moreover, due to their varying characteristics, it is necessary to explicitly do this for every city. Hence, in this chapter characteristics for slums in the investigated areas of interest will be discussed. The purpose of this chapter is, therefore, to determine appropriate image features to define slums in a morphological context for the investigated cities Sao Paulo and Rio de Janeiro. Doing this, firstly a concept for describing the characteristics of slums will be presented. Afterwards, it will be determined which features are suitable for defining slums and finally which shaping of these features can be found in the areas of interest.

To present the high amount and diversity of slums in an ordered structure, Kohli et al. (2012) developed a generic slum ontology (GSO). It consists of the three spatial levels 'Environs', 'Settlement' and 'Object' (*see figure 2)*, describing the physical characteristics from large scale to a small scale. Features of the highest hierarchical level 'Environs' include the location and the neighborhood characteristics of slum and therefore describe the spatial context of the slum. The latter mainly refers to the fact that slums are usually built close to employment opportunities. Compared to that, the level 'Settlement' represents the peculiarities of the housing scheme and hence the relation of the buildings to each other. They include the density of building housing as well as the shape of the settlement. Finally, 'Object' level describes features of the settlement containing object such as roofing material, building size and orientation. Moreover, it depicts the access network and by this the road structure.

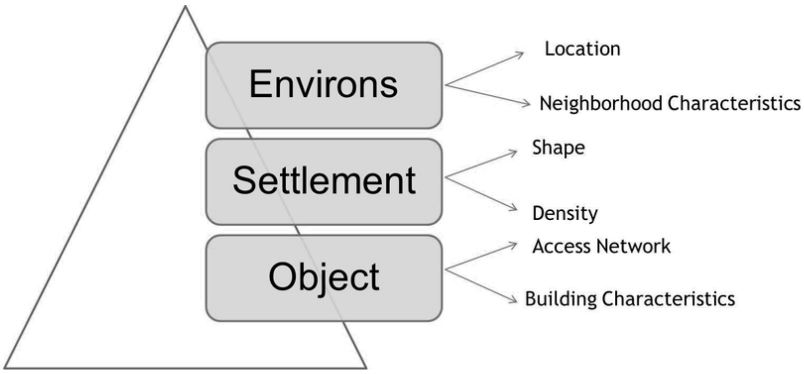

Figure 2. 'Slum ontology' after Kohli et al. (2012)

After having defined features describing the morphology of slums, in a next step, it is necessary to describe how slum areas distinguish from formal built-up area with respect to these features.

In this context Hacker et al. (2013) created a list of suitable features and their characteristic value in general. Those characteristics include features of the settlement level (density, pattern) as well as object-related ones (size) and environs ones (location).

Table 1: Typical morphological characteristics for slum areas and formal built-up areas

Features	Slum areas	Formal Built-Up Areas
Size	• Small (substandard) building sizes	• Generally larger building sizes
Density	• (very) high roof coverage densities • lack of public (green) spaces within or in the vicinity of slum areas	• low to moderate density areas • provision of public (green) spaces within or in vicinity of planned areas
Pattern	• Organic layout structure (no orderly road arrangement and noncompliance with set-black standards)	• regular layout pattern (showing planned regular roads and compliance with set-black rules)
Site characteristics	• often at hazardous locations (e.g, flood-prone, close to industrial areas, steep slope) • proximity to infrastructure lines and livelihood opportunities	• Land has basic suitability for being built-up • (Basic) infrastructure is provided

Source: Hacker et al. 2013

Though slums usually fulfill those characteristics to a different degree, as shown in chapter 2.1 slums vary considerably from city to city. Therefore, those characteristics need to be adapted to the local level of the AOI for both settlement structures: Slum areas as well as formal built-up areas. This is done by analyzing literature and evaluating very-high resolution (VHR) Satellite images. Yet the ontology requires a local adoption as not all indicators are relevant for a specific local slum identification. Thus, slums are different from non-slum areas, but not among them. Hence to map slums from space the most practical solution to define the term is to determine what distinguishes a slum from a non-slum in the AOI (Kuffer et al. 2016).

Referring to Gueguen (2014) Rio de Janeiro slums are characterized by small roof sizes, high density, irregular patterns and diverse roofing materials such as corrugated iron or ceramic tiles (Veysseyre 2014). Furthermore, they are often located in disadvantaged areas such as steep slopes or close to factory sites. It is hard to quantify those features, due to a lack of available information and the dynamic nature of slums. Analyses by Fricke (2015) have derived density values between 40-80% for 80% of the slums. Moreover, favelas tend to be located on steep areas (slope higher than 10%).

Obviously, it is difficult to find unified properties of regular built up areas as they usually vary even more in their appearance. In general, regular built-up areas in Rio de Janeiro are characterized by a roof size that is taller on average, lower building density and a more regular pattern compared to slum areas. They are also characterized by an availability of green areas and are located on land that is suitable for construction. Problematically they show a similar diversity of roofing material ranging from ceramic to metallic roofs. Hence a differentiation between slums and formal built-up areas appears challenging.

Contrarily, clearer major differences in the distinction occur in Sao Paulo. While slums are similarly defined by small roof sizes, high density and irregular patterns, major differences occur in regards to the roofing material. Statistics show a high percentage (84%) of fibre-cement roofing in slums (Mariana et al. 2013). Contrarily most roofs in formal built up areas are covered by roofing tiles (up to 64%) (Mariana et al. 2013). Moreover, identical to Rio they show a more regular pattern, whereas differences to slums subjectively seem to be higher in Sao Paulo.
In conclusion, in a visual interpretation, slums are easier to distinguish from non-slum areas in Sao Paulo. The used parameter of the methodological approach to represent this differences comprises Haralick's texture parameters. Their capabilities will be explained later in chapter 3.4.

Above mentioned criteria are important for the creation of reference data, that is introduced in chapter 3.2. At this point, it is important to clarify, that the outlined definition of slums differ from a socio-economic or legal definition (e.g referring to Instituto Brasileiro de Geografia e Estatística (IBGE) definition). Wurm & Taubenböck (2017) investigated differences in the coverage of slums defined by a socio-economic or legal definition (IGBE census data) and slums defined by morphological criteria (equalizing the reference data in this thesis). Their study indicates, that in the case of Rio de Janeiro 93.7% of the area of morphological defined slums agree with census slums. However, only 30.8% of the total area of census slums are included in the morphological slums. Hence, there is a small percentage of legally built areas showing morphological characteristics similar to slums, e.g. by having a high building density or high diversity of roofing material. On the contrary, there is a high number of favelas that do not show typical slum attributes and are therefore erroneously (from a socio-economic or legal viewpoint) not regarded as such. Reasons for this are the economic growth and slum upgrading programs described in chapter 2.1 that let to improved housing condition in numerous favelas (Magalhaes & di Villaroase 2012).

Furthermore, the transition between regular settlement areas and favelas is often fluid, as the latter are not only upgraded by residents, but also by state slum upgrading programs (Magalhães & di Villarosa 2012). The result is that some favelas can hardly be distinguished from formal settlements in their form (Pallier 2010).

2.3. Types of slums

As mentioned in the previous chapter slums do not only vary from city to city but also within cities. Subsequently, they fulfill the in the previous chapter mentioned characteristics to a different degree. This topic will be discussed in detail in the following with the limitation, that a quantitative designation is not possible due to a lack of official statistics.
Therefore, this chapter will outline different slum types and the characteristics of the investigated areas.

2.3.1. Slums in Rio de Janeiro

In general, four different main types of slums in Rio can be distinguished, whereas a clear distinction is not always possible as subtypes do exist. Definitions in this chapter refer to the contemporary meaning of the terms in urban politics.
The growth of Rios favelas started in the beginning of the 20th century with the demolition of 'Cortiço' (social housing) as part of a reorganization of the city center *(see figure 3)*. Thousands of homeless people of the underclass subsequently resettled illegally in disadvantaged spots in the periphery of the city center by building favelas. A further expansion of favelas happened later between 1930 and 1950. Reasons for this were technical progress as well as economic crisis combined with empty public ground as a result of speculative ground ownership. Subsequently, poor populations groups settled along main transportation routes and in open space near the city center.

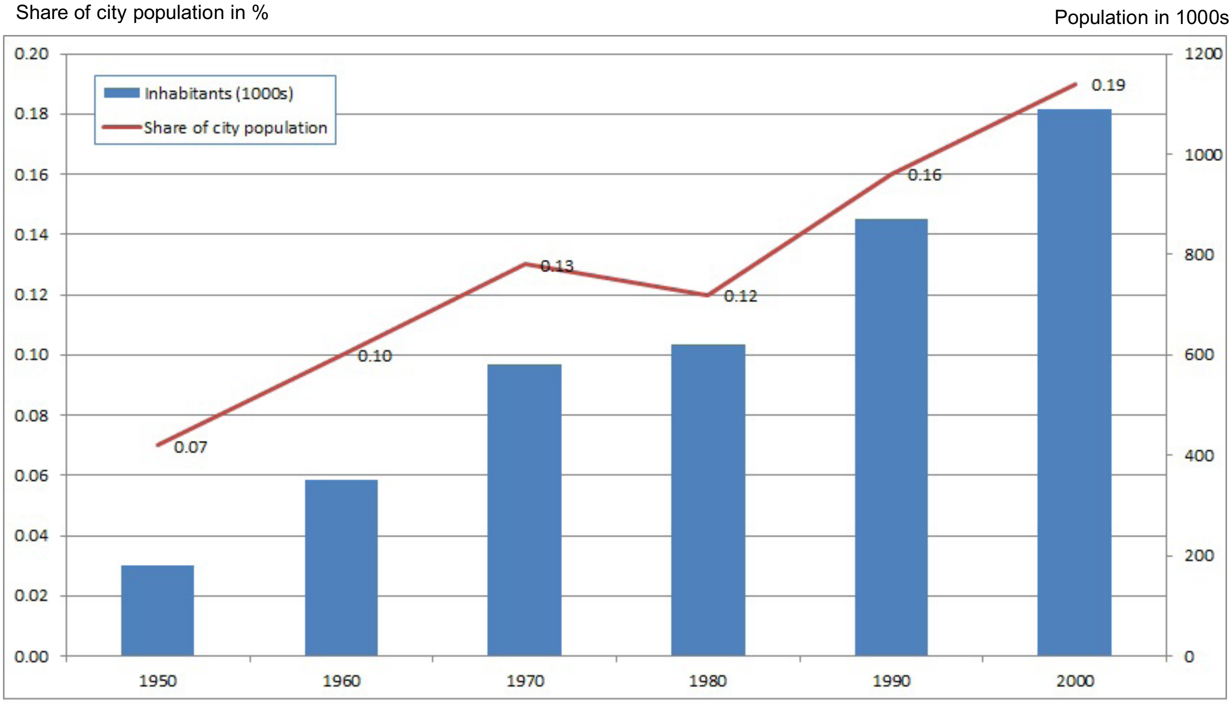

Figure 3. Growth of Rio's favela inhabitants and the share of favelas in the city. (Source: IBGE Census, various years, cited in Soares, 2005)

Nowadays four main groups of slums can be distinguished referring to UN Habitat (2003) visualized in *figure 4*:

The first two types are favelas and 'Invasoes' (cf. squatter settlements in chapter 2.1). They are both self-built and established illegally on occupied public or private land without following any rules of urban planning. They only differ in their state of consolidation and their spatial distribution. While favelas are characterized as highly consolidated, 'Invaseos' are defined as still being in the process of consolidation. Moreover, favelas can be found all over the city, whereas 'Invasoes' can mainly be found in environmentally fragile areas which are avoided for public building, e.g. spots that are: steep, nearby industrial areas, hazardous of being flooded or affected by landslides.

'Loteamentons irregulars' (illegal subdivisions) are illegal subdivisions of land and can mainly be found in western parts of the city. Indeed, they do not follow official planning but show structures similar to regular built-up areas. Moreover, they do not comply with official building regulations, hence their look is usually more heterogeneous than regular settlements.

'Cortiço', are a form of social housing with the limitation that rooms are rented or sub-leased without an official permission. In contrast to the favelas and 'Invasoes' the term is not related to larger areas but rather to a single or smaller number of houses. However, living conditions usually are similar to characteristics of slums. Including a lack of inadequate services and often overcrowding.

Figure 4. Example of a Favela (top left), a Loteamenton (top right), a regular built up area (lower left) and a hybrid (lower right) in Rio de Janeiro

As a result, one can say, that ‘Invasoes’ and favelas highly match the characteristics of slums. Furthermore, ‘Lotamentons’ usually do not fulfill the attributes of an informal settlement, however, their irregular patterns of roofing material may differ from patterns of regular built-up areas. ‘Cortiço’ seem hardly to be distinguished from space using morphological features. On the one hand, the areas they cover are too small, on the other hand they lack of slum specific attributes (O’Hare & Barke 2002; Xavier & Magalhães 2003; United Nations 2003).

2.3.2. Slums in Sao Paulo

Referring to literature we find a different subdivision of slum types in Sao Paulo (Mariana et al. 2013). Moreover, definitions of form existing in both cities vary slightly.

This resulted from a different historical city development in Sao Paulo. Population growth and economic importance started to rise far later than was the case in Rio. Contrarily to Rio, São Paulo’s ‘Cortiço’ in the city center, therefore, remained untouched for a long time and kept growing steadily in size and number. Consequently, the settling of favelas took place far later as there was no need to resettle illegally for the poorer classes. This has not changed until the government could not control the population pressure resulting from migration and economic growth in the 1970s. As a consequence, the poor classes occupied free spots of land all over the city, but mainly in border regions due to an already high building density in the city center. Later even those favelas in nearby city center locations were removed by authorities and forced to find new locations in either environmentally fragile regions or on the outskirts of Sao Paulo.

The slums in Sao Paulo can be divided into two groups: ‘Favelas’ and ‘Cortiço’. Similar to Rio, the types differ in terms of their legal status of ownership. While ‘Favelas’ indeed are created by illegal land occupation, the building owners are still the residents themselves. ‘Cortiço’ however, although usually have a legal status because they are government subsidized housing, but they do not belong to the residents but are (sub-)leased. This fact is also reflected in the characteristics of their design. The majority of the ‘Cortiço’ have tile roofs (64%) and have a regular structure, which is almost identical to that of ‘regular’ settlements. By this, they might be called a transitional form of regular and informal settlement. ‘Favelas’ in Sao Paulo, on the other hand, show slum typical morphological features such as fibre-cement roofs (84% of buildings), an irregular structure and a lack of green areas. With regards to their location, favelas comply much more with the basic features of a slum than ‘Cortiço’: due to the resettlement measures of recent years, they are located either in extreme peripheral locations or in endangered areas such as steep slopes or flooding areas. ‘Cortiço’, on the other hand, are usually built in a central or semi-central site and are located close to workplaces and public services (Saraiva 2016; Mariana et al. 2013; König 1996).
In summary, it can be said that ‘Favelas’ in Sao Paulo have slum typical features and, because of their morphology, appear to be detectable using remote sensing, whereas ‘Cortiço’ tend to have a morphology similar or even identical to a regular settlement. However, as in Rio, hybrid forms of the two types are not excluded.

Figure 5. Examples for a Favela (top left), a Cortiço (top right), a regular built-up area (lower left) and a hybrid (lower right) in Sao Paulo

After having identified characteristics of favelas in the AOIs, it needs to be investigated how those features can be detected using remote sensing. Therefore, a knowledge base of the current state of research is necessary.

2.4. State of research (Slum Mapping)

This chapter will give an overview of the current state of research in the field of mapping informal settlements (slums) from space. The aim is hereby to create a knowledge basis for the upcoming derivation of an own approach. In literature, the term 'slum mapping' is often used and so in this chapter it will be used for the mapping of all introduced kinds of informal settlements, squatter settlement, slums, favelas etc. A difficulty resulting from the high diversity of slums is the transferability of methods involved. Since the characteristics of slums and regular development structures are very different from city to city, different data, features and methods for their classification may be necessary. Hence successful approaches in preliminary research can be unsuitable for this case study in Brazil. Due to a lack of Brazil related works, Slum mapping studies from all over the world had to be analyzed. A summary of all evaluated papers in provided in table 2.

Kuffer et al. (2016) have provided an extensive literature survey in this field by analyzing a majority of the published scientific works in this context with regards to inter alia the used data, applied method and achieved results. Accuracy values in this context must always be considered as preliminary, since they depend on the classification key, the AOI, the used data, etc. and are therefore not comparable. Hence high achieved accuracies only show that the selected approach was capable in this single context but does not necessarily mean it is transferable to other cases.
In total 87 related papers were analyzed showing a large diversity in used data and applied approaches. Reasons for this are caused by different morphological characteristics of slums.
In a first step an overview about different used satellite images will be provided, for slum mapping in general and for the analysis of urban structures in Brazil. The data basis hereby strongly depends on the aim of the studies. While Slum detection on object level requires a high spatial resolution and hence VHR data (resolution of at least 5m), for mapping on settlement level resolutions with a medium spatial resolution (5m-10m) are sufficient. Their investigations have shown that publications in the field of slum mapping are correlating to the number of launched VHR satellite mission underlining the need for high resolution image data to map complex urban structures such as slums.
Hence, the most frequently used sensors are either VHR Sensors (e.g. Quickbird, IKONOS) or medium resolution (sometimes also called high-resolution sensors), in this case SPOT. As new satellite missions are launched continuously, these lists are limited in how representative they are as new launched missions such as ESA's Sentinel 2 are not included. The spectral resolution studies either used only a panchromatic band or a varying number of multispectral bands. As applied approaches are too different to compare, deriving a general conclusion from the results is difficult. However, Zhang et al. (2014) have shown, that if multispectral

information is available, all bands should be used to extract features (e.g. for texture parameters) to represent heterogeneous appearances of slums and achieve higher accuracies.

As Brazil launched a series of own satellite missions which are available as open source data, a short summarization of studies related to the Chinese Brazil Earth Resource Satellite Program (CBERS) is provided with the limitation that they did not focus on slums. (Wang et al. 2009; Lu et al. 2012) used the panchromatic CBERS 2 HRC images to monitor urban growth and to classify urban landscapes. They conclude that the data only shows limited eligibility as the quality of radiometric resolution shows deficiencies.

In a next step, the applied methods will be compared, herby three groups of classification approaches can be distinguished.

The most common one is an object based image analysis (OBIA). Depending on the image data resolution used, either slum patches (Hofmann 2001), equalizing the settlement level of the slum ontology, or objects (Brito et al. 2008), equalizing the third level of the ontology, are extracted. The parameters are usually texture parameters (Kohli et al. 2013) and/or the height and shape of buildings (Brito et al. 2008). These studies led to high accuracies in all cases (80-95% for slums). In a comparison of the accuracies as a function of the parameters, the highest precision (94% and 98%, respectively) were obtained with the texture parameters GLCM and Local Binary Pattern method (LBP). The disadvantages of an object-based approach, on the other hand, lie in the high time expenditure and the local dependence of the decision tree, hence it cannot be transferred to another area, but must always be redefined.

A further approach is the visual image interpretation. It has lost importance in recent years due to its obvious disadvantages such as high time expenditure, objectivity only by achieved by a high number of interpreters and a complex evaluation key. However, it is still a frequently used approach for slum mapping, since here the disadvantages are relativized because of the complex and heterogeneous structure of the slums. In addition, there is the advantage that the use of VHR data from Google Earth (GE) does not incur any costs. All studies that applied this approach only focused on a small AOI and not whole countries (Kuffer et al. 2016).

As a third method, the pixel-based approaches need to be mentioned, whereby they include a wide field of classification methods. Since for the analysis of slums however a larger spatial context is needed in order to cover the heterogeneity of the slum structure, machine learning methods were mostly applied. The most common algorithms are support vector machines (SVM), multi-core learning, or 'Random forest' (RF). As parameters, above all texture parameters were used, including GLCM with Haralick Texture parameters (Bekkari et al. 2012), Differential Morphological Profiles (DMP) including 'Opening', 'Closing', etc (Lu et al. 2012). Moreover, several researches compared different morphological feature sets regarding their capabilities (Wurm et al. 2017a; Abeigne Ella et al. 2008). Abeigne et al. received accuracies between 73% and 100% depending on the slum type using a SVM and Quickbird data. Moreover, except for one Slum type consistently higher accuracies (96% to 99%) were achieved by using the DMP. However, they concluded that LBP seems to be more powerful but requires a higher feature space dimension and more computing power. Wurm et al, on the other hand, compared different GLCM Kernel sizes with DMP and a combination of both features. Results show, that high accuracies were obtained with GLCM whereas larger kernel sizes lead to better results due to a smoothing effect.

A further paper is the research of (Kuffer et al. 2016) about the usage of VHR images and texture parameters to detect slum areas. Thereby they compared the accuracies of different VHR satellite missions (Worldview 2, Quickbird, Orbview 3) using an approach of texture parameters and machine learning. They took their focus on investigating if the free available Orbview 3 images produce significantly poorer results than comparable fee-based data in terms of slum mapping. They came to the conclusion that Orbview shows some limitations in the radiometric resolutions but not at the expense of significantly lower accuracies.

Finally, Kuffer et al (2016) draw the conclusion that machine-learning methods seem to be more successful when extracting slum patches at city scale, while OBIA approaches work better when mapping slum objects. Hereby machine learning requires features that represent the slum typical morphology like GLCM, LBP or DMP which can be derived from media to high resolution images. In contrast OBIA approaches have to be applied on VHR images to use building shape and form as features. Visual images analysis only seems suitable for deriving reference data.

Table 2. Overview of all analyzed papers

Scope	AOI	Data	Method	Results	Key message	Source
Extraction of urban built-up areas	Beijing and Tianjin (China)	Bi-temporal Landsat TM/ETM+	Combine multi-band spectral data and multivariate texture information in comparison with GLCM	Lowest results for spectral features, increasing results with the addition of one band texture and/or multivariate textures	Multivariate texture outperforms the use of only spectral information	Zhang et al. (2014)
Application of CBERS Imagery for Urban Growth Monitoring	Changchun (China)	CBERS2 CCD	Maximum Likelihood Classification		CBERS 2 CCD is suitable for urban growth monitoring with some limitations due to a medium resolution	Wang et al. (2009)
Classification of CBERS-02B Imagery using Morphological Features for Urban Areas	Bejing (China)	CBERS 02B HRC	SVM Classifier using only spectral information or adding Mathematical Morphology features	OA 56% without MM OA 80% adding DMP	Adding morphological features improves classification accuracies significantly. With multiscale morphological feature sets, it is possible to distinguish between different urban surfaces	Lu et al. (2012)

Detecting Informal Settlements from Ikonos Image Data Using Methods of Object Oriented Image Analysis	Cape Town (South Africa)	Ikonos	OBIA using eCognition and texture, spectral information and neighbourhood relations		The applied approach was capable to detect informal settlements in Cape Town	Hofmann (2001)
Recognition of Urban Patterns (incl. informal settlements) using OBIA and Aerial Images	Salvador (Brazil)	Aerial Images (RGB with 0.16m spatial resolution)	OBIA using eCognition and geometrical and spectral characteristics		The study shows, that it is possible to analyse even complex urban structures (incl. informal settlements) using an OBIA. The added value of a NIR band is assumed to be high	Brito et al. (2008)
Transferability of Object-Oriented Image Analysis Methods for Slum Identification	Ahmedabad (India)	Pan-sharpened GeoEye-1 (RGB with 0.5m spatial resolution)	OBIA using eCognition using Haralick's texture parameters, spectral and geometrical information	Depending on the subset, accuracies for slums differ from 47% to 68%	Study confirms the need to adopt a GSO to a local context. Haralick's texture parameters are suitable to describe slums	Kohli et al. (2013)

SVM and Haralick Features for Classification of High Resolution Satellite Images from Urban Areas	unknown	Quickbird	Three independent classification runs using SVM and either spatial information (Haralick Features), spectral information, or both combined	Spatial features: OA 83% Spectral features: OA 87% Combined: OA 94%	Combining spectral and spatial information leads to highest accuracies	Bekkari et al. (2012)
Slum mapping in polarimetric SAR data using spatial features	Mumbai (India)	Dual co- and crossed polarized TerraSAR- X (TSX) and TanDEM-X (TDX) images	LDA and RF using the texture features DMP and Haralick	Highest Sensitivity for Slums was obtained from LDA with a 11x11 Kernel (79%), highest Positive Predictive Value with RF and a 81x81 kernel (60%)	RF has shown high efficiency and is suitable for slum mapping even in very challenging areas. GLCM features can represent the morphology of complex urban structures.	Wurm et al. 2017b
Exploitation of textural and morphological image features in Sentinel-2A data for slum mapping	Mumbai (India)	Sentinel-2A	RF Classifier using Haralick Features or DMP	Highest Sensitivity resulted from GLCM with 19x19 kernel size (60%). Highest Positive Predictive Value from Opening	The approach was capable to detect larger slums. Adding DMP did not lead to higher accuracies.	Wurm et al. 2017a

				and Closing Profiles (89%)		
A comparison of texture feature algorithms for urban settlement classification	Soweto (South Africa)	Quickbird Pan (0.6m spatial resolution)	SVM using different sets of texture features (GLCM, LBP i.a)	Highest OA was obtained by GLCM with a 200x200 kernel size (94%) and LBP (98%). For two out of three informal settlement types LBP performed slightly better than LGCM as well	LBP features are more powerful than the com-monly used GLCM features for detecting informal settlements. However, they come along with a higher computing effort	Abeigne et al. 2008
Extraction of Slum Areas from VHR Imagery Using GLCM Variance	Mumbai (India), Ahmedabad (India), and Kigali (Rwanda)	Orbview 3 (Ahmedabad), Worldview 2 (Mumbai), Quickbird (Kigali)	RF Classifier using homogenous urban patches, GLCM variance and Normalized Difference Vegetation Index	Highest Sensitivity was obtained with spectral and texture information (same results with included NDVI). Highest Positive Predictive value resulted from spectral, texture and NDVI information	GLCM variance is suitable to distinguish between formal built-up areas and informal settlements. RF Classifier using the combination of spectral layers, GLCM variance, and NDVI lead to a high overall classification	Kuffer et al. 2016

					accuracy of 88%–95% for detecting slums.	
Object based classification and structural comparison of informal settlement in Greater Cairo	Cairo (Egypt)	Worldview 2	OBIA using arithmetic band combinations, shape and neighbourhood relations	High Sensitivity for one type of informal settlements (89%) as well as a high Positive Predictive Value (82%)	An approach using no texture parameters was capable to detect some types of informal settlements reaching high accuracy values	Mahjen 2016

2.5. Choice of a method

Based on the previously provided overview about the state of research, this chapter will deal with the derivation of an own approach based on three criteria. Firstly, what are the goals of the thesis. Secondly, what data is available and thirdly what approaches have shown good results.

Regarding the first point, the primary goal is the detection of slums in cities of Brazil in form of slum patches (equalizing slum neighborhoods in contrast to slum buildings). But secondly, the process shall be transferable to the other regions and capable of classifying huge areas.
Those requirements are also influencing the second aspect, as they make choosing open source data essential to avoid high costs. With the Sentinel 2 being the satellite mission with the best combination of a temporal, spatial and radiometric resolution the choice seems obvious. Moreover, the availability of an exhaustive reference data set of morphological slums for the AOI enables automatic classification algorithms including machine learning or traditional supervised classification approaches. Including additional classes is not a concern due to the availability of (almost) worldwide land cover (LC) data from Open Street Map (OSM) or global urban footprint (GUF).
The third aspects have been analyzed in detail in the previous chapter, having shown that both, OBIA and Machine Learning approaches have produced high accuracies. Yet, an OBIA approach is not suitable for this work for several reasons. Firstly, OBIA requires VHR Data usually with a resolution of under 5 meters to detect slum objects (Cleve et al. 2008) and is used to detect slums on an object level and not on patch level. Secondly, OBIA is a very time consuming approach and requires an adoption of parameters and values to a AOI. Hence, it is not transferable to other cities or countries. Visual image interpretation was used in a preliminary stage of this thesis to derive the reference data but it seems not suitable for huge AOIs due to its time-consuming character. However, it needs to be mentioned that reference data does not have to be produced by visual interpretation, neither does it have to be exhaustive. Based on these reasons, a machine learning approach seems to be most suitable. Literature research has shown, that texture parameters are most powerful to represent the morphology of slum areas. Regarding the data basis, different satellite images can be taken into account, as there is no unified rule in respect to the resolution. Therefore, in this paper, a machine learning approach using texture parameters will be applied and different satellite images are tested.

3. Data and areas of investigation

This chapter will provide information about the data basis for the subsequent classification process. Information will include characteristics of the satellite images, acquisition of the reference data, statistics about the area of interest and finally basics of the applied texture parameters and GLCM.

3.1. Satellite images

As described in chapter 2.4, a high number of satellites ranging from medium to very high-resolution sensors are eligible for slum mapping in Brazil. The choice of satellite imagery was mainly based on the availability of seamless data with a sufficient resolution. As shown in chapter 2.5, a spatial resolution of 10 m is recommended for the chosen approach. In order to determine the importance of the radiometric resolution for the slum detection, data of different resolutions was chosen in this study. Another important point influencing the choice of data was their repetition rate. Since areas in Brazil are likely to be heavily clouded, it is important that the satellites have a high repetition rate to ensure that (almost) cloud-free shots of the cities exist. This is given by Sentinel due to the high repetition rate and tall swath width, but is problematic for the other two chosen satellites. Since a high number of tiles are needed for a city and the repetition rate is much lower than for Sentinel, it was not always possible to find scenes for the whole city with acceptable degrees of cloudiness.
Based on these criteria, the three satellites Sentinel 2, Orbview 3 and CBERS 2B HRC were chosen whose main characteristics are presented in table 3. In addition, there may be others which would in principle be suitable, but it was not possible to test all available satellites within the framework of the work. In the following, the chosen satellites are briefly introduced with their most important characteristics.

The world-wide available Sentinel 2 data were already successfully used with the chosen approach for slum detection (Wurm et al. 2017a; Pesaresi et al. 2016). The advantages of this satellite mission lie in the fact that it offers a unique combination of spatial (10m), spectral (13 bands) and temporal resolution (5 days at the equator) due to its two identical satellites. Hence, it can almost ensure an availability of cloud-free scenes even in tropical regions. As only four (red, green, blue and near-infrared) of the Sentinel’s 13 bands provide a 10m resolution, only those were used (ESA 2017). A limitation of medium resolution Sentinel data is, that it requires a minimum mapping unit of 10x10 meters, but many slum buildings are smaller than this. Thus a high number of mixed Pixels (see *figure* 6) will occur in the image, which limits the meaningfulness of texture features.

Furthermore, CBERS provides data in different resolutions. Since the range of multispectral data was already covered with Sentinel, the very high-resolution Panchromatic HRC data with a resolution of 2.7m was used to cover the VHR range. This satellite started in 2007, but had to stop its services in 2010 due to a technical error. Because of its low repetition rate of 130 days, only a low number of scenes per city is available. Additionally, they are often cloud covered limiting the number of suitable scenes. Moreover, the program had problems with automatic coregistration of the images, making a manual georeferencing necessary (De Vecchi et al. 2015). Among the used satellites, CBERS has the lowest radiometric resolution with 8 bit equalizing 256 gray scales. In comparison to Sentinel with 12 bit, equalizing 4096 gray scales, and Orbview's 11 bit, equalizing 2048 gray scales, this is an obvious disadvantage (INPE 2017).

In addition, the former commercial satellite mission Orbview 3 was chosen. The data has now been able to be downloaded for research purposes free of charge for several years. The images have a resolution of 4m in the multispectral band red, green, blue and near-infrared and 1m in the panchromatic. Thus, they have a very high spatial resolution and at the same time a medium spectral resolution sufficient for urban remote sensing. The satellite was launched in 2003 and operated until 2007. Since 2012 180,000 scenes have been made available for free download for research purposes at USGS (Kuffer et al. 2016). A small disadvantage of the satellite is the fact, that it cannot acquire panchromatic and multi-spectral images at the same time, so it is not possible to pan-sharpen a panchromatic and multispectral image from the same acquisition time. Moreover, the satellite provided on demand images and did not cover the whole earth surface. Hence scenes covering an entire city often do not exist (Orbital 2017).

Table 3. The main characteristics of the used satellite

Characteristic	Orbview 3	CBERS 2B HRC	Sentinel 2
Imaging mode	PAN + MS	PAN	MS
Resolution	1m (PAN)/4m (MS)	2.7m	10m (RGB+NIR)
Number of bands	1(PAN)+4(MS)	1	12
Radiometric resolution	11bit	8bit	12bit
Swath Width	26.3x8.3km	28x28km	100kmx100km
Repetition rate (Nadir at the equator)	15-20 days	130 days	5 days

Source (INPE 2017; ESA 2017; Orbital 2017)

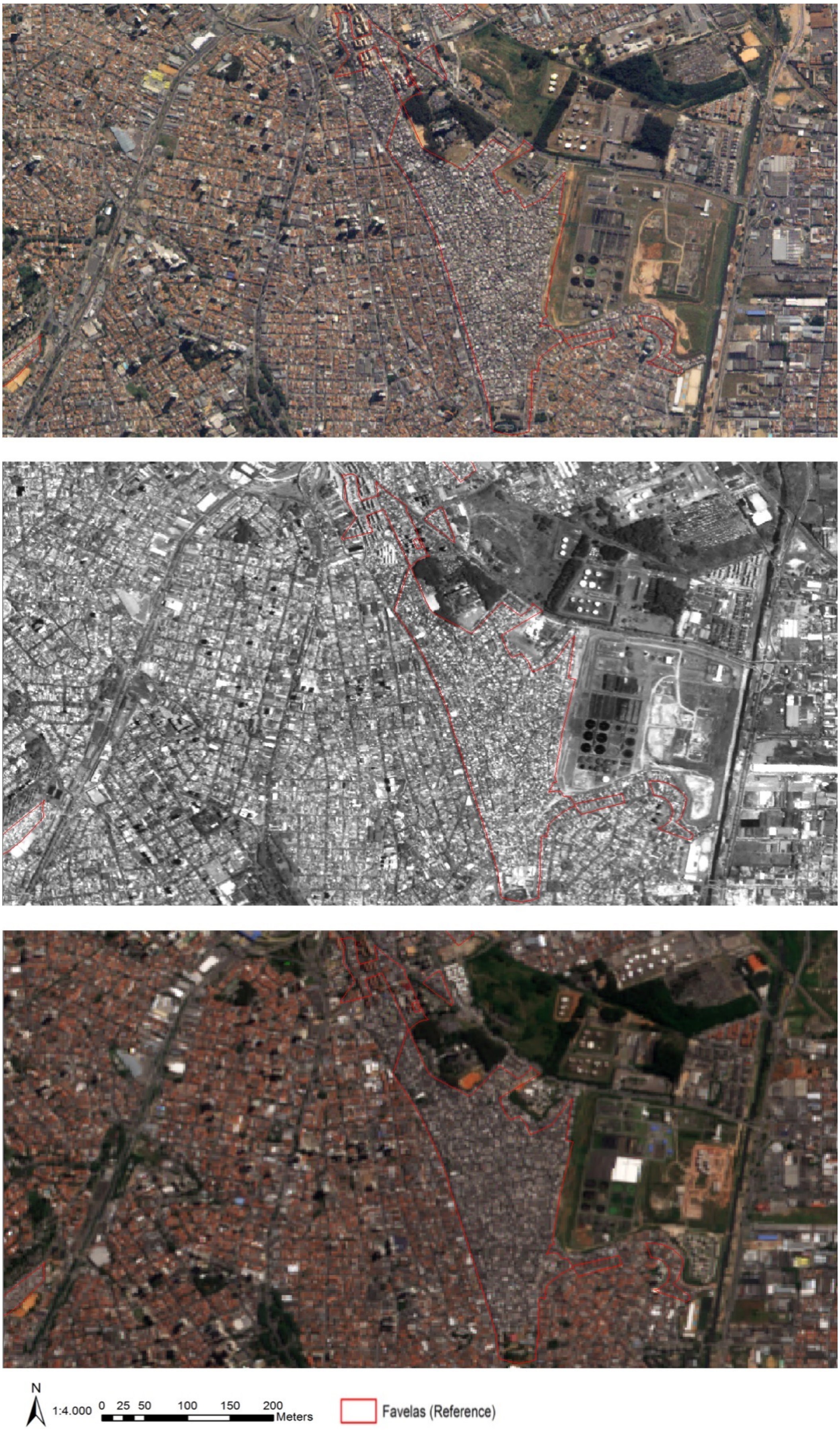

Figure 6. Favelas in the Orbview 3 (Acquisition date: 18.8.2010), CBERS 2B HRC (Acquisition date: 21.8.2009) and Sentinel 2 (Acquisition date:13.9.2016) scene (top to bottom)

3.2. Reference data

Reference data are required for classification, as training data and for evaluation by means of an Accuracy Assessment. In this work, the four classes of favelas, urban, water and vegetation were used. For the latter two classes Open Street Map (OSM) data could be used, since these are available for both areas of investigation. While the urban class was necessary to demarcate favelas, the classes of water and vegetation served only the better extermination. For the urban class, global urban footprint data from the German Aerospace Center were used (Esch et al. 2013). These data are available worldwide and contain all settlement areas. Of these, the favela areas were subtracted, since the latter is, strictly speaking, a subclass of the urban class. Due to other appearing LCs in the AOI, the chosen classes did not cover the areas exhaustively. Therefore, in the later Accuracy Assessment those areas were set to 'Nodata' and thus did not influence accuracy descriptive values. Moreover, it need to be mentioned, that the appearance of the classes is extremely unbalanced. The class urban is in all cases the dominant one, covering approximately 50% of the area. Water and forest combined cover up almost the remaining 50% of the AOIs, favelas in contrast represent only between 1-2% of the total area. This fact has to be kept in mind, for the following classification process.

As the main goal of this thesis was to detect favelas, this class has of course the highest priority. Reference data was obtained by visual image interpretation following the morphological criteria outlined in chapter 2.2. Despite those above guidelines, however, the class favela posed a problem. While common classification keys like CORINE provide a complex policy catalog with guidelines of how to map classes like forest by defining a certain degree of protection to guarantee uniform records, those collections do not exist for favelas or slums. Thus, only characteristics adapted from the literature and the subjective perception of the interpreter can be used. As a consequence of the lack of clear unified characteristics, reference data is not representing general result of the interpretation. Instead, every interpreter would probably produce an individual favela reference set. This results from the mentioned fact that there are areas that have morphological characteristics very similar to slum which are either regarded as slums or regular built-up areas. This is less of a problem for the training process, since the morphological characteristics are covered, but problematic for the Accuracy Assessment. In this step, the algorithm will identify areas classified as favelas as wrongly classified if they were not included in the reference data though they may have the same morphological characteristics and hence can be treated as favelas. As a consequence, the results obtained for favela areas reflect only the result for a point of view and ignore the fact that other morphologically similar identified areas can also be regarded as a correct solution by the classifier.

In a next step the reference data for favelas needs to be investigated to obtain helpful information about the AOI for the classification process.

3.3. Area of investigation

In this chapter, a closer look will be taken over the investigation area to gain important general information over the AOI as well as about the favelas in this area.

As areas of investigation, the cities of Rio de Janeiro and Sao Paulo were chosen as they accommodate the highest number of favelas and favela inhabitants in Brazil (IBGE Census 2010). Due to the lack of availability of suitable CBERS and Orbview 3 data, only Sentinel covers the entire urban area of the two cities. The investigated area for CBERS 2B and Orbview 3 was therefore only a smaller part of the total area. This might lead to a limited comparability of the results; however, a wide range of favela types is present in every AOI. An overview of the different AOIs is shown in the *figures 7* and *8*. The statistics listed in the following therefore always refer to the entire urban area and thus to the investigation area of Sentinel 2 data. In the following, basic information about the two cities of Rio de Janeiro and Sao Paulo will be provided as well as statistics about favela areas in the AOIs.

Figure 7. The investigated areas of Rio de Janeiro in dependence of the sensors (Data source: ArcMap World Imagery)

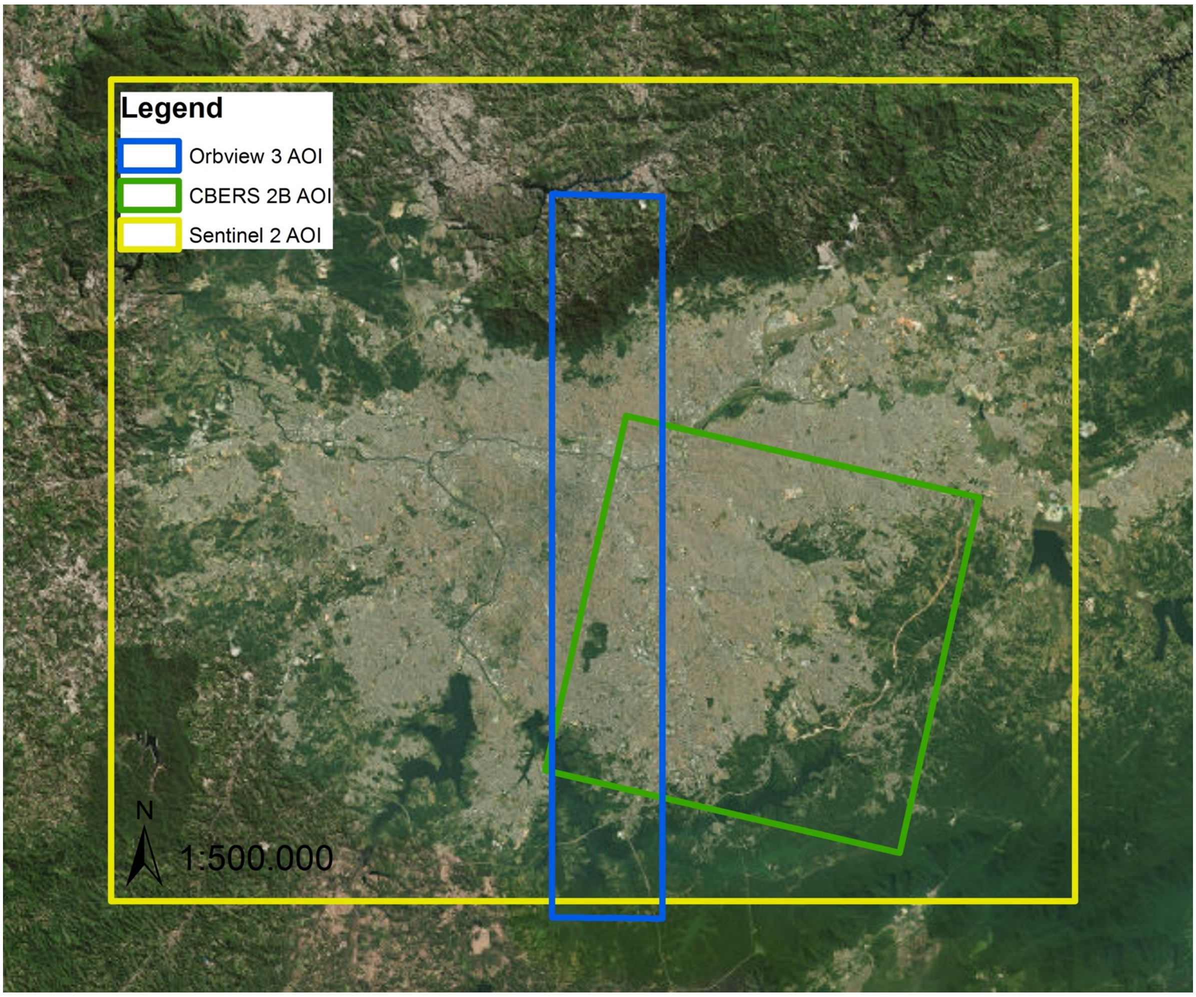

Figure 8. The investigated areas of Sao Paulo depending on the satellite sensors (Data source: ArcMap World Imagery)

3.3.1. Rio de Janeiro

The entire urban area of Rio de Janeiro covers 1182km^2, that of the metropolitan region even 6567km^2. It is home to 6.4 million, or 11.9 million people (metropolitan region). According to the estimates of the census 2010, 1.7 million of those are favela residents. Official estimates are based on a total number of 525 favelas, which is opposed to a number of 646 favelas in the used reference data (Xavier & Magalhães 2003). If these are statistically determined, their average size is 0.9 ha, with a mode value of an area between 0.7 and 2.1 ha *(see figure 9)*.

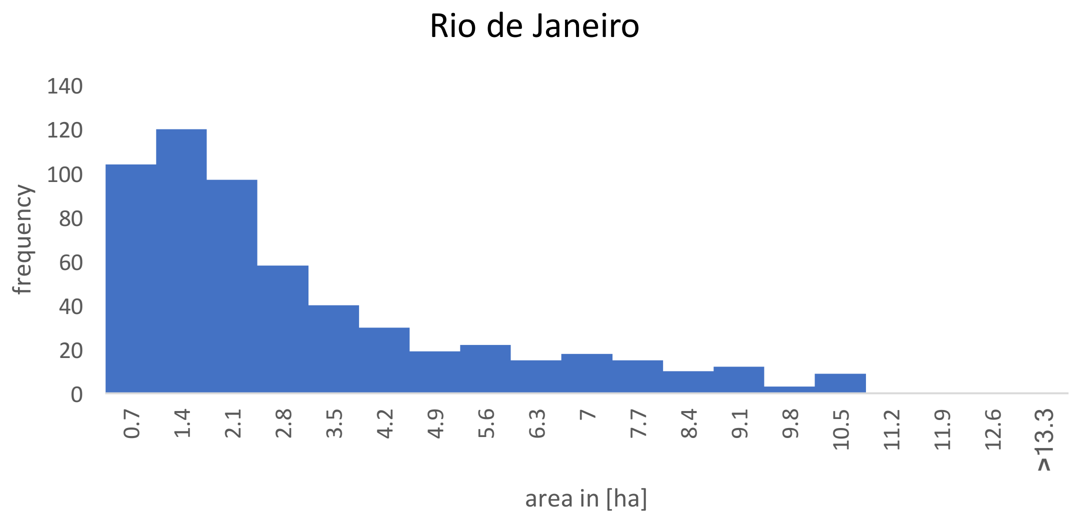

Figure 9. Frequencies of favela areas in Rio de Janeiro

3.3.2. Sao Paulo

The total urban area of Sao Paulo is bigger than Rio de Janeiro and covers an area of 1523km^2, the metropolitan region even 7947km^2. The population is thereby 11.2 million, respectively 21.2 million people (metropolitan region). The city is thus significantly larger than Rio, especially in terms of population. According to the estimates of the census, there are 1.2 million Favel residents and hence half a million less than in Rio de Janeiro. Official estimates are based on a total number of 1,628 favelas (block level), which is opposed to a number of 1850 favelas in the reference data (Saraiva 2016). If these are statistically analyzed, their average size is 3.6 ha, with a modal value of 0.7-2.1 (*see figure 10)*. The favelas of Sao Paulo are hence similar to those of Rio in their distribution of the frequency of size, but are on average considerably larger and there is a larger number of very large favelas (> 13.3 ha). Those numbers are important for the upcoming derivation of texture parameters.

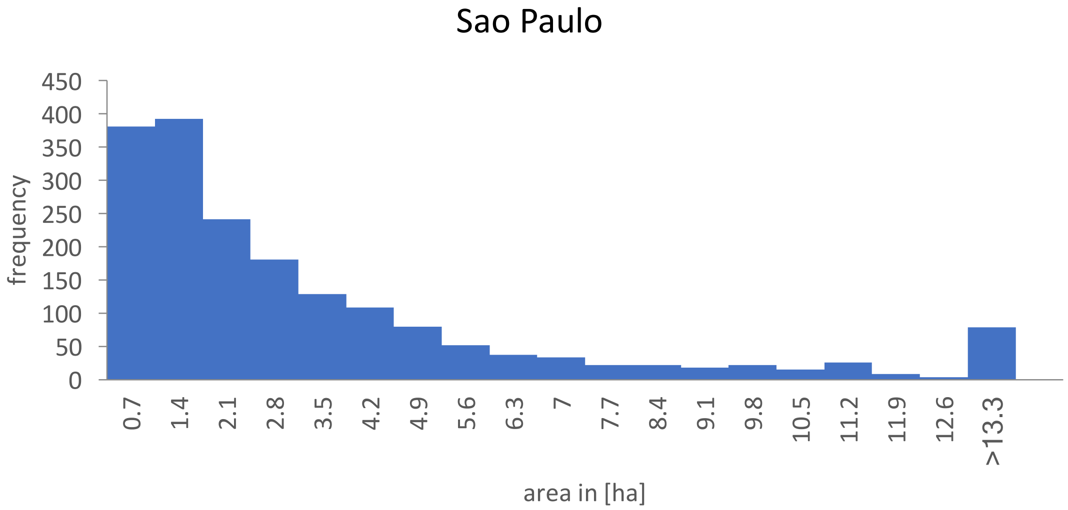

Figure 10. Frequencies of favela areas in Sao Paulo

3.4. Texture parameters

This chapter will explain the terms texture, GLCM and Haralick's features and how they are used to detect slums in this thesis.

Starting with what actually is texture in this context: Texture in the field of image interpretation is the spatial variation of spectral values in a limited spatial scale. The derivation of the texture from the image information can thereby be divided into four groups: Statistical, geometric, model-based or signal processing. The co-occurrence matrix hereby belongs to the category of statistical evaluation. This matrix indicates how often a certain combination (neighborhood relation) of gray values occurs in a picture segment and saves this in tabular form. The dimension of the resulting matrix depends on the number of occurring gray values and thus on the radiometric resolution of the image data.

Certain parameters determine in this process how the GLCM is calculated (Acharya 2015):

- order of the static analysis /texture calculation:
    - first order: the texture calculations relate only to the output pixel, pixel neighborhood relationships are not used, e.g. variance
    - second order: the relationship of two (mostly) adjacent pixels is examined, e.g. Angular 2nd moment.
    - Third or higher order: The relationship of three or more pixels is examined. However, this is hardly used because of the complex calculation.
- Kernel size: As mentioned before, the texture always refers to a certain image area, which is defined by the window size (aka kernel size). Since the window is square-

shaped around an output pixel, this always has to be an odd number e.g. 3x3. The larger the window, the greater the spatial context analyzed. Thus, the value to be selected depends on the object or the land-use class to be classified. In order to measure the texture of favelas in this work, the kernel size must be chosen to represent the average or modal value of the favela size. Since most favelas have sizes between 1 and 3 ha, the corresponding kernel size for Sentinel would be between 10x10 and 30x30 pixels and for Orbview due to the 2.5 times higher resolution between 25x25 and 75x75 pixels. However, it has to be taken into account that a smoothing effect occurs as a result of the larger kernels, since the influence of individual pixels decreases. Smaller favelas are therefore no longer represented in larger kernels.

- directions: outgoing from the central pixel, the neighborhood can be evaluated in four different directions *(see figure 11)*. Horizontal (0°), vertical (90°), and two diagonal pixels (45° to 135°). These directions can also be specified by a shift as in a coordinate system, then they correspond to the values horizontal (0,1), vertical (1,0) and diagonal (1,1) respectively (1, -1). If all directions are used for the calculation, a rotationally invariant matrix is obtained by taking the average of the four previous directions.

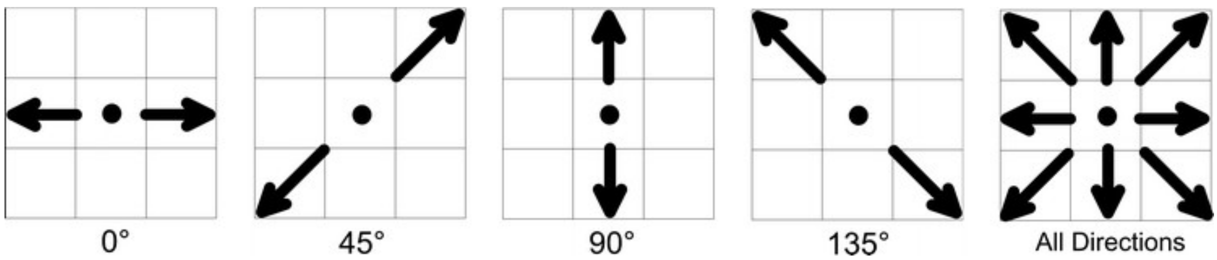

Figure 11. Figure 10. Possible GLCM directions (Source: Zhao et al. 2016)

Based on this GLCM, texture parameters can now be calculated. The best known are the statistics developed by Haralick (1973) for describing the texture of an image. Out of the 14 Haralick features 7 were applied in this thesis (*shown in table 4*), as they were proven to be capable in previous studies as outlined below.

Table 4. Used Haralick's features with a description

Feature	Description
Angular Second Moment [asm] or Energy	Energy is derived from the Angular Second Moment (ASM). ASM measures the uniformity of the kernel and hence describes its homogeneity. ASM is therefore high when pixel values in the kernel are very similar. Value 1 equals a constant image.
Contrast [con]	Large contrast reflects large intensity differences in GLCM: The contrast feature describes the amount of gray level variations in the image. A high contrast value means a large variation between the central pixel and its neighboring pixels. For contrast = 0 the image is constant.
Correlation [cor] or Dissimilarity	Correlation (also called Dissimilarity in R) measures the linear dependency in the image. Hence, it describes how correlated a pixel is to its neighboring pixels. -1 means a negative correlated, +1 a positive correlated image. Only NaNs equals a constant image.
Inverse Difference Moment [idm] or Homogeneity	Inverse Difference Moment (IDM) is the local homogeneity. Homogeneity determines the deviation of the GLCM elements from the diagonal of GLCM. It is high when local gray values are uniform. Homogeneity usually increases and decreases contrarily to the contrast. Value 1 means GLCM is a diagonal matrix.
Mean	Mean determines the average value of the image kernel. Mean is small and mean is large when they are far from the origin.
Entropy [ent]	Entropy measures the randomness or the degree of disorder in the image. 1 equals a constant image, 0 a complete unequal image
Variance [dva]	Variance measures the distribution of the elements around the mean value. Hence, it is similar to entropy. A variance value of 0 means a complete constant image.

Source Zayed & Elnemr (2015)

While GLCMs and Haralick's features have successfully been used several times to detect slums (Wurm et al. 2017a; Weigand 2017; Kohli et al. 2016; Kuffer et al. 2016), a comprehensive analyzation of limitations and qualifications using Haralick's texture parameters for slum mapping has not yet been published (Kuffer et al. 2016). Moreover, it seems likely that due to the complex and diverse structure of slums features are not suitable in a unified way. Hence what works in one city doesn't necessarily have to work in another.

At this point, it will be outlined in which way the mentioned features are suitable to separate favela surfaces from regular built-up areas. According to Kuffer et al. (2016), those features can be divided into three subgroups:

1) Contrast group: these features describe the variation within the kernel, which includes contrast

2) Order number group: indicates the regularity or irregularity of pixel values, e.g. Entropy

3) Statistics group: the descriptive statistics within the kernel, such as Variance or Mean

Out of the first group, 'Contrast' is capable of capturing urban areas and to map (Kohli et al. 2016; Kuffer et al. 2016). As contrast indicates the local variation of the gray values, slum areas and regular settlements differ, since in the latter case the variation is usually lower.

For this reason 'Entropy', a feature from the 2nd group, is also suitable. Since the entropy value is maximal, when all the elements of the GLCM are equal, they represent the homogeneity of the kernel. For example, the roof structure of slums is usually more heterogeneous than the regular settlement structures, and consequently the entropy value for slums is usually lower (Kohli et al. 2016).

Furthermore, the statistical value 'Variance' can be used for the distinction between different settlement form, including urban areas and slums. Since high variance values represent large differences or deviations of the gray values within a kernel, these are mostly characteristic for slums (Kuffer et al. 2016)

Additionally, 'Homogeneity' seems to be suitable to represent the high diversity of roofing materials, since regular settlements usually have a more homogenous roof structure, so their homogeneity value is higher than that of informal structures (Kuffer et al. 2016).

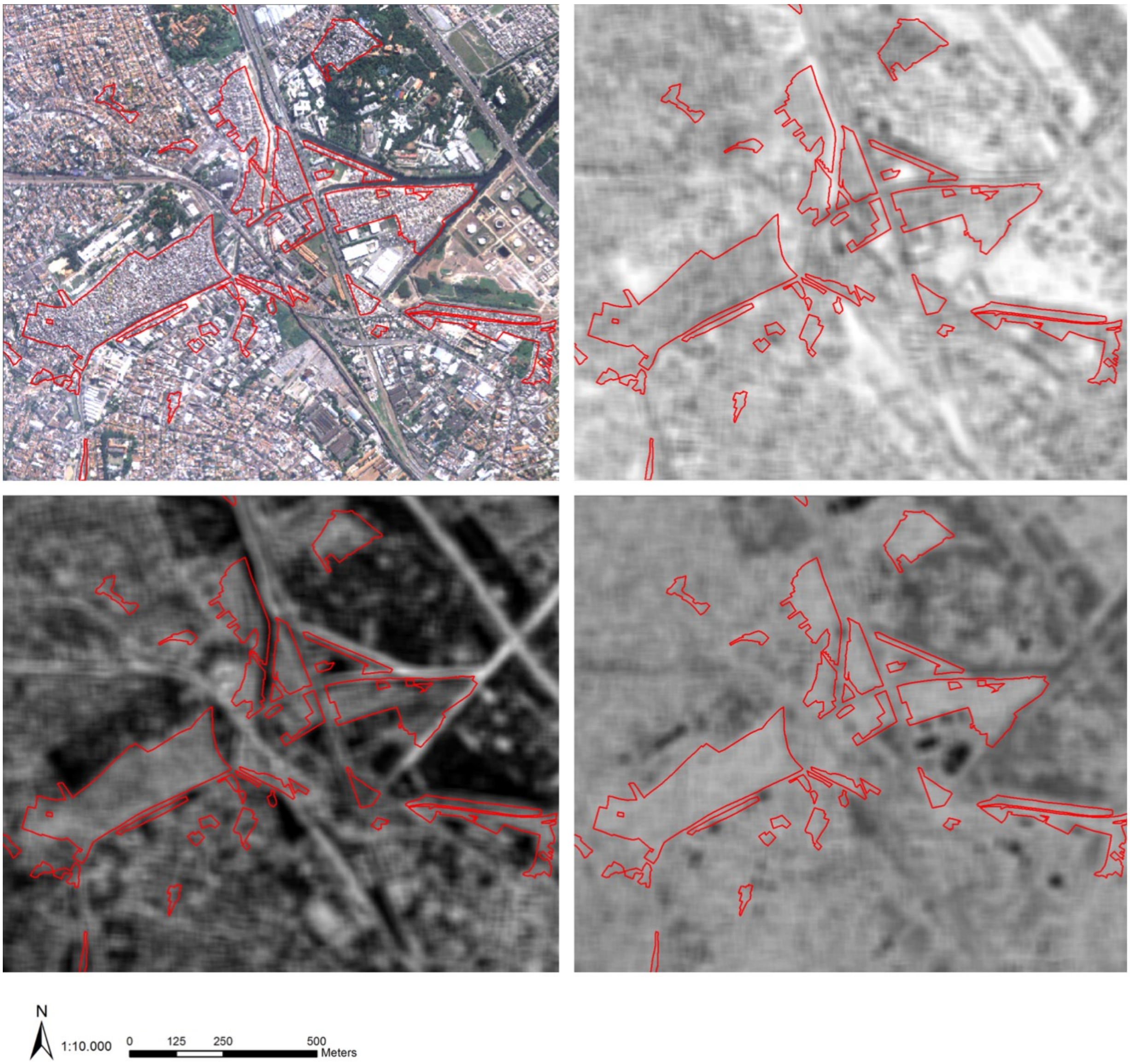

Figure 12. Favela areas in the original Orbview 3 image, as 'Dissimilarity, 'Homogeneity' and 'Variance' using a 9x9 Kernel (from upper left to lower right)

4. Image Classification

The following chapters deal with the main part of the work, the image classification and thus the detection of the favelas. The theoretical background of the components, including data sampling, machine learning and accuracy assessment, are discussed here. The last part of the chapter explains and illustrates the workflow of the image classification. Based on this, the results of the classification process are later outlined and discussed.

4.1. Data Sampling

In the terms of remote sensing, data sampling is the sampling-based extraction of image information, which represents the complete data set with its characteristics. Sampling is used for both, the training of a classification procedure as well as for the Accuracy Assesment (AA). Within this thesis, it is used for the training process of the random forest classifier.
There are two main reasons to use only samples instead of the complete data set for training. On the one hand it is often too time-consuming to use the whole data set and on the other hand, the whole data often requires a too high computing effort (Stopher 2012).
Data Sampling is one of the most important steps in a classification process, as hereby the image information is extracted that is used for the creation of the feature space, that is supposed to correctly represent the complete data set. Therefore, it is important to choose the correct sampling method and sampling size. For this purpose, general guidelines for sampling are decisive (Stopher 2012; Belgiu & Dragut 2016; Mu et al. 2015):

- the most statistically valid sampling strategy is reached with the minimum bias
- training and validation data must be statistically independent
- pixels of geographic objects are auto correlated, as adjacent pixels as well as near objects are usually more similar than distant ones

In this thesis, the reference data is used to extract class related image information from Haralick's texture parameter. In this process, specific prerequisites come along with regards to the classification key and chosen approach

- chapters 1 and 2 have outlined, that favelas are very diverse and differ a lot even within a city. In contrast other occurring classes, including water and vegetation, have a more homogenous appearance.
- considerations in chapter 2 lead to the assumption, that the feature spaces of the classes 'Urban' and 'Favelas' are very similar
- as favelas form only a small part of the total urban area, the reference data shows an extremely imbalanced class distribution where favela areas are far underrepresented

- the classification approach uses texture features determined using a moving-window approach. Hence, as explained in chapter 3.4, a single pixel represents a larger kernel area

Those considerations influence both, the appropriate sampling technique and the sampling size. Latter defines the number of sampling points total or per class. Therefore, this parameter is of crucial importance. The guideline is that all the occurring forms of appearance of a class in the AOI have to be covered. In some homogeneous classes, that show a low variability in their appearance, this could require only a few samples. More sites are needed in classes with a high diversity. Thus, it may be necessary to individually set the number of sampling points per class, so that oversampling of one or more classes might be inalienable. Considerations towards the sampling sizes in this thesis are (Colditz 2015; Stopher 2012):

- the optimal sampling size is a compromise between the higher representability and the higher computational effort
- benefits of a larger sampling are increasing less with a larger sampling size, hence a saturation is reached
- sampling Size per class influences the outcome of the classification, however, this effect decreases with higher sampling number

However, it need to be mentioned, that no matter how many samples are used, all sampling techniques lead to an at least small bias as they are always only a subset and hence cannot represent the whole range of characteristics of the complete data set. Yet, by choosing the right sampling pattern and size, the bias can be minimized to not influence the classification outcome significantly.

In addition to the number of sampling points, sampling methods differ in their spatial arrangement of the sampling points and the class balance. These can be distinguished in three main types of sampling strategies (McCoy 2005):

• Random
• Systematic
• Stratified

Based on the above-mentioned guidelines and preconditions, the sampling method most suitable for this work has to be selected in order to reduce sampling bias and obtain the best possible classification results. For this purpose, the most common sampling methods are evaluated with regard to their suitability (Stopher 2012; Colditz 2015; McCoy 2005):

Random Sampling *(figure 13)*

In Random Sampling, the points are randomly distributed over the investigation area. This has the advantage that the process is the most objective since each pixel has the same chance to be selected. However, the method comes along with the disadvantages, that an element (pixel) might be selected twice and subgroups/classes might not be represented at all due to their spatial sparsity. Therefore, this method is unsuitable for this work, since the unequal distribution of classes leads to the risk that too few samples will be chosen for the class favelas. Furthermore, applied texture parameters represent a larger area. Subsequently, too low distances between sampling points lead to redundant information extraction.

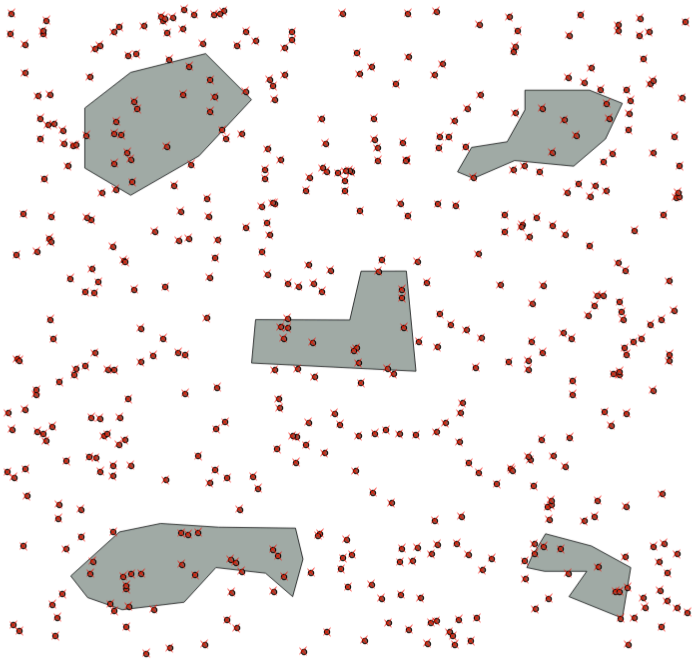

Figure 13. An example for 'Random Sampling'

Systematic Sampling *(figure 14)*

Contrary to Random Sampling, Systematic Sampling is based on a specific scheme. This can be any *x-th* element of a group or, as in the case of remote sensing, each pixel after a certain spatial distance. If the starting element is randomly determined, a randomization is also given here.

The method offers the advantage that no element (pixel) is selected twice, all pixels have a certain distane to one another and are thus more spatially independent. However, the disadvantage of an equally class distributed sampling approach, the deficient representation of favelas, remains.

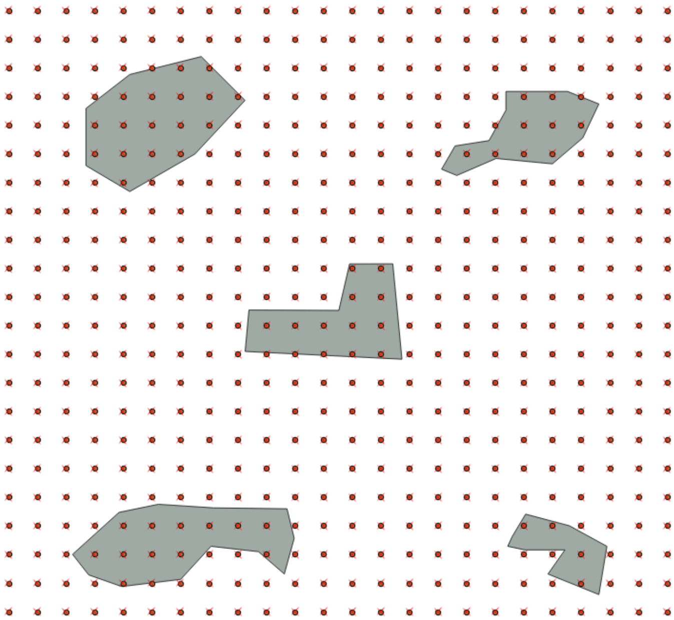

Figure 14. An example for 'Stratified Sampling'

Stratified Sampling *(figure 15)*

In all the afore mentioned patterns, the samples are taken from the total area. If these is previously subdivided into subgroups, so-called stratas, this is called Stratified Sampling. Out of these stratas, it is possible to apply different sampling sizes on. This solves the problem, that smaller subgroups are often not represented with a sufficient number of the total quantity leading to an unprecise delimited feature space. In the field of remote sensing, the different stratas are usually applied to the existing classes. Thus, it is possible to assign different sampling sizes to the classes (Buchroither 2001).

Consequently, a combined systematic stratified sampling seems most suitable to face the problems of an underrepresented class favelas and its heterogeneity. In this way, this class can be oversampled to ensure to have a high enough number of samples and hence a well-defined feature space. Therefore, the class ‘Favelas’ was significantly oversampled in this thesis with an approximately 4 times higher sampling size. All in all, approximately 400,000 training samples were extracted. More details regarding the sampling will be provided in chapter 4.4.

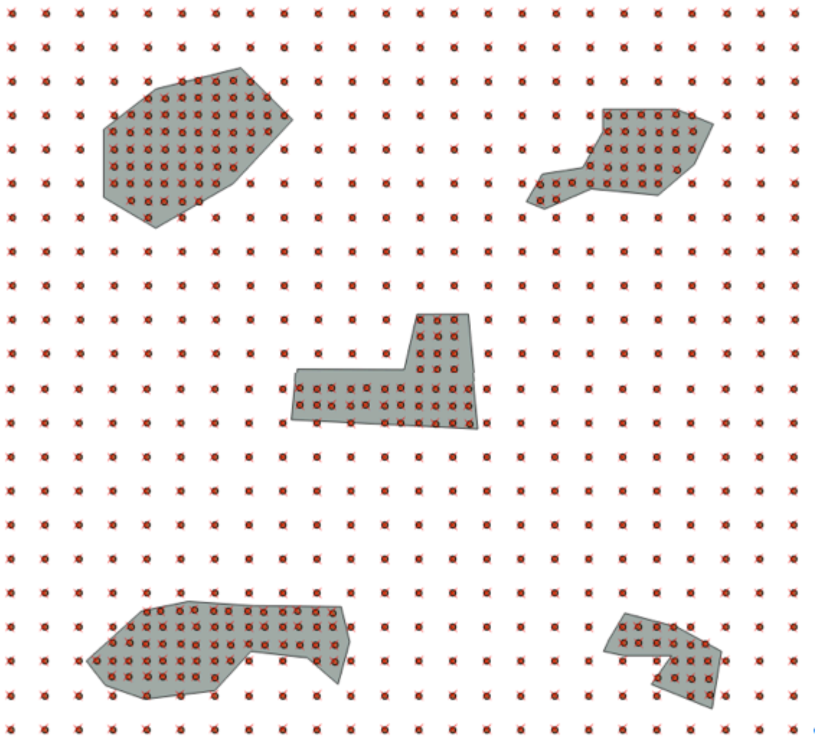

Figure 15. An example for 'Systematic Sampling'

However, one problem remains in regards to the later upcoming Accuracy Assessment. Using the entire reference data for training leaves no independent data for testing the classification. Subsequently, the model is trained and tested with the same data leading to a falsification of the outcome. To solve this problem, a split sampling approach is applied (*see figure 16)*. Thereby, the AOI is split in half (for example North and South) and one of the halves (e.g. North) is used as a training set to predict the other half (South). Afterwards, the process is repeated with the South half as training data to predict the North part. Finally, the Accuracy Assessment is carried out with the merged halves.

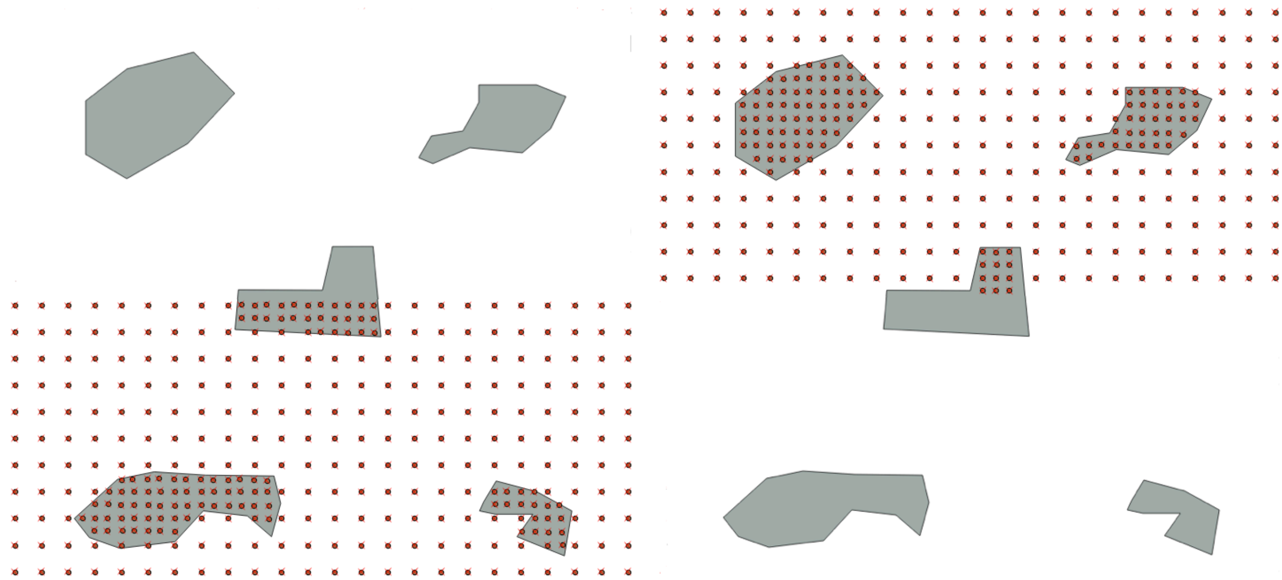

Figure 16. Illustration of a 'Split Sampling approach'

Having defined a sampling approach, those samples can be used in the upcoming image classification for the training of machine learning.

4.2. Machine Learning

Machine learning (ML) is a concept in which algorithms generate knowledge in a learning phase by means of training data and transfer this to new data for prediction and generalization. It recognizes relationships through statistical analysis and pattern recognition and transfers these to unknown data. It is, therefore, a subfield of Artificial Intelligence and strongly connected to terms like Data Mining and Knowledge Discovery in databases (Barber 2012; Shalev-Shwartz & Ben-David 2014).

The techniques have grown significantly in importance not only in remote sensing but also in many other fields, including: Medicine, financial markets, autonomous driving, etc.

There are two main reasons to use ML: On the one hand, to simplify routine tasks of human's everyday life, for example by developing speech recognition, autonomous vehicles or facial recognition. Furthermore, ML can be used where human capacity meets its limits. The amount of the input data is usually only limited by the computer performance, and algorithms can recognize highly complex relationships and patterns that are not visible to humans. This is of particular importance in times of Big Data, since the immense amounts of data can no longer be handled by humans alone. Thus, for example, data from different sources can be combined to predict the weather, pandemics and for crime prevention (Bruzzone & Persello 2010; Perner 2017; Rudin & Wagstaff 2013).

Depending on the learning style of the algorithm and the input data one can distinguish between several ways of ML, however, the following presents not a complete list of algorithms (Shalev-Shwartz & Ben-David 2014; Barber 2012):

4.2.1. Supervised Learning

The majority of ML algorithms uses supervised learning. Supervised Learning works with labeled input data, so-called training data in a training process for predicting unknown data. Based on the known data, the training process thereby continues until the model achieves a desired level of accuracy. Once the model is trained it can be used to transfer this knowledge on new data by generalizing from the training data to unknown examples.

Supervised learning problems can be further grouped into classification and regression problems:

- **Classification**: Classification problems have categorical output variables, in this thesis for example a LU class such as 'favela' or 'urban'
- **Regression**: In contrast to classification, a regression problem has a real value as an output variable, for instance, the probability of a class membership. In this thesis, this would be the probability of a pixel being a favela pixel

Examples for supervised classification algorithms are:

- Logistic regression as an example for regression approach

- SVM as an example for a classification method

4.2.2. Unsupervised Learning

In contrast to supervised learning, the input data is not labeled and does not have a known result. Therefore, the model tries to recognize a structure or pattern in the input data to learn about it and extract rules. This can be done through a mathematical process to systematically reduce redundancy or by organizing the data by similarity.

In between unsupervised learning problems, one can further distinguish between:

- **Clustering**: Clustering means grouping elements with similar characteristics. As a result, the elements in one group are more similar to each other than to the elements in another group
- **Association**: Association describes an approach where a model tries to find patterns and rules in the data that are applicable to large portions. Discovered rules are therefore describing correlation for appearing characteristics. The most common example of this method is cross marketing: People buying a certain product also often buy a specific second product, e.g. a toothbrush and toothpaste.

Algorithms using the mentioned approaches include:

- k-means for clustering problems
- Apriori algorithm for association rule learning problems

4.2.3. Semi-Supervised Learning

Semi-Supervised Learning is a mixture of the both before listed approaches. Subsequently, input data includes both: labeled and unlabeled examples. In the real world, this is a common problem, as often out of a big amount of data only some are labeled (for instance by humans) whereas most data are unlabeled. Depending on the algorithm, either unsupervised techniques are used for learning or supervised techniques to make a prediction for the unlabeled data. A real-world example is for instance represented when one considers a big photo database where some of the pictures are labeled as cats, dogs, etc. and algorithms use this information to predict the content of the unlabeled images.

Example for semi-supervised learning algorithms include:

- transductive support vector machine, or TSVM
- Generative models (e.g. using Baye's rule)

4.2.4. Decision Tree Algorithms

Decision tree methods are strictly seen an example for supervised learning as they use labeled data for a prediction. The algorithms thereby construct a model of decisions based on the features of the data. The decisions are organized in a tree structure where each node is either a leaf node (also called child nodes) or an internal node. Latter is always a question (resp.

decision) on features leading to two child nodes representing the answers. These always have a class label determined by the training data. The tree continues splitting till a prediction decision is made. In a next step, the model can be used on unlabeled data.

Similar to supervised learning one can distinguish between classification tree analysis and regression tree analysis depending on whether the outcome of the prediction is a class or a real number. However, as the listed algorithms show, approaches providing both exist, by saving not only the final decision on a class but also the numbers of votes derived from the internal nodes.

The most popular decision tree algorithms are:

- Classification and Regression Tree (CART)
- C4.5 and C5.0
- Random Forest

4.3. Random Forest Classifier

RF is, as mentioned above, an example of a decision tree classifier. The algorithm was introduced by Breiman (2001), as he extended the approach for the construction of random decision trees from Tin Kam Ho (1995). The method uses the basic technique of decision trees but extended it by a component of controlled variance and randomization. The exact approach will be explained in detail below.

4.3.1. Functioning

Random Forests use the bootstrap aggregating (short bagging) method developed by Breiman that combines the predictions of several independent classification or regression trees to determine the class allocation or prediction value. As in bagging, these predictions are made by randomly generated uncorrelated decision trees. These are built by selecting a random sample with replacement from the training data. Random Forest expands this process by selecting a randomly selected subset of the data at the candidate splits during the bagging process. The class allocation is made by assigning an element the class with the majority vote. In case of regression, individual votes of the trees represent a real value, for instance, a class probability. The workflow of this method is illustrated in figure 17 (Breiman 1996; Breiman 2001; Breiman & Cutler 2014).

The left part of figure (A) illustrates the Training Phase of the algorithm. Thereby the dice represents the random selection of features from the rows (j) representing variables and columns (i) representing their feature values (observations). Those samples are used to build a user defined number of decision trees where the splitting of the nodes is made using subsets of the features.

During the classification phase illustrated in the right part (B) new unlabelled data is used for a class prediction. Each of the trees generated during the training phase now votes for one class based on the decision rules (represented by nodes). Finally, the class is determined by summing up the votes from the individual trees leading to a majority vote.

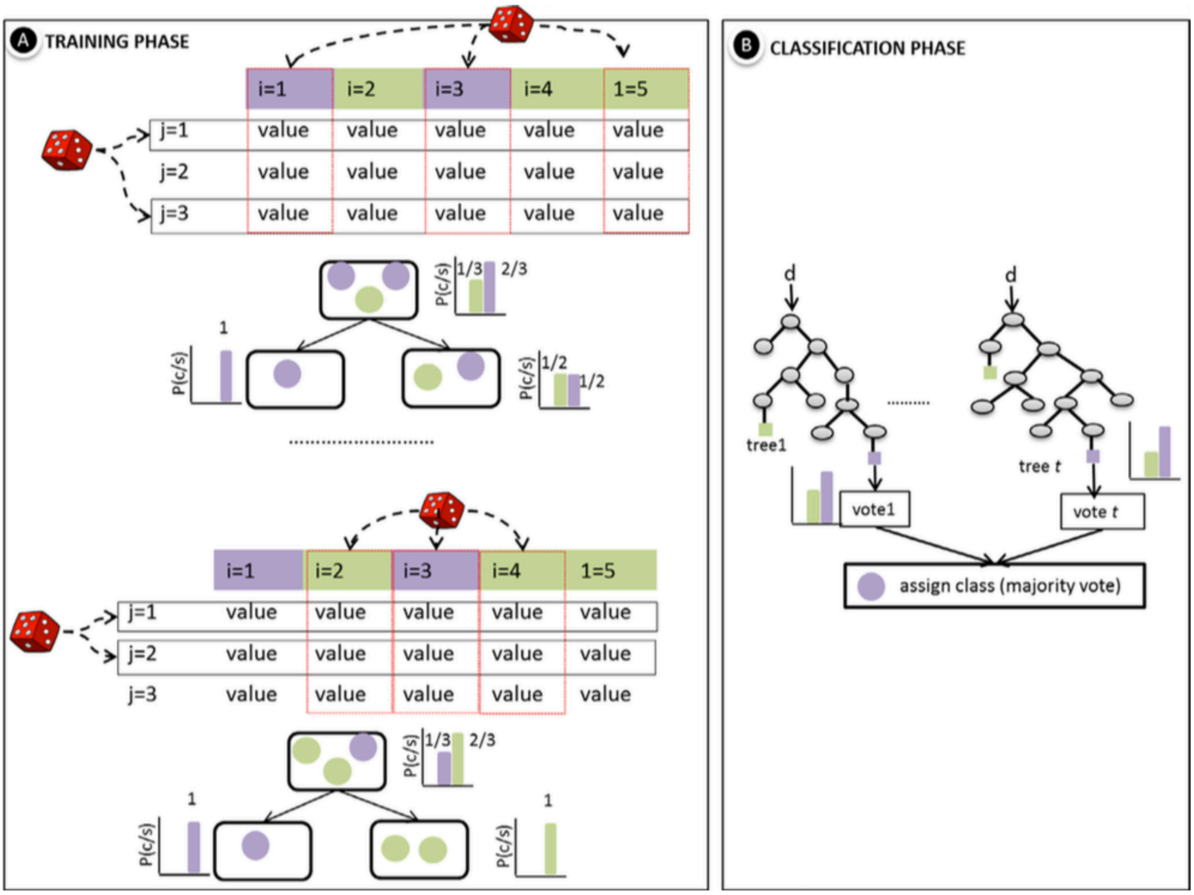

Figure 17. Training and classification phase of Random Forest classifier (image source: Belgiu and Dragut (2016))

4.3.2. Statistical fit and parameters

After the basic function of the RF Classifier has been explained, it is important to define how the model can be customized by the user and how to measure the performance of the model. While basics of assessing the classification accuracy assessment will be explained in chapter 4.3, fundamentals of machine learning performance evaluation will be shortly outlined here. Thereby the terms of generalization error, overfitting and underfitting are important as they are necessary to understand advantages of the algorithm.

Generalization error measures a machine learning algorithm's ability to generalize a model adjusted to a learning dataset to unseen new data. Generalization error and especially its measuring is a complex topic which will therefore not be discussed here. Easily spoken, Generalization error can be minimized by avoiding overfitting in the learning algorithm.

Overfitting in statistics and machine learning means that the model maps the training data too much in detail. This occurs whenever too many variables/observations with feature expressions are included in the training process. As a result, noise and random deviations also flow into the model and are regarded as a general feature.

Underfitting is the opposite of overfitting. An underfitted model is not capable to model the training data nor generalize it to new data (Bousquet & Elisseeff 2002; Shalev-Shwartz & Ben-David 2014; Segal 2004).

The parameters of the RF vary according to the implementation in the respective programming language. In the following, the parameters are described by the example of the statistical programming language R. Two basic parameters are 'ntree' and 'mtry'. 'Ntree' defines the numbers of trees to grow. The optimal value should be high enough to stabilize the error but not too high so the model is over correlated leading to overfitting. The number thereby depends on the number of independent variables.

'Mtry' number defines the variables randomly sampled as candidates at each split. By default, this is usually set as the square root of the number of variables ($\sqrt{p}$) for a classification process and as $\frac{p}{3}$ for a regression process. Choosing a too high number for 'mtry' will lead to overfitting again. In practice, however, investigations have shown that in most cases accuracies will just start stagnating by the cost of higher computing efforts (Nicomedus et al. 2010; Snobe et al. 2014)

Predict randomForest provides the possibility to change the output of the prediction which is by default set to the class. Apart from that, the probability matrix of class probabilities, or matrix of vote counts is also possible (Breiman et al. 2015).

Some implemented algorithms offer more tuning parameters which will not be discussed here, as they did not influence the outcome of the classification process.

4.3.3. Advantages and disadvantages

RF provides several advantages towards other ML algorithms wherefore it was applied in numerous remote sensing case studies (Millard & Richardson 2015; Rodriguez-Galiano et al. 2012; Segal 2004; Mellor et al. 2013; Wurm et al. 2017a). However, the facts that it is widely used and shows advantages against other techniques does not necessarily mean it is the best or only suitable ML algorithm. It just shows it has been successfully applied for the below mentioned reasons:

RF is hardly vulnerable to generalization error. This is due, on the one hand, the formation of several trees, as well as to the fact that not the best variable is used at a node split, but instead the best of a randomly selected subset. Therefore RF is neither sensitive to overfitting, as the importance of a tree declines with an increasing number of trees leading also to a decrease of the correlation between the trees (Breiman 2001; Shalev-Shwartz & Ben-David 2014). In general, RF works well on a high variation of input parameters and requires only a few number respectively it works usually well on the default values. These advantages lead to the fact that RF has achieved higher classification accuracies compared to other classifiers in several studies and requires a comparatively low calculation effort (Belgiu & Dragut 2016). The algorithm is also suitable for a wide range of applications since it does not require normally distributed data and thus also works with unbalanced class distribution. Moreover, the algorithm also handles extremely large data sets (Mellor et al. 2013).

4.4. Accuracy Assessment

In order to evaluate the results of the classification process, an Accuracy Assessment (AA) must be carried out. AA refers to the comparison of a classification outcome with a reference, therefore any data that is regarded to be correct. A classification is thereby considered to be accurate, if the outcome agrees to a high degree with the reference. Subsequently, a classification error is any kind of discrepancy with the reference. In terms of remote sensing, a reference can be any kind of geographical data that is regarded to be true. To obtain an unbiased independent accuracy assessment, reference data should not be used in a training process (Foody 2002; Liu et al. 2007).

Yet AA is not only undertaken to obtain the degree of agreement with the reference data. They are also capable to evaluate the performance of the classifier (software, algorithm, etc.) and to identify weaknesses and problems in the classification setup. Thereby numerous different approaches exist, either comparing pixel by pixel or patches (Congalton 1991). To gain meaningful information, it is necessary to choose a suitable approach for AA. In this thesis, it is of overall interest to evaluate the classification of Favelas, which are significantly underrepresented and to compare results of different kernel sizes, sensors and cities.

The state of the art approach in terms of AA is a confusion matrix (also called error matrix, confusion table, contingency table).

4.4.1. Error Matrix

An Error Matrix (*see figure 18*) is a square array with n x n elements, where *n* equals the number of classes. For easier understanding, the following examples will all be outlined for a binary classification case including only the classes Favela (1) and No Favela (0).

An Error Matrix compares the class allocation of each investigated element with its actual class membership. Thereby, the columns usually indicate the reference, whereas rows express the prediction (class allocation)

.

		Reference		
		1 (Favela)	0 (No Favela)	
Prediction	1 (Favela)	TP	FP	PC (Positive Calls)
	0 (No Favela)	FN	TN	NC (Negative Calls)
		Positive	Negative	n (total amount of pixels)

Figure 18. Error Matrix for a binary classification

Based on this information, it is possible to analyze the classification by calculating statistical values (Liu et al. 2007; Foody 2002):

- True positive (TP): TP is the number of correct predictions that an instance is positive.
  Example: Classifier predicts the class "Favela", the pixel's reference is "Favela"
- False positive (FP): FP is the number of incorrect predictions that an instance is positive
  Example: Classifier predicts the class "Favela", but the pixel's reference is "No Favela"
- True negative (TN): TN is the number of correct predictions that an instance is negative
  Example: Classifier predicts "No Favela", the pixel's class membership is indeed "No Favela"
- False negative (FN): FN is the number of incorrect predictions, that an instance is negative.
  Example: Classifier predicts "No Favela", but the pixel's reference is "Favela"

On the basis of the Error Matrix, different descriptive statistics can be computed, of which the following will be explained (Stehman 1997; Liu et al. 2007):

Overall Accuracy (OA): OA is the most common statistic to describe the quality of classification. It determines the total number of correct classified proportional the total number of pixels (n). Thus, the formula is $\frac{TP+TN}{n} = \frac{TP+TN}{TP+TN+FP+FN}$

Cohen's Kappa: Cohen's Kappa (often simply called Kappa) is a measure of agreement between the classification and the reference. Kappa, therefore, takes into account a correct classification by chance and is therefore more robust than OA.

Formula for kappa k is $\frac{\Pr(a)-\Pr(e)}{1-\Pr(e)}$,

where Pr(a) is the relative observed agreement = $\frac{TP+FP}{n}$

and Pr(e) is the hypothetical probability of chance agreement = $\frac{PC}{n}\times\frac{P}{n}+\frac{NC}{n}\times\frac{N}{n}$.

Kappa's value ranges from -1 to 1, where 1 equals a completely correct classified image. (Koch & Landis 1977) introduced a guideline for verbal equivalents for Kappa values illustrated in table 5.

Table 5. Explanation on Kappa values according to Landis and Koch

Kappa value	Strength of agreement
< 0.00	poor agreement
0.00 - 0.20	slight agreement
0.21 - 0.40	fair agreement
0.41 - 0.60	moderate agreement
0.61 - 0.80	substantial agreement
0.81 - 1.00	almost perfect agreement

In most classification cases OA and Kappa are suitable to describe the classification outcome. However, this is not the case in this study. As Favelas equalize only between 1 and 2 percent of the total area for the each AOI, high OA values would still be reached with no correct classified Favelas pixel at all. Thus, other statistics are necessary in order to describe the classification outcome for a particular class, for instance for Favelas.

To face this problem, Altman & Bland (1994) developed several descriptive statistics measuring different errors:

A statistic that describes the correct classified pixels of a class in comparison to the complete reference of this class is *Sensitivity* (also called *True Positive Rate* or *Producer's accuracy, short SEN*). The corresponding formula is, therefore, $Sensitivity=\frac{TP}{P}=\frac{TP}{TP+FN}$. Thus, *Sensitivity* describes how much per cent of a class has also been correctly classified as this class (Altman & Bland 1994a). However, this value alone would lead to incorrect conclusions, as Sensitivity is not taking False Positive into account.

A further statistic is the *Positive Predictive Value (PPV),* also called *User's accuracy.* It describes the proportion of correct positive prediction of the total amount of positive calls. The corresponding formula is, therefore, $PPV=\frac{TP}{PC}=\frac{TP}{TP+FP}$. Subsequently, PPV describes the number of pixels of a predicted class that actually also have that class in the reference (Altman & Bland 1994b).

The introduced descriptive statistics are illustrated with specific examples in the following figures 19. For easier understanding, they refer to binary cases with the two classes Favela and No-Favela.

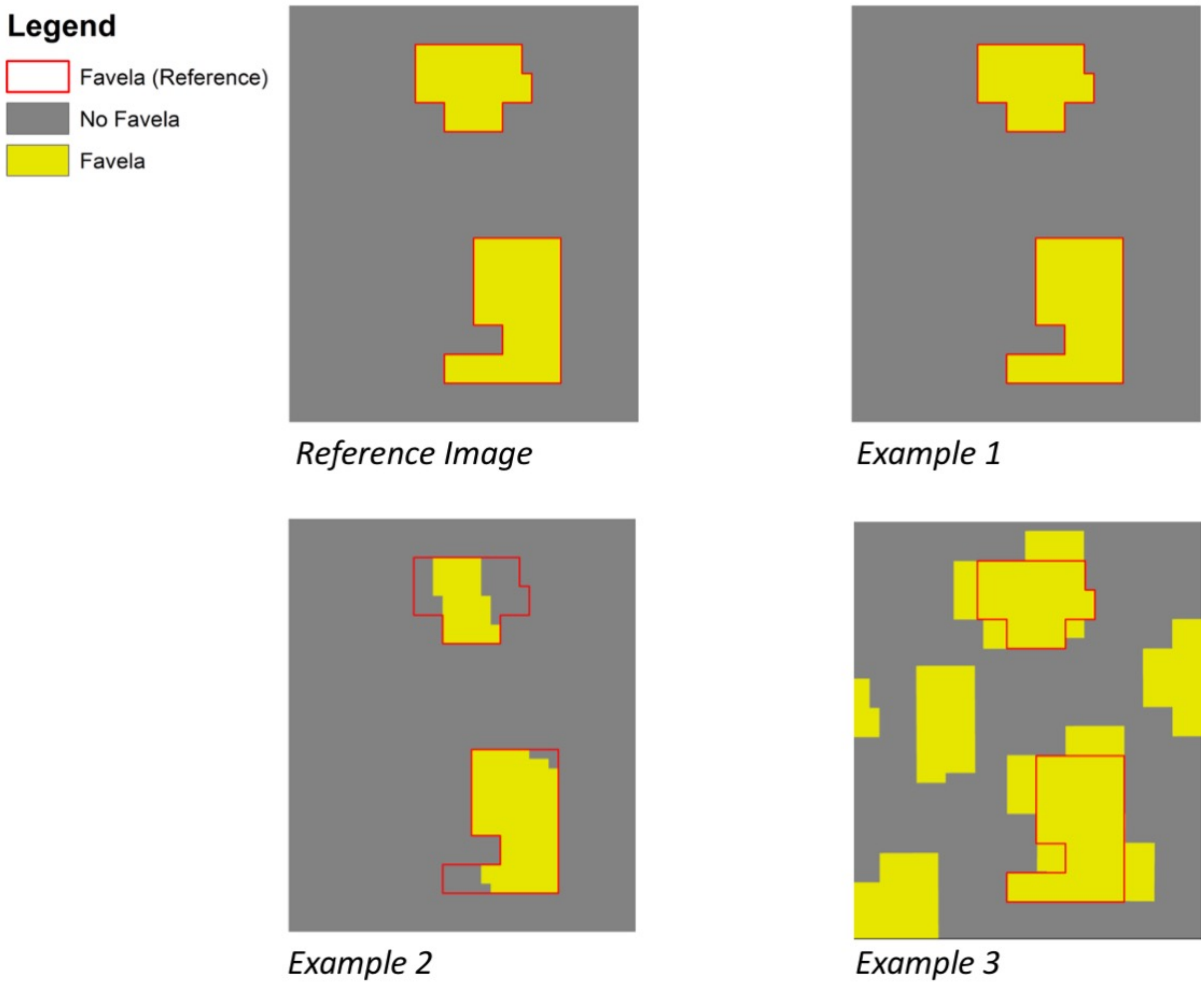

Figure 19. Illustration of examples for different classification outcomes

Example 1 shows a case where all predicted pixels equal their actual class in the reference. Therefore, values for descriptive statistics are: OA = 1, k=1, SEN =1, PPV =1

Example 2 shows a case where all No-Favela reference pixels are correctly classified as No Favela. Moreover, all pixels predicted as Favelas are Favelas so that all positive predictions are indeed positive. However, not all the Favela reference pixels were classified as Favelas, some are wrongly labeled as No-Favelas. Therefore, descriptive values are as follows: OA = 0.96, k=0.83, SEN = 0.9, PPV = 1.

Example 3 shows a contrary case to example 2. All Favela reference pixels were correctly predicted as Favela. Yet, also No-Favela reference areas were incorrectly labeled as Favela areas, so that there are positive predictions that are actually not positive. Therefore, descriptive values are: OA = 0.8, k = 0.48, SEN = 1, PPV = 0.76.

Examples 2 and *3* illustrate that isolated descriptive values can lead to wrong conclusions. Positive Predictive Value and Sensitivity of 1 is regarded as perfect agreement, however, in *Example 2* it is combined with missed favela pixels. In the case of *Example 3* is obtained by a significant over-classification. Thus, only if Sensitivity and Positive Predictive Value are evaluated combined, they allow a correct conclusion in terms of the accuracy of a class.

4.4.2. Limitations of Confusion Matrix:

Though Confusion Matrix is regarded as state of the art, it comes along with several weaknesses and limitation of which some are of particular interest for this study:
Often there is a distinct pattern to the spatial distribution of classes and neighboring pixel values lead to a spatial correlation of errors occurring at class boundaries. Those refer either to mixed pixels or in case of texture parameters to frequently occurring neighborhood relations which resemble patterns of other classes, in this case, Favelas.
Unfortunately, however, the confusion matrix and the accuracy metrics derived from it provide no information on the spatial distribution of error. Those errors cannot be covered and directly described by the confusion matrix and the descriptive statistics. However, those errors occur as will be seen in chapter 5. Therefore, those errors must be detected in a visual assessment (Zhang & Goodchild 2002; Mowrer et al. 1996).
As mentioned before, the AA can only check the accordance with the Reference Data. It is a black-white approach, class of a pixel is either completely correct or completely incorrect. However, in terms of slum mapping, a pixel could also accord to a certain degree to a slum pixel.

4.5. Workflow

This chapter explains the experimental setup of this thesis that is illustrated in figure 20. It is designed to investigate the main research issues:

- *Is it possible to detect Favelas using texture parameters and machine learning?*
- *Which kernel size leads to highest accuracy?*
- *How do difference sensors influence the outcome?*
- *How does the city's morphology influence the accuracy?*

In the process, Haralick's Texture parameters are used as image features and Random Forest Classifier is applied as a machine learning algorithm.

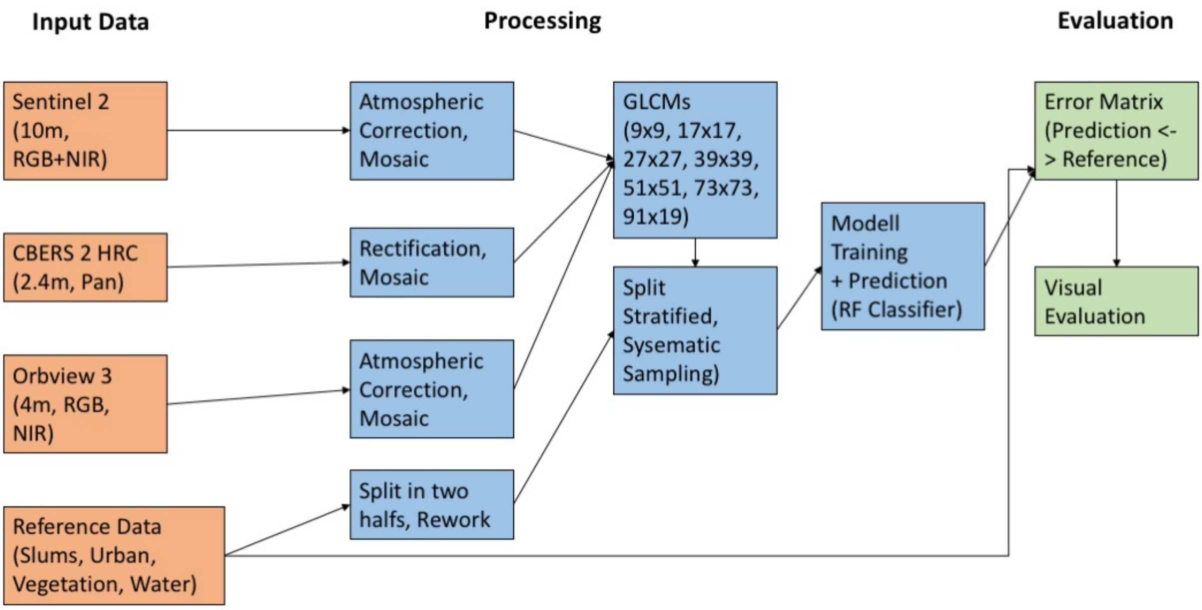

Figure 20. Illustration of the applied workflow

In a first step, preprocessing was necessary to correct the misregistration of CBERS data *(cf. chapter 3.1)* and to mosaic the data *(compare figure 20).* The remaining setup was implemented in R to enable a complete execution of the whole process after having defined input data. Used packages include 'RandomForest', 'caret', 'sp', 'raster', 'rgeos'.

As image features Haralick Features were applied representing the generic slum ontology on block level. Their principal suitability was outlined in chapter 3.4. Kernel sizes were thereby chosen with regards to the mode values of favela sizes and the corresponding kernel size expression of the different sensors. Therefore, approximately 10 pixel steps were applied. In total, the kernel sizes 9x9, 17x17, 27x27, 39x39, 51x51, 73x73, 91x91 were tested. Moreover, computing effort increases significantly with the kernel sizes, so limitations where caused by hardware equipment. To extract image features for training the RF model, a split stratified systematic sampling pattern is applied *(cf. chapter 4.1*). To face the problem of the underrepresented class 'Favel', its sample size was 4 times higher. All in all, approximately 400,000 samples where extracted for each run. As classes Favela and Urban are more heterogeneous they were applied a higher sampling numbers. Depending on the area proportion of the classes, number of points per class where on average as follows: Urban 80,000, Favela 50,000, Water 35,000, Vegetation 35,000. Previous experiments with different sampling sizes and numbers have shown, that with sampling number on this scale slight variations in proportion and number have no significant influence on the outcome.

Moreover, the influence of applying different classes was investigated in advance by proceeding the identical setup with classes Favela, Urban, Vegetation and Water and only the two classes Slums and Others. As accuracies were almost identical, the class partition with four classes was applied as they provide an added value of information for a visual accuracy evaluation.

In the prediction step, RF produces a classification image based on the majority votes of the independent decision trees (cf. chapter 4.2). RF settings were chosen with “ntree” set to 750 and “mtry” used with default value ($\sqrt{p}$).

Afterwards, the outcome is compared with a reference map to compute the error matrix (cf. chapter 4.3).

As the experimental setup was applied to the two cities Rio de Janeiro and Sao Paulo, with three different sensors and seven different kernel sizes, in total 42 different outcomes were computed. Those results are afterward evaluated in regards to their accuracy values and the visual outcome in order to answer/concern the research issues. These aspects will be faced in the upcoming chapter 5 “Results and discussion”

5. Results and Discussion

This chapter outlines and evaluates the results of the classification process. The main goal is to answer the research issues and discuss the results in regard to their validity and consistency. The chapter is structured as follows: Results are ordered by city and in addition, by sensors. Class specific descriptive values (SEN, PPV) are always related to the class 'Favelas'. In a first step, the results are illustrated and later in the second part analyzed and discussed.

5.1. Classification Results

Classification results are structured in numeric results, diagrams and visual evaluation. In the end, results are summarized to address the research issues of this thesis. This section does not contain all images of the classification results, but only selected figures to illustrate the results. Thereby, for each illustration, kernel-sizes were chosen that illustrate issues best. A complete collection of classification results is provided in the *annex*.

5.1.1. Rio de Janeiro

Chapter 4.4 has shown, that OA and kappa only have a low explanatory power in this study, as the class 'Favelas' equals only between 1-2% of the total AOI and hence is not adequately represented in OA and kappa. Moreover, PPV and Sensitivity are only meaningful in combination. This issue has to be kept in mind when analyzing error statistics. As mentioned previously in chapter 3.2 the reference data does not cover the AOI exhaustively, therefore they contain white areas that were set to 'NoData'.

Numeric comparison

Table 6 shows the numeric results of the AA for Rio de Janeiro. Highest values per descriptive statistic are outlined in green, lowest in orange. Highest OA and kappa was achieved with Orbview 3 Data and a 91x91 kernel. Highest Sensitivity with CBERS 2B and a 27x27 kernel and highest Positive Predictive value with Orbview 3 and a 51x51 Kernel. Lowest OA and kappa resulted from a 9x9 kernel and CBERS 2B. Lowest Sensitivity occurred with a combination of Sentinel 2 and a 91x91 kernel. Lowest PPV again at CBERS 2B 9x9 kernel. In general, CBERS 2B values for all categories except SEN are significantly lower than kernel corresponding values of the other two sensors. While OA and kappa values are quite similar for Sentinel 2 and Orbview 3 especially for small kernel sizes, major differences occur for PPV. Increasing with larger kernels, PPV is significantly higher for Orbview 3 sensors than it is the case for Sentinel 2.

Table 6. Numeric results for descriptive statistics of Rio de Janeiro in %

Sensor	Kernel Size	OA	Kappa	SEN	PPV
Sentinel 2	9x9	83,68	76,70	68,46	11,39
	17x17	85,22	78,82	44,96	7,72
	27x27	86,42	80,27	41,71	11,05
	39x39	86,57	80,37	32,85	9,04
	51x51	88,19	82,51	16,07	8,56
	73x73	88,45	82,77	7,72	8,00
	91x91	88,23	82,39	4,07	7,04
CBERS 2B	9x9	49,33	30,83	66,06	3,40
	17x17	56,48	38,28	71,79	4,24
	27x27	61,08	43,76	72,84	4,74
	39x39	65,21	49,54	70,04	4,90
	51x51	66,02	50,20	67,51	4,92
	73x73	68,55	53,03	60,22	4,92
	91x91	69,18	53,29	56,18	4,93
Orbview 3	9x9	81,21	72,26	65,49	15,93
	17x17	88,18	82,11	66,41	23,20
	27x27	89,93	84,65	63,99	27,51
	39x39	90,75	85,84	59,70	29,98
	51x51	91,02	86,21	54,49	31,29
	73x73	91,22	86,44	37,33	27,98
	91x91	91,33	86,58	29,87	27,67

Diagrams

As illustrated in figure 21, OA and kappa are increasing for all sensors with higher kernel sizes, but less strong for the two largest kernel sizes. Sensitivity decreases for all sensors for kernels larger than 51x51, however for Sentinel 2 it reaches its peak at the 9x9 kernel, for CBERS 2B at 27x27 and for Orbview 3 at 17x17. PPV generally increases with larger kernels for CBERS 2B and Orbview 3, with a maximum at 51x51 for Orbview 3 and at 91x91 for CBERS 2B. Sentinel's PPV values are not stringent and decrease at 17x17 but increase at 27x27 again before they start decreases till the end again.

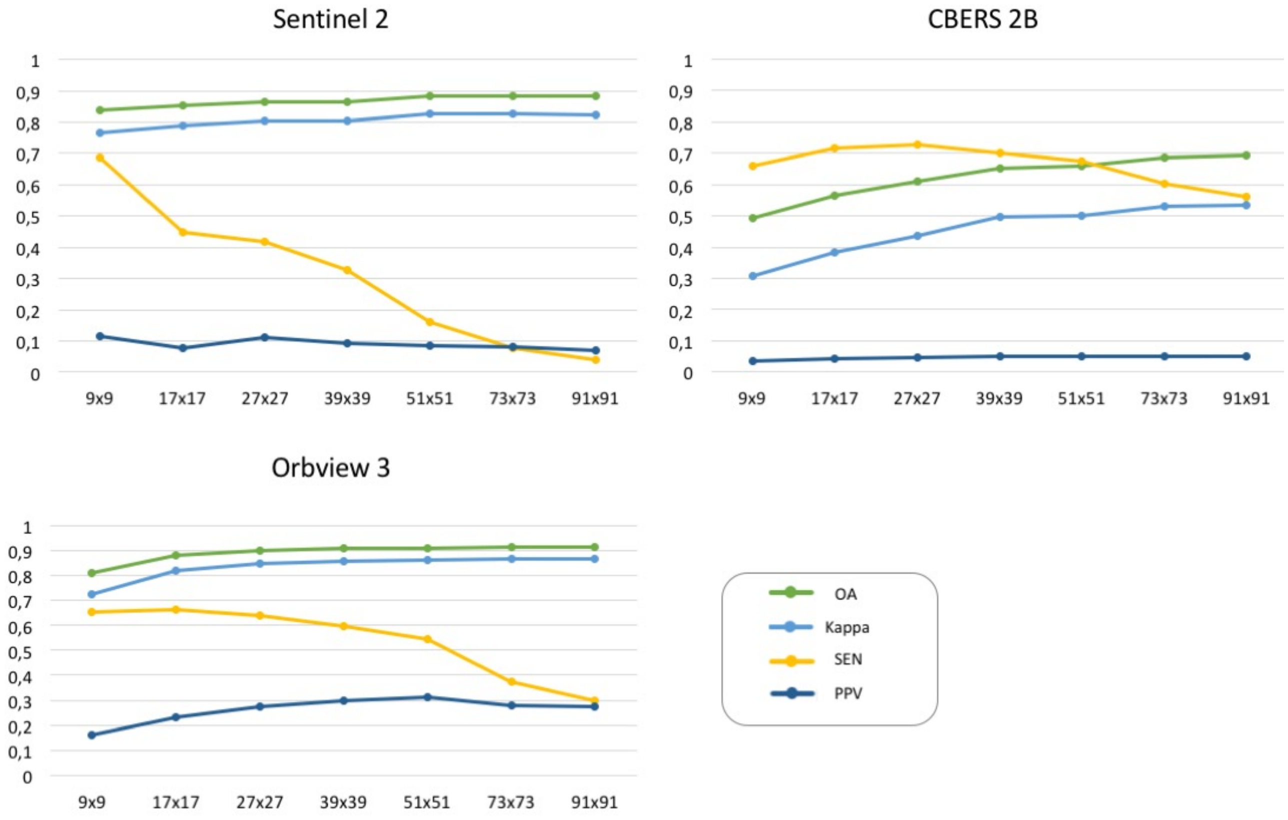

Figure 21. Diagrams of accuracy statistics of the three used Sensors for Rio de Janeiro

Visual Evaluation

Apart from the evaluation of descriptive statistics, it is also of importance to visually evaluate the visual classification outcome. In this way, it is possible to investigate weakness of the sensors and determine reoccurring errors.

The distinction between water, vegetation and built-up area shows a high level of agreement with the reference for all sensor and kernel-size combinations. Yet, high numbers of incorrectly classified favela pixels occur on class boundaries, especially at the border of vegetation and urban areas. Moreover, as assumed, problems occurred for the differentiation between favelas and other urban areas. Here major differences between the sensors can be found.

Sentinel 2: Most obvious is the fact, that the number of as favelas classified pixels decreases with larger kernels. Therefore, Sensitivity decreases at the same time. Moreover, as elucidated by stagnating PPV, true positive pixels and false positive pixels decrease in an almost same amount.

CBERS 2B: The sensor failed completely to separate favelas from other built-up areas (*see figure 22*). For smaller kernels, this resulted in built up area almost completely misclassified as favelas. Leading to high values for Sensitivity, but PPV values of almost zero. For larger kernels, this effect decreases, however, over-classification of favelas is still significantly high. Fair to moderate Kappa mainly results from the correct classification of water and vegetation.

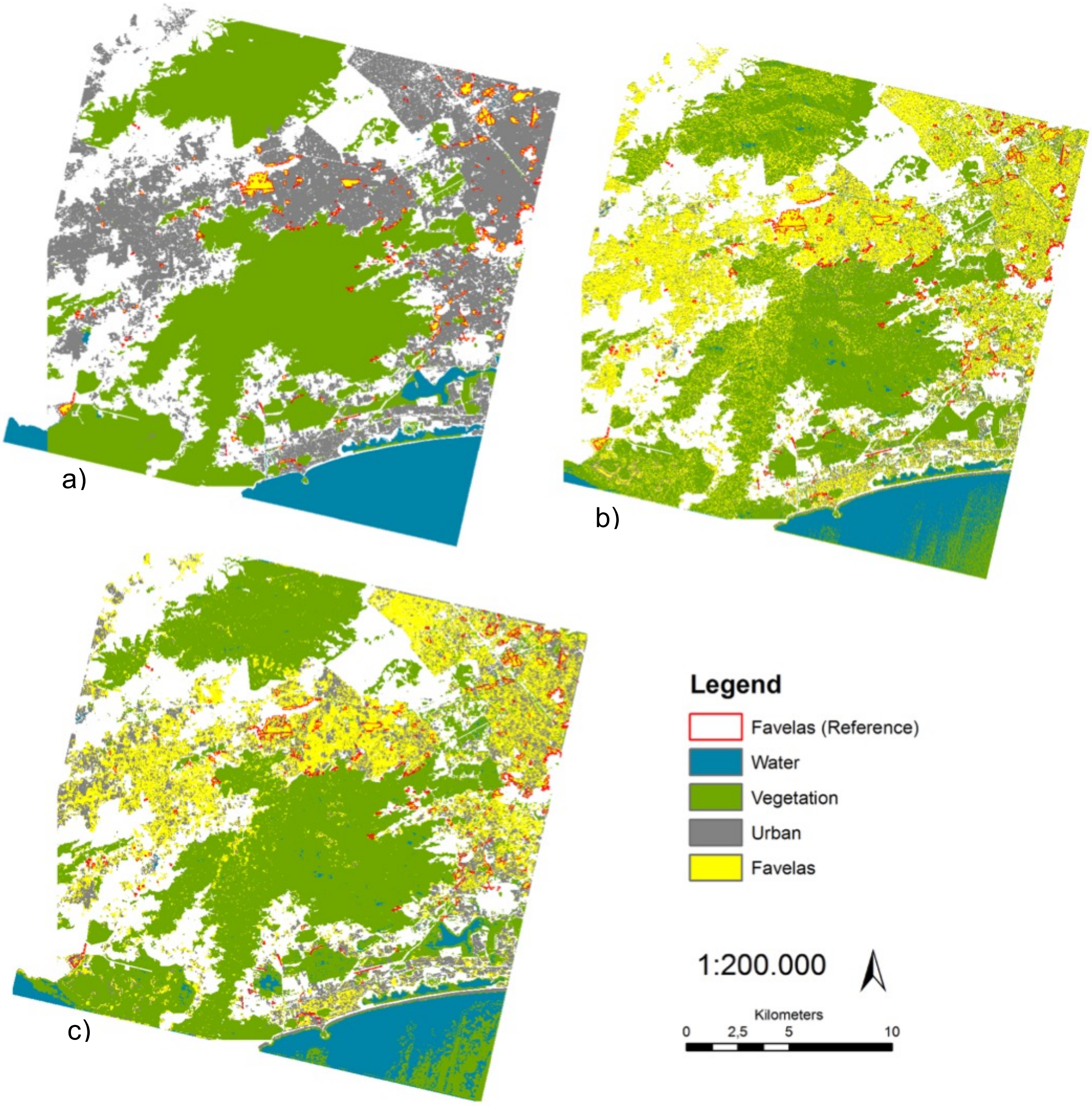

Figure 22.. Classification images for CBERS 2B using kernel sizes 17x19 (b) and 73x73 (c). The reference image is shown on the upper left (c).

Orbview 3: Identical to CBERS 2B and Sentinel 2, favela pixels decrease with larger Kernels. However, contrarily to the other sensors, thereby mainly FP pixels decrease, at least until the kernel size 51x51, leading to the increase in the PPV, that can also be seen in the diagram in figure 21. Moreover, Orbview 3 seems to map favela patches to the highest coverage, as it is not only detecting portions but the whole patch and its shape (*see figure 23*). As the figure illustrates, especially large favela patches are detected very accurate.

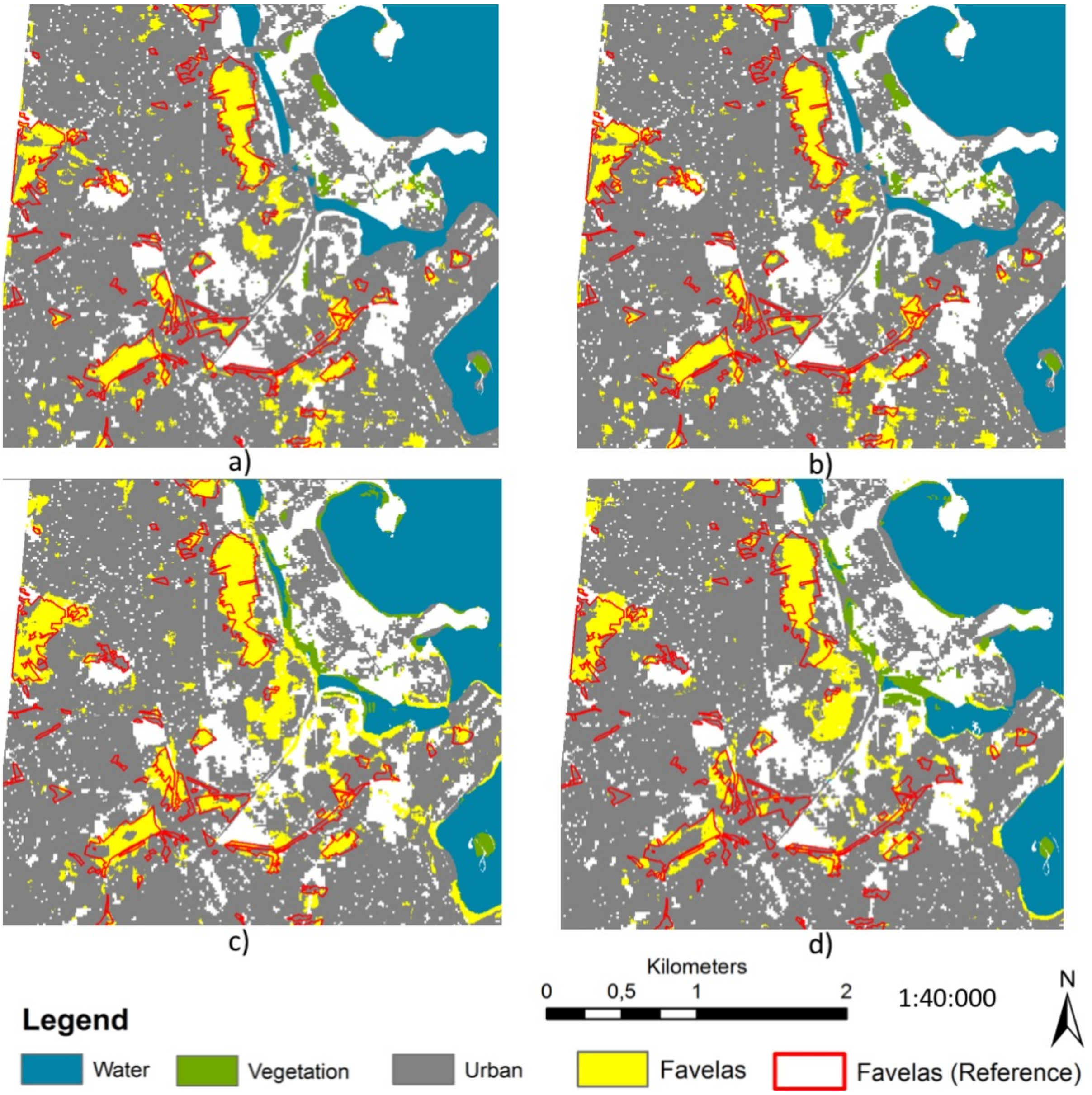

Figure 23. Comparison of the performance of mapping favelas for the sensors Orbview 3 (figures a and b) and Sentinel 2 (c and d). Used kernel sizes are 27 and 39 for Sentinel 2 and 39 and 51 for Orbview 3

5.1.2. Sao Paulo

Results for Sao Paulo show some consentaneity to Rio de Janeiro. But there are also major differences in some cases.

Numeric comparison

Identical to Rio de Janeiro, highest OA and kappa values occur for the combination Orbview 3 and 91x91 kernel. Also, the highest PPV values was again obtain with Orbview 3 and the 91x91 kernel. Contrarily, highest Sensitivity was reached with Sentinel and a 9x9 kernel. Minimal accuracies show patterns similar to Rio de Janeiro as well. Lowest accuracies for OA and Kappa appeared with CBERS 2B and a 9x9 kernel. Also, identical to Rio the lowest PPV. However, lowest Sensitivity resulted from Orbview 3 data and 91x91 kernel.

Table 7. Numeric results of statistics for Sao Paulo

Sensor	Kernel Size	OA	Kappa	SEN	PPV
Sentinel 2	9x9	78,88	67,97	81,07	9,45
	17x17	81,94	71,94	77,93	10,92
	27x27	83,86	74,36	68,03	11,49
	39x39	85,33	76,17	54,84	11,59
	51x51	86,62	77,82	41,30	11,30
	73x73	87,87	79,42	24,84	10,25
	91x91	88,48	80,18	18,16	10,46
CBERS 2B	9x9	73,31	42,64	21,55	4,10
	17x17	75,72	47,09	29,78	6,35
	27x27	77,53	51,84	34,62	6,82
	39x39	78,20	52,86	36,93	6,52
	51x51	78,66	54,31	33,60	6,73
	73x73	79,62	55,96	31,33	6,44
	91x91	80,54	57,22	28,23	6,23
Orbview 3	9x9	79,17	34,65	49,39	7,60
	17x17	87,92	79,30	52,59	10,30
	27x27	90,27	82,90	48,84	12,59
	39x39	92,04	85,66	39,96	14,84
	51x51	92,94	87,08	31,81	16,29
	73x73	93,50	87,90	21,00	17,29
	91x91	93,50	88,30	15,28	17,95

Diagrams

Sentinel 2: The Sensors shows very similar trends for all descriptive statistics, though Sensitivity value are significantly higher than the corresponding values for Rio de Janeiro.

CBERS 2B: Kappa and OA are slowly increasing with larger kernels. PPV is stagnating at a very low level. Sensitivity values are slowly increasing until they reach their peak at the 39x39 kernel and decrease again.

Orbview 3: Trends are identical to Rio de Janeiro. Yet, values for Sensitivity and PPV are far lower than in Rio de Janeiro's case. Sensitivity peak is reached again for a 17x17 kernel.

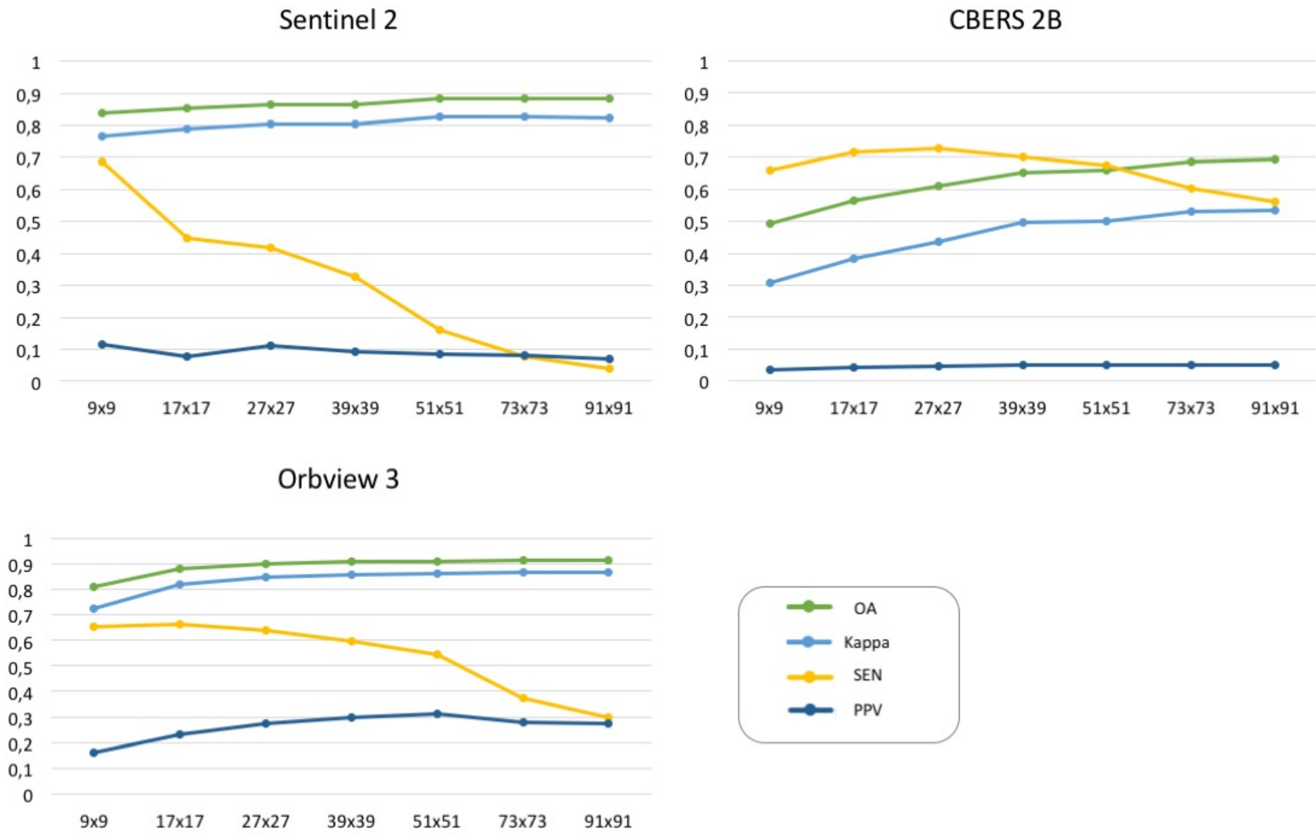

Figure 24. Diagrams show the different accuracy results of three used sensors for Sao Paulo

Visual Evaluation

Sentinel 2: The sensor show spatial differences in mapping favelas. With larger kernels, favela pixels decrease in the western part to a higher amount than in the eastern. Identical to Rio, false and true positive pixels decrease in the same number, leading to the stagnating PPV.

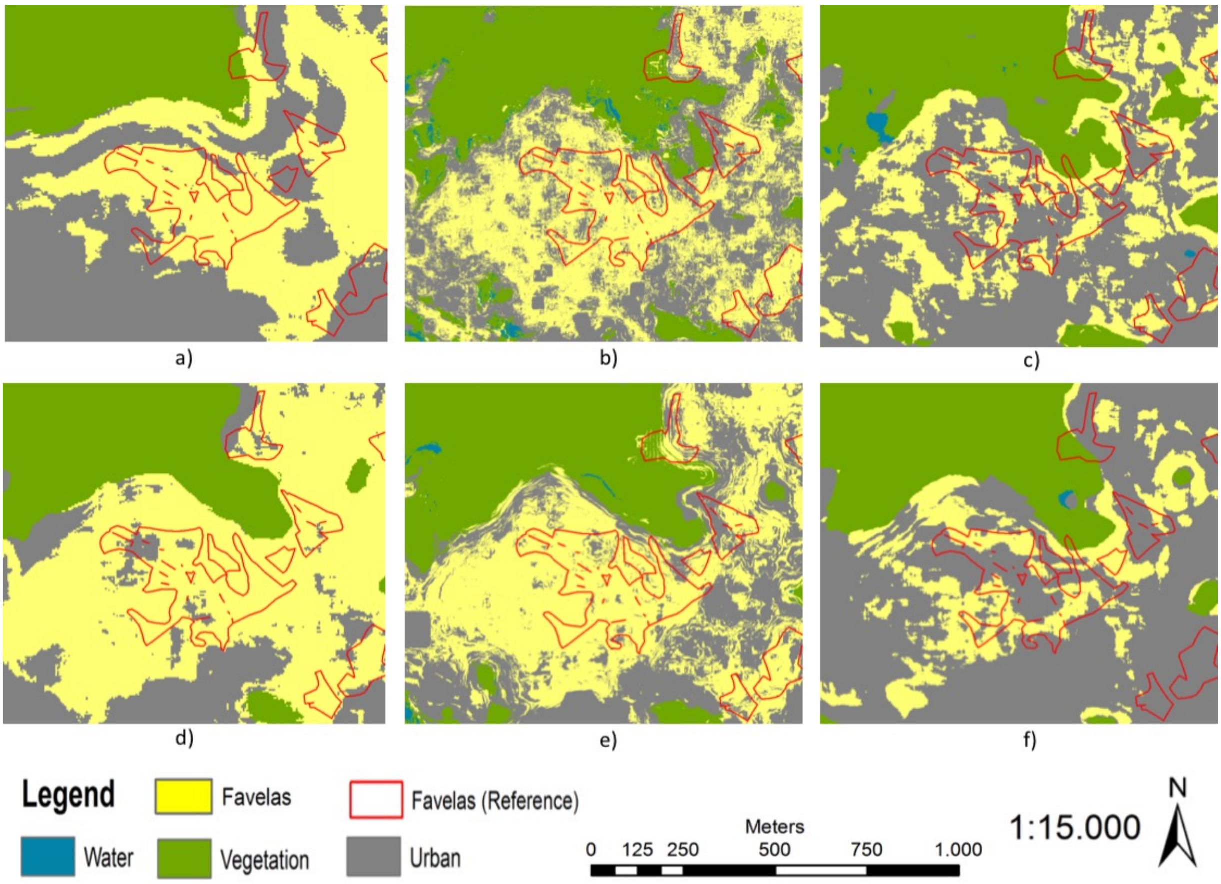

Figure 25. Comparison of classification outcomes for the three sensors Sentinel 2 (a and d), CBERS 2B (b and e), Orbview 3 (c and f). Kernel size 27 is illustrated in the upper row, kernel size 73 in the lower row.

CBERS 2B: The sensor shows a sieve-like mapping of favelas for smaller kernels with mapped favela areas having gaps with urban areas in between *(see figure 25 b)*. Starting with the kernel size 51x51, favela areas are getting smoother (*see figure 25 e*), yet they only cover reference favelas to a small degree.

Orbview 3: An over-classification of favelas occurs similar to Sentinel mainly in the eastern part of the city. However, Orbview 3 shows the smallest degree of over-classification, but in this way also fails to detect favelas (*see figure 25 c and f*). This causes the low Sensitivity values, as Orbview 3 seems to predict favelas very guardedly. Moreover, the effect of favela misclassification at the boundary to vegetation occurs very pronounced/significant here.

5.1.3. Summary of the results

To address the research issues, in this part the key findings of the results are summarized:

Kernel size

OA and kappa increases with larger kernels. This applies to all sensors and both cities. Sensitivity shows different behavior depending on the sensors and city. In the case of Orbview

3 and CBERS 2B, it increases first before it is decreasing again. In the case of Sentinel 2 it decreases from the beginning on. PPV shows a very differentiated behavior depending on the sensor and city. In the case of Sentinel 2 and CBERS 2B, values remain so low, that no significant trend occurs. In the case of Orbview 3 values reach their peak for the 51x51 kernel (in case of Rio) respectively 91x91 (for Sao Paulo), constituting the highest overall value in both cities.

Sensor comparison:

- CBERS 2B: The sensor performed worst of all tested sensors. On both overall classification results and mapping of Favelas. This is underlined by the obtained results in both cities. CBERS 2B has for all kernels the lowest OA and kappa values. Indeed, CBERS 2B achieved comparatively high values for Sensitivity. However, they came along at the expense of a very high over-classification of favelas. Subsequently, CBERS 2B has also the lowest PPV values.
- Sentinel 2: Performed very well on overall classification accuracy. It obtained continuously almost perfect agreement in regards of kappa. However, it performed poorly on mapping favelas. Sensitivity values are high for small kernels, but PPV values are almost zero. PPV values remain on this level, as with a decreasing over-classification detection rate of favela decreases as well.
- Orbview 3: Highest OA and kappa values overall were obtained with Orbview 3. Moreover, it has highest values for each kernel size in both cities as well. Slum mapping results vary for the cities. While Orbview 3 produced at least acceptable results in Rio with SEN 0.66 and 0.31 PPV, it performed worse in Sao Paulo. PPV of 0.17 is indeed the highest achieved value but has still be regarded as a poor result. Sensitivity values of Orbview 3 in Sao Paulo are moreover significantly lower than those of the other two sensors.

City comparison

Moreover, as the summary of the sensors show, partially significant differences between the cites occur. Table 8 shows a ‘subtraction table’ presenting the differences in achieved accuracies for Sao Paulo and Rio de Janeiro. Hence, the values were obtained by a cell wise subtraction of corresponding values. Values are unsigned, as the color represents where higher values occurred. Yellow colored cells show a higher value for Rio de Janeiro, blue colored represent Sao Paulo.

Table 8. Subtraction of achieved accuracy values for Sao Paulo and Rio de Janeiro. Higher values for Rio de Janeiro a marked in yellow, for Sao Paulo in blue

Sensor	Kernel Size	OA	Kappa	SEN	PPV
Sentinel 2	9x9	4,80%	8,73%	12,61%	1,93%
	17x17	3,28%	6,88%	32,97%	3,20%
	27x27	2,56%	5,91%	26,32%	0,44%
	39x39	1,24%	4,20%	22,00%	2,56%
	51x51	1,56%	4,69%	25,23%	2,74%
	73x73	0,58%	3,35%	17,11%	2,25%
	91x91	0,24%	2,20%	14,09%	3,42%
CBERS 2B	9x9	23,99%	11,81%	44,51%	0,70%
	17x17	19,24%	8,82%	38,00%	2,11%
	27x27	16,45%	8,08%	38,23%	2,07%
	39x39	12,99%	3,32%	31,11%	1,62%
	51x51	12,63%	4,11%	33,91%	1,81%
	73x73	11,07%	2,93%	28,89%	1,52%
	91x91	11,36%	3,92%	27,95%	1,30%
Orbview 3	9x9	2,05%	37,60%	16,10%	8,34%
	17x17	0,27%	2,81%	13,82%	12,90%
	27x27	0,34%	1,75%	15,14%	14,92%
	39x39	1,29%	0,18%	19,75%	15,13%
	51x51	1,92%	0,87%	22,68%	15,00%
	73x73	2,29%	1,45%	16,33%	10,68%
	91x91	2,17%	1,72%	14,60%	9,72%

5.2. Discussion

Here, the results of the experimental setup are discussed in terms of their meaning, background and reliability. Therefore, considerations and background information from chapter 2 are taken up. The main goal of this section deals with the answers of the research issues. In this process, a ‘Favela probability map’ was used, that was obtained by changing the output of the prediction process to the class probability for the class ‘Favela’. In this way, the images show the agreement with this class and allows a more precise analyzation of the approach (cf. figures 26 and 29).

Detecting Favelas using texture parameter and Machine Learning

In this section, the research issue 'Can one detect favelas in Brazil cities using texture features and machine learning' will be discussed. The approach was capable to detect favela areas that show a morphology typical for slums. Moreover, visual evaluations have shown, that the approach is capable to distinguish between different morphological urban profiles. Using a favela probability map (*see figure 26*) and comparing it with the VHR basemap, one can clearly see, that urban areas of different morphology, including different degrees of homogeneity, shape and regularity are mapped with different probabilities. However, none of the kernelsize-sensor combinations could reach values close to those Wurm et al. (2017a) obtained with the same approach in Mumbai. Though Sensitivity reached high values (0.81 for Sentinel 2 with a 9x9 kernel size in Sao Paulo), yet they were always combined with very low PPV values. In contrast, highest obtained results in Mumbai are significant higher with a Sensitivity value of 59.87 and Positive Predictive Value of 78.58.

Reasons for the differences in the accuracies are assumed to be manifold, but mainly the following three points:

- Slums differ too much from city to city and in between a city: As outlined in chapter 2 slums are a very heterogeneous phenomenon. Slums in Mumbai differ very much from regular built-up areas. However, this is barely the case in Brazil. A unified GSO is very hard to define in Brazil. As mentioned before, Slum upgrading had been a big topic in recent years and favelas are no longer necessarily areas of poverty. Thus, their visual appearance and morphology are far more diverse than it is the case in Mumbai. Moreover, the demarcation of regular built-up areas plays an important role. The larger the differences in terms of the morphology are, the easier is the detection of favelas. How those circumstances behave in the case of Sao Paulo and Rio de Janeiro will be discussed in the section 'Influence of the morphology of the city'
- The second problem is related to the first one and refers to the reference data. As mentioned in chapter 3 the creation of the reference data is a big challenge for slums due to a missing explicit definition or guidelines for mapping slums. Moreover, the absence of an objective reference data lowers the explanatory power of the results. Visual interpretations show, that especially in Sao Paulo there is a high number of mixed areas showing at least some favela typical characteristics. This makes a strict separation of urban areas in favela and regular built-up areas almost impossible. As figure 26 outlines there are areas with probabilities up to 0.8 that are not included in the reference data, but thus show a favela typical morphology (referring to the classifier and feature space).

- Favelas in both cities are significantly smaller than they are in Mumbai. Investigations by Weigand (2017) and Wurm et al. (2017a) have shown, that class related accuracies increase with larger slum patches and RF Classifier has difficulties in mapping small slum patches (Wurm et al. 2017b). Moreover, due to the forced resettlement, favelas in Brazil often show a long, narrow shape. This is an extreme disadvantage shape for a classification approach using square kernels as their typical texture cannot be captured.

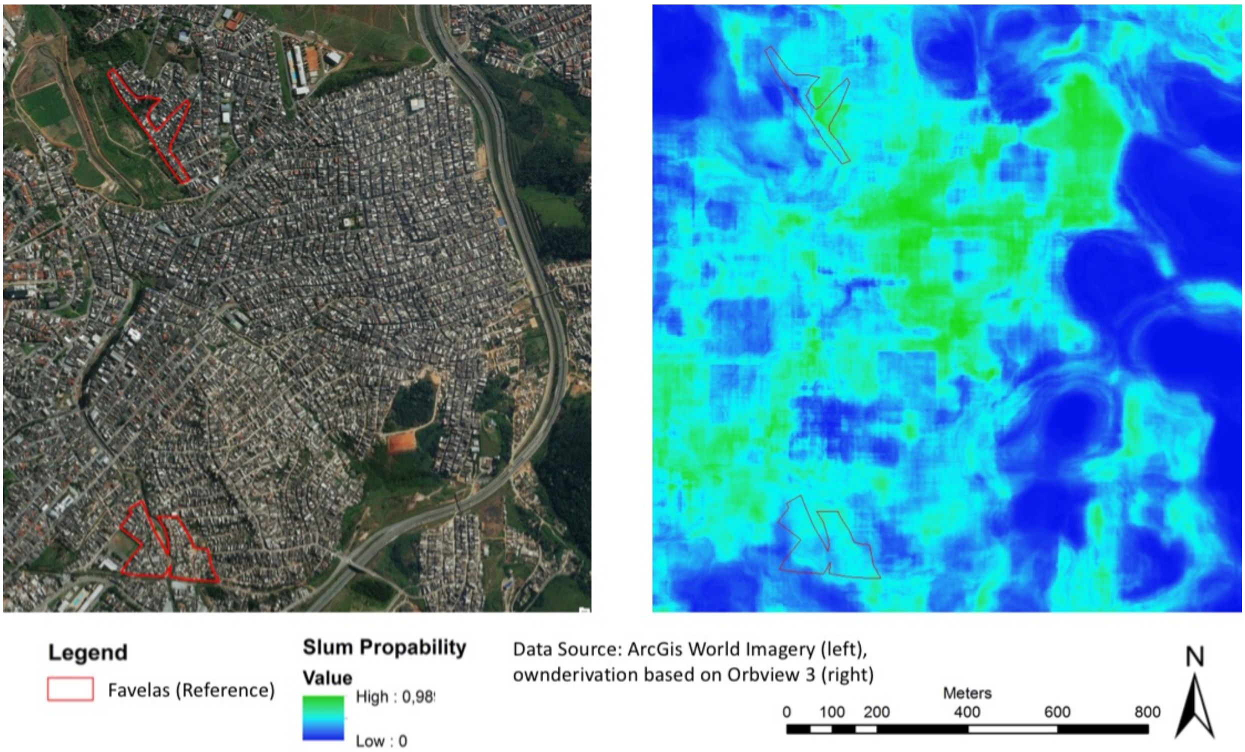

Figure 26. Example of areas not included in the reference data showing a high conformity with favela areas

Influence of the Kernel Size

Obtained results show increasing values for OA and kappa for all sensors and cities. Thus, results confirm previous findings from Weigand (2017) and Wurm et al. (2017a). Visual interpretations have shown, that increasing OA and Kappa values mainly refer to a reduced misclassification of urban areas as favelas. Small kernels show (depending on the sensors) high to very high over-classifications of favelas. In the case of CBERS 2B, not in form of patches but isolated pixels. Thus, smaller kernels fail to represent the characteristic texture of appearing LC classes and misinterpret heterogeneous areas as favelas. With larger kernels, however, a smoothing effect occurs. Due to a smaller influence of outlier gray values, kernels better represent larger dominating LC classes. Therefore, with larger kernels, over-classification of favela pixels decreases. This leads to a higher percentage of correct predicted favela pixels, so that larger kernels result in higher PPV values. In some cases, this effect reverse for very large kernels, as other effects cause misclassification as well.

Problematic areas for approaches using texture parameters are class boundaries. The so-called “Edge effect” leads to misclassification at class borders where applied classes do not occur at all. This happens when the neighboring classes show the typical Variance, Entropy, etc. that usually represents the texture of the applied class (Ferro & Warner 2002). Visual interpretations indicate this phenomenon at class boundaries of urban and vegetation leading to false favela predictions *(see figure 27*). While true negative favela predictions decrease in urban areas, this effect increases at the named class boundaries with increasing kernels. Yet, as its influence is lower, OA and Kappa still increase.

Moreover, results confirm the importance of the kernel size in relation to the ground size of objects. Highest Sensitivity values in Sao Paulo were reached with a 9x9 kernel equalizing 90x90m on the ground for Sentinel 2, 39x39 kernel equalizing 105x105m on the ground for CBERS 2B and a 17x17 kernel in case of Orbview 3, equalizing 68x68 m. Hence, optimal sensor kernel combinations cover similar areas on the ground. Moreover, this area represents very well the median value for the most frequent favela size. Values for Orbview 3 deviate slightly from this pattern, but the sensor also shows the lowest Sensitivity values.

Similar relations occur in Rio de Janeiro. Highest Sensitivity values resulted from a 9x9 kernel for Sentinel, equalizing 100x100 m on the ground, a 27x27 kernel for CBERS 2B, equalizing 73x73m on the ground, respectively a 17x17 kernel equalizing 68x68m on the ground for Orbview 3. In the case of the CBERS 2B AOI in Rio, favelas were significantly smaller, showing a mean value of 0.6 ha. Thus, to certain degree results underline the relation between applied kernel sizes and the size of the object of interest on the ground.

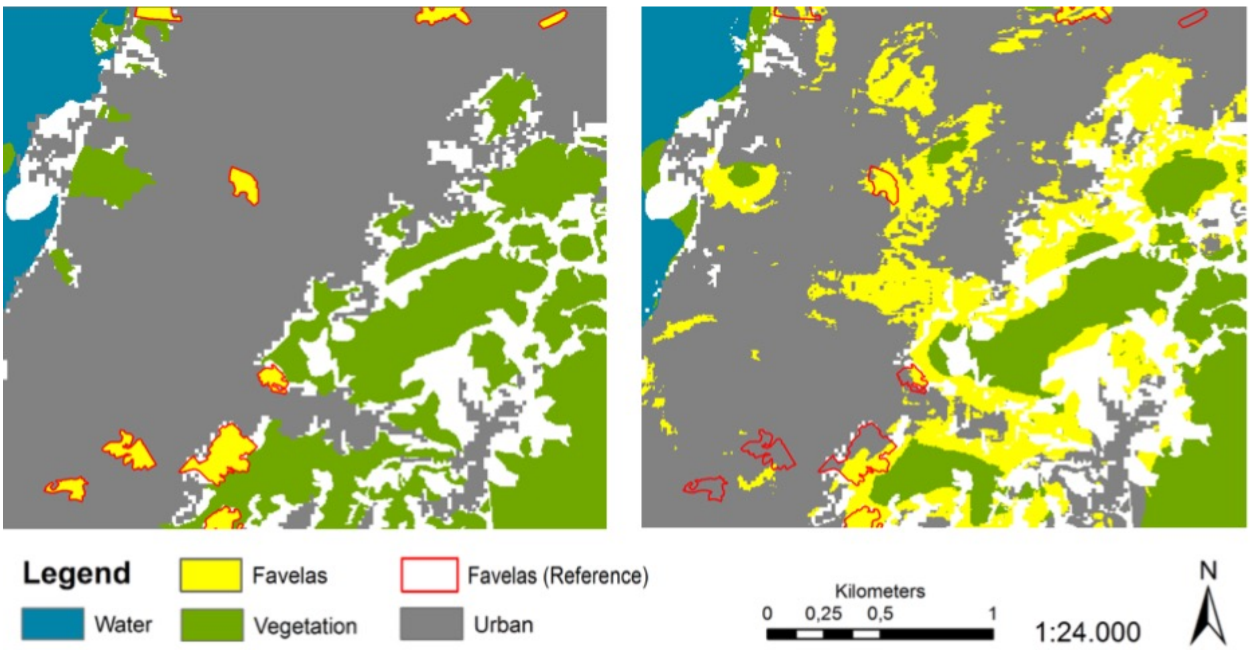

Figure 27. Illustration of occurring misclassification at the class boundaries of vegetation and urban areas. Classification outcome of Sentinel 2 data and a 51 kernel size

Influence of the sensor

Obtained results show significant differences in OA and kappa, as well as for favela specific statistics for the different sensors. Thus, the different spatial, spectral and radiometric characteristics of the sensors seem to have an influence on their capability to detect favelas. As the sensors also show significant differences in obtained accuracies for investigated AOI, the results indicate furthermore, that different local circumstances lead to different requirements for sensors. This is most likely due to different GSOs. The more similar feature spaces for the classes “Urban” and “Favelas” are, the higher are the requirements regarding the radiometric, spectral and spatial resolution. CBERS 2B has the highest spatial resolution with 2.7m. For slum mapping, this would be assumed to be of importance as single favela buildings are often only a little bigger. Consequently, Sentinel 2 with a spatial resolution of 10m will portray them with mixed pixels. Yet, CBERS 2B failed to distinguish between favelas and regular built-up areas in the case of Rio. Thus, the GSO in Rio seems to require additional information that is gained by an increased radiometric and spectral resolution. The gain of information with additional spectral bands is considerable, as four instead of one band result in a four times higher feature space. In the context of this study, it equals 28 instead of only 7 image features. Yet, no detailed evaluation of the importance of single image feature was carried out, but visual interpretations show huge differences in the delimitation of favelas and regular built-up areas in different bands. Moreover, reasons for low accuracies in case of CBERS 2B relate to its image quality. A visual comparison of the satellite images shows that the stated 2.7m resolution of CBERS 2B is especially compared to Orbview 3 not visible on the images as Orbview 3 with only 4m resolution provides more detail. Figure 28 shows a typical Favela area in Rio de Janeiro on CBERS 2B (left) and Orbview 3 (right). The illustration shows, that the image information of the CBERS 2B scene is insufficient to distinguish between favelas and regular-built up areas, as both settlements forms have the same appearance. Visual distinguishability thereby depends to a high degree on the sharpness of an image. In terms of remote sensing this depends on the radiometric resolution. The higher the radiometric resolution is, the more gray values are available to characterize objects. As shown in chapter 3.1 Orbview 3 has 8 times, Sentinel 2 even 16 times more gray values than CBERS 2B. Using texture parameters with a moving window, the gain of additional image information is limited to the number of pixels in between the kernel, e.g. a 51x51 kernel has 2,601 pixels equalizing the number of possible different gray values. Yet, in case of the 256 gray values of CBERS 2B, the low number is likely to negatively affect the detection of favelas. As contrast measures the variation of gray levels in the kernel, a higher amount of available gray values enable are a more specific description of the GSO. With lower numbers of gray values, contrast of regular built-up area or kernel with mixed LC are more likely to have contrast similar to favelas. Same considerations affect the feature 'Homogeneity'.

Those limitations in describing the feature space for favelas are likely to be responsible for poor obtained results for CBERS 2B. Thus, the study confirmed previous investigations showing limitations of CBERS for urban analyzation (Wang et al. 2009).

Having the same number of spectral bands and both a high radiometric resolution, Sentinel 2 and Orbview 3 seems suitable to analyze the importance of spatial resolution. In the case of Rio, results indicate both, higher OA and kappa values, as well as higher accuracies for favelas measured by Sensitivity and PPV in the case of Orbview 3. Furthermore, visual evaluation shows a better representation of the favela shape for Orbview 3 data. However, in Sao Paulo Sentinel achieved higher accuracies for Sensitivity, so that results do not allow a distinct conclusion. Reasons for this phenomenon will be discussed in the following section addressing the influence of the morphology.

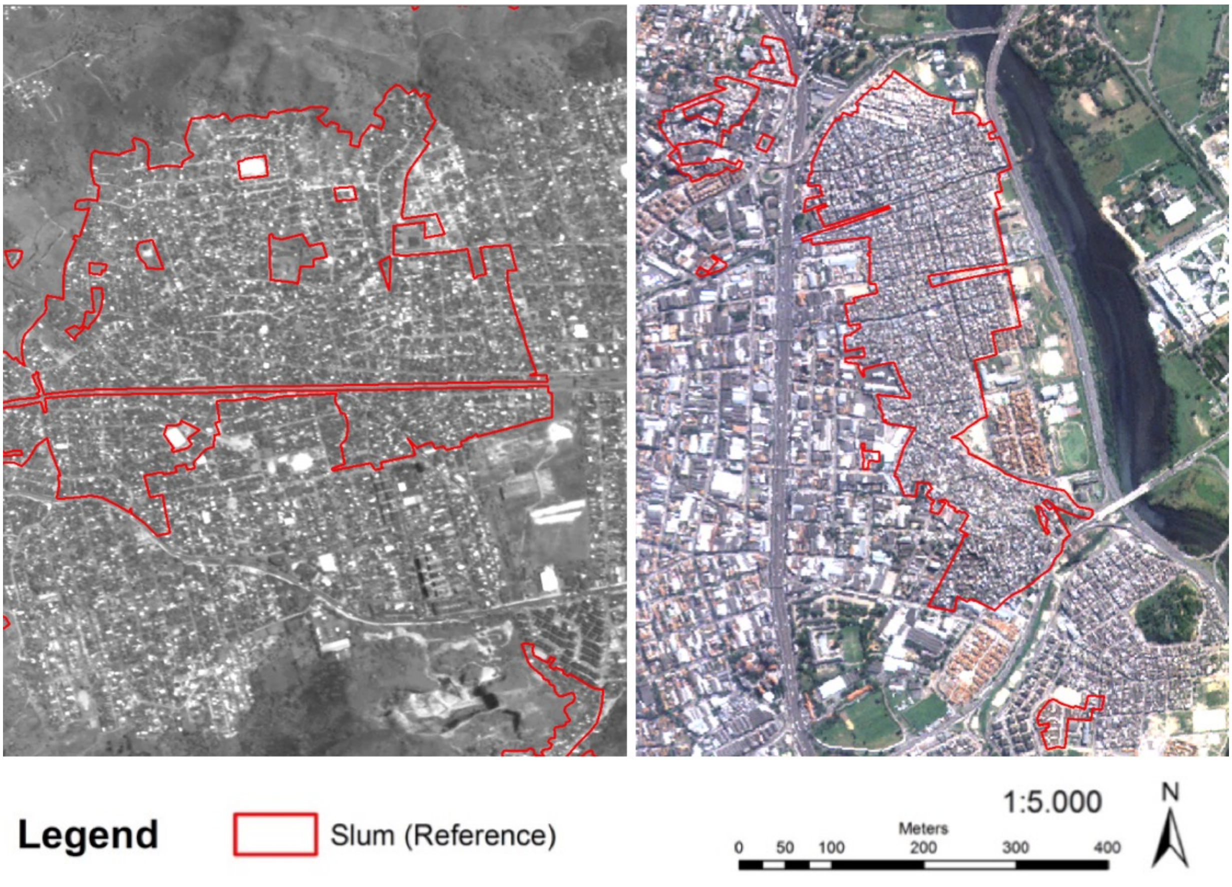

Figure 28. Comparison of the visual distinguishability between favelas and regular built-up areas in the CBERS 2B scene (left) and the Orbview 3 scene (right). Due to missing sharpness, the CBERS 2B scene shows no differences in the morphology between favelas and regular built-up areas

Influence of the morphology of the city

Table 8 has indicated partially significant differences for a sensor between the cities. Highest differences appear in case of CBERS 2B. However, they refer to some degree to the disadvantageous AOI. In the case of CBERS 2B, the investigated AOI has significantly smaller favela blocks than the whole AOI, making them even harder to detect. In addition, the previous section concerning the quality of CBERS 2B data has shown, that it misses sharpness due to its low radiometric resolution and poor sensor quality. This resulted in an immense over-classification of favela pixels that caused high Sensitivity values but low Positive Predictive values. Therefore, CBERS 2B is inappropriate to analyze the influence of the morphology.

Further significant differences occur in the case of Orbview 3, showing 23 percentage points higher Sensitivity values and 15 percentage points higher PPV values in Rio in contrast to Sao Paulo. These results contravene the first assumption in cp. 2.2, that the GSO is clearer separated from regular built-up areas in Sao Paulo than it is the case in Rio de Janeiro. This was based on the different roof materials used in Sao Paulo, with favela areas having mostly fibre cement roofs, whereas in regular built up areas red brick roofs are widespread. Yet, it turned out that this drawback was premature. Visual analysis show, that the classifier performs very well on classifying brick roof areas as urban. However, as figure 29 illustrates it often misinterprets regular built-up area with a diverse roofscape as favelas. The diverse roofing material seems to cause ‘Homogeneity’, ‘Contrast’ etc. values similar to favelas areas. This leads in the case of Sao Paulo to a high number of favela misclassifications, lowering the number of correctly predicted favelas pixels. This aspects only refer to low PPV values, but can not explain why Orbview 3 reaches far lower Sensitivity values in Sao Paulo than in Rio. Previous findings by Wurm et al. (2017b) have shown, that RF Classifier maps slums conservative in general. In Sao Paulo in the case of Orbview 3 to a greater degree than CBERS 2B and Sentinel. Reasons for this will among others originate from the sensors ability to analyze the morphology of the city. However, further research is necessary to provide a precise explanation regarding this issue.

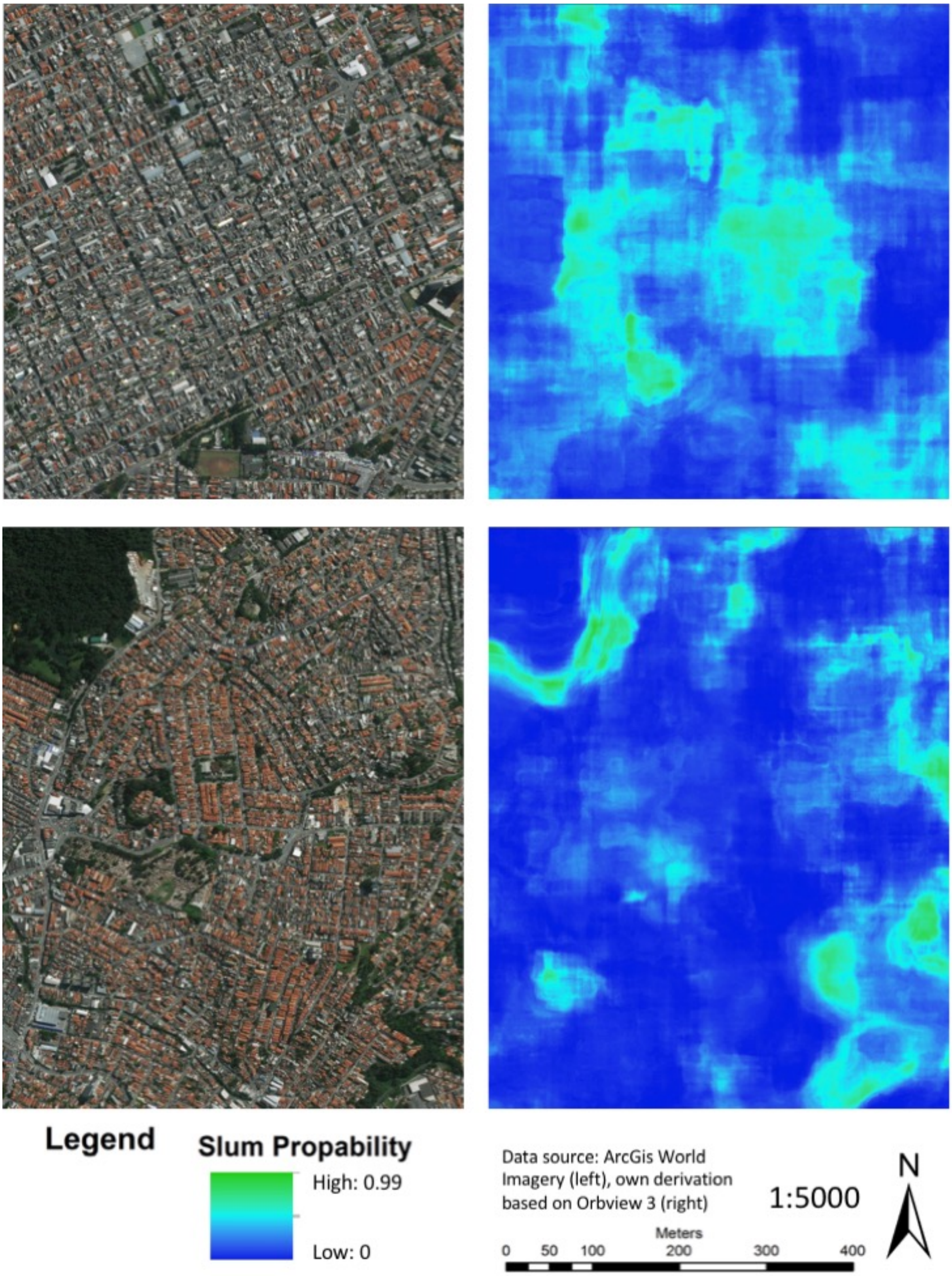

Figure 29. Illustration of the favela probability for urban areas with mixed roof materials (upper row) and predominantly brick roofs (lower row)

6. Conclusion and outlook

As outlined in the first chapter of this thesis, slums are a very dynamic and diverse phenomenon, not only differing from country to country but also from city to city and in between a city. In the case of Brazil, more specifically the two investigated cities of Sao Paulo and Rio de Janeiro, this makes the challenge of mapping slums obviously significantly harder than it is the case for instance in the most frequent case study Mumbai. Indeed, the approach was capable to detect larger favelas with a typical morphology and to detect different morphologies in between the AOIs, but obtained results were significantly lower than in the Mumbai case study.

The existence of different subtypes of favelas (Cortiço, Invasoes, etc), the wide occurrence of mixed forms, and transformation of quarters of poverty to middle-class housing make it hard to define a feature space for favelas and distinguish them from regular built-up area. Moreover, a strict segregation of favelas and regular built-up seems hard to apply in Brazil. Areas with a typical slum morphology do exist, but on the other hand, there are numerous areas that show some characteristics of slums but also characteristics of regular built-up areas. Therefore, the Brazil case study shows two major problems that need to be faced for further slum mapping studies.

Firstly, most cities require a local adoption of the classification approach. With every city having an individual GSO, they require different image features and sensors that are capable to represent those characteristics. Therefore, approaches are hard to transfer from one city to another in case of slum mapping.

Secondly, the creation of objective reference represents a big challenge. To produce meaningful error statistics one requires either transferable unified guidelines for mapping slums or an approach that is not producing a hard demarcation between slums and regular built-up area. Especially for cities that show a high amount of mixed or transformation areas, a classification outcome that maps the agreement with the slum morphology can be more informative. Therefore, in Brazil a more informative outcome seems to be a probability map trained with areas that express typical favela areas to represent morphological accordance to those areas (cf. figures 26 and 29 in chapter 5). In a further step, one can set a threshold of accordance to transform the probability map into a slum mask.

Investigations concerning the influence of the kernel size have underlined previous studies results. Larger kernel sizes cause a smoothing effect that leads to higher OA and kappa values. For favela descriptive values this applied only to a sensor specific limit, that was close to the mode value of favela sizes. This has shown that kernel sizes should be chosen with respect to local conditions of the AOI.

Moreover, obtained results illustrate the importance of choosing a suitable sensor in regards of the aims of a classification. Different spatial, radiometric and spectral resolution influence the detection rate of slums and the representation of different morphologies.
Therefore, the study leaves space for further investigations. Especially a detailed analysis of the capabilities of different texture parameters to describe morphological characteristics of slums seems important. Moreover, investigations of the influence of the shape of favelas are of interest, to figure out if the degree of deviation from a square is correlated to a patch based accuracy. Thus, a proper adoption of the GSO to the local circumstances is enabled. This is of further importance to choose the right sensor, that fits best to cover those texture features. In this field, further analysis of the influence of sensor-specific abilities regarding the influence of the radiometric and spatial resolution on the texture parameters are of further interest.
Those investigations are important to face the problems of rapid urban growth and an increase in slum population. While urban growth in Brazil is stagnating with Rio de Janeiro and Sao Paulo have an expected growth of only two million inhabitants till 2030, tremendous growth is expected in Asia and Africa. Karachi (Pakistan), Lagos (Nigeria) and Kinshasa (Congo) are some examples of cities that will see a growth of about 10 million people till 2030 (United Nations 2014). With new findings, Remote Sensing and in particular suitable classification approaches can help to face the upcoming challenges that come along with this development.

AFFIDAVIT

I declare that I have authored this thesis independently, that I have not used other than the declared sources/resources, and that I have explicitly indicated all material which has been quoted either literally or by content from the sources used. The text document uploaded to TUGRAZonline is identical to the present master‘s thesis.

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Date Signature

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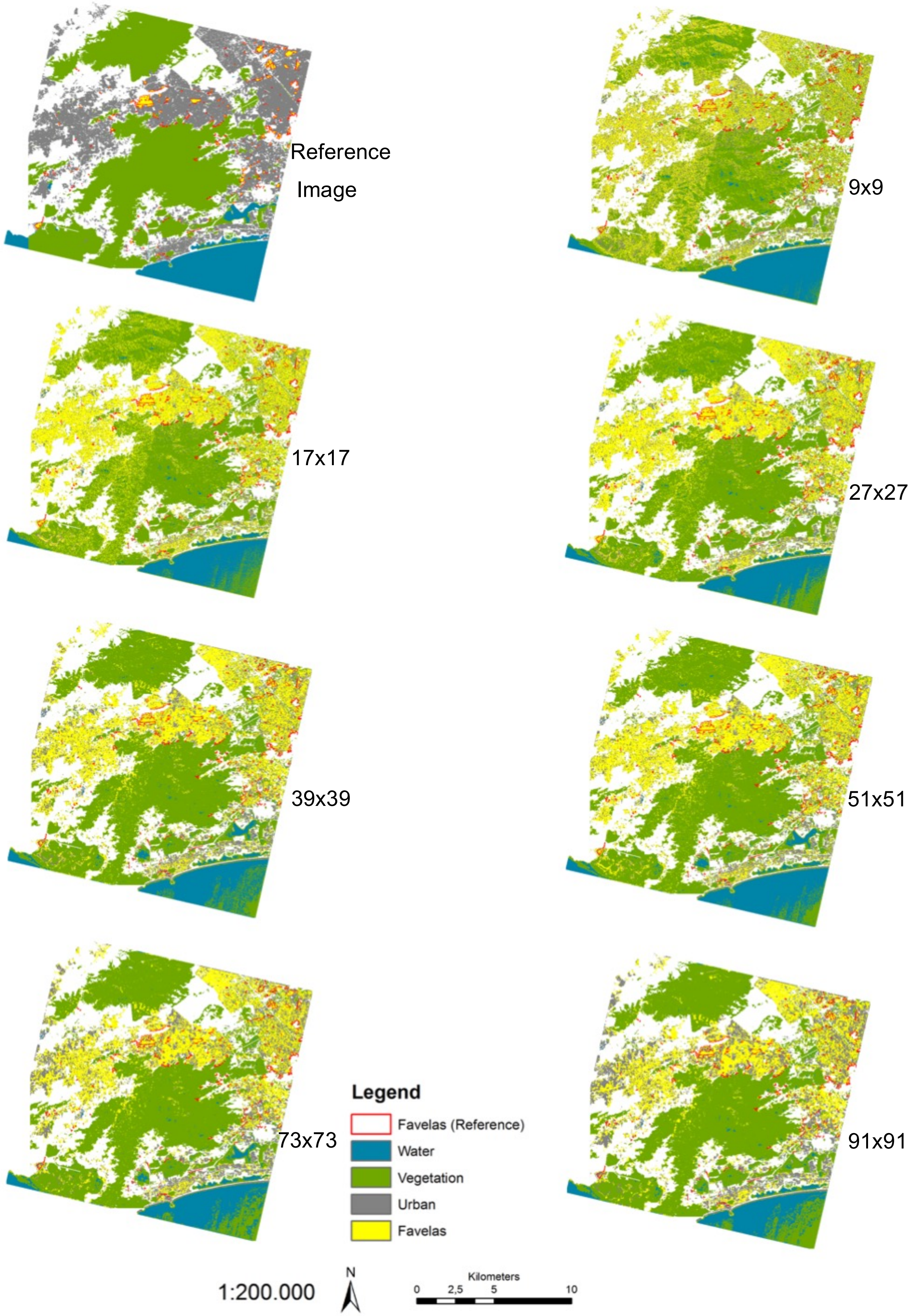
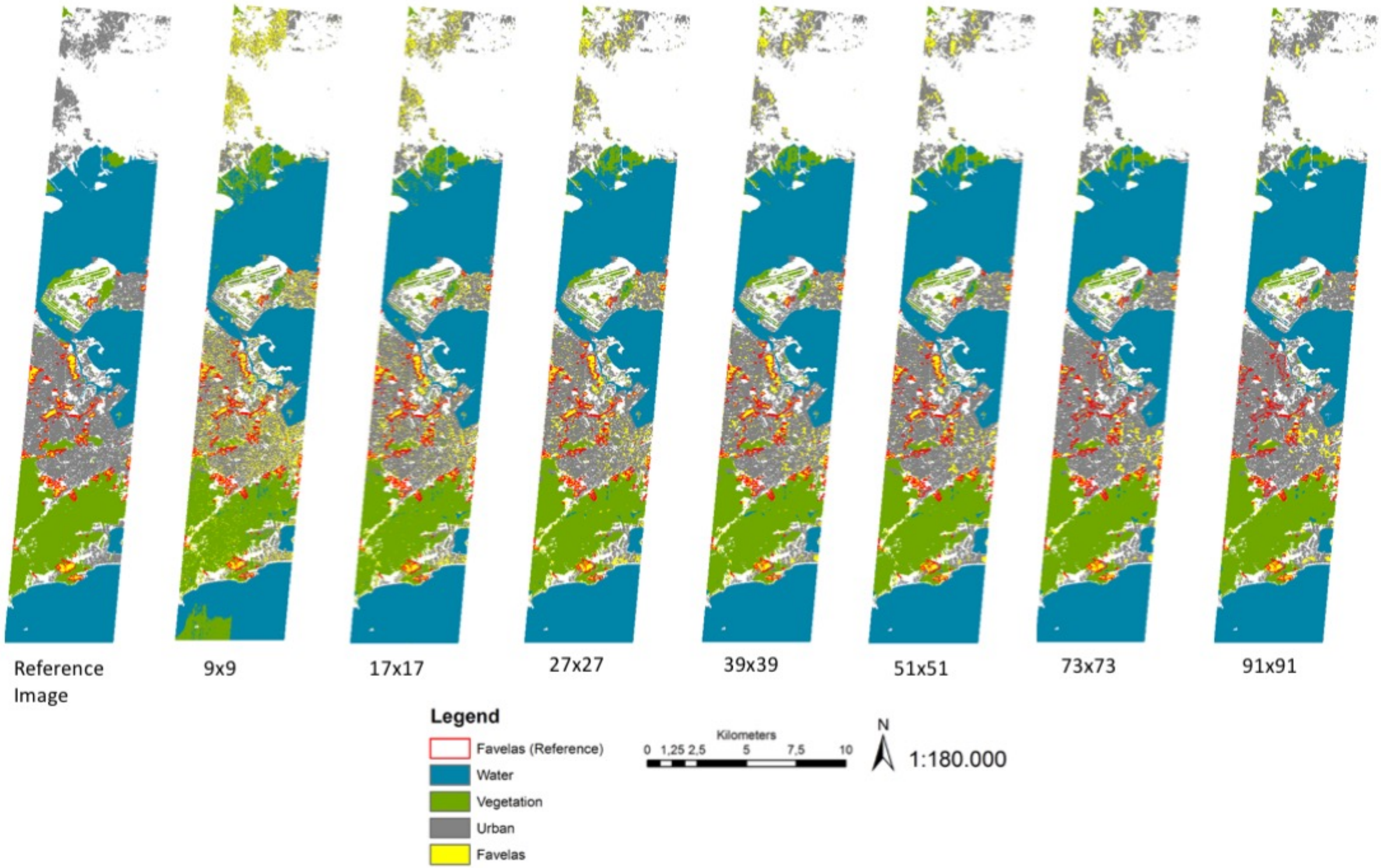
Annex

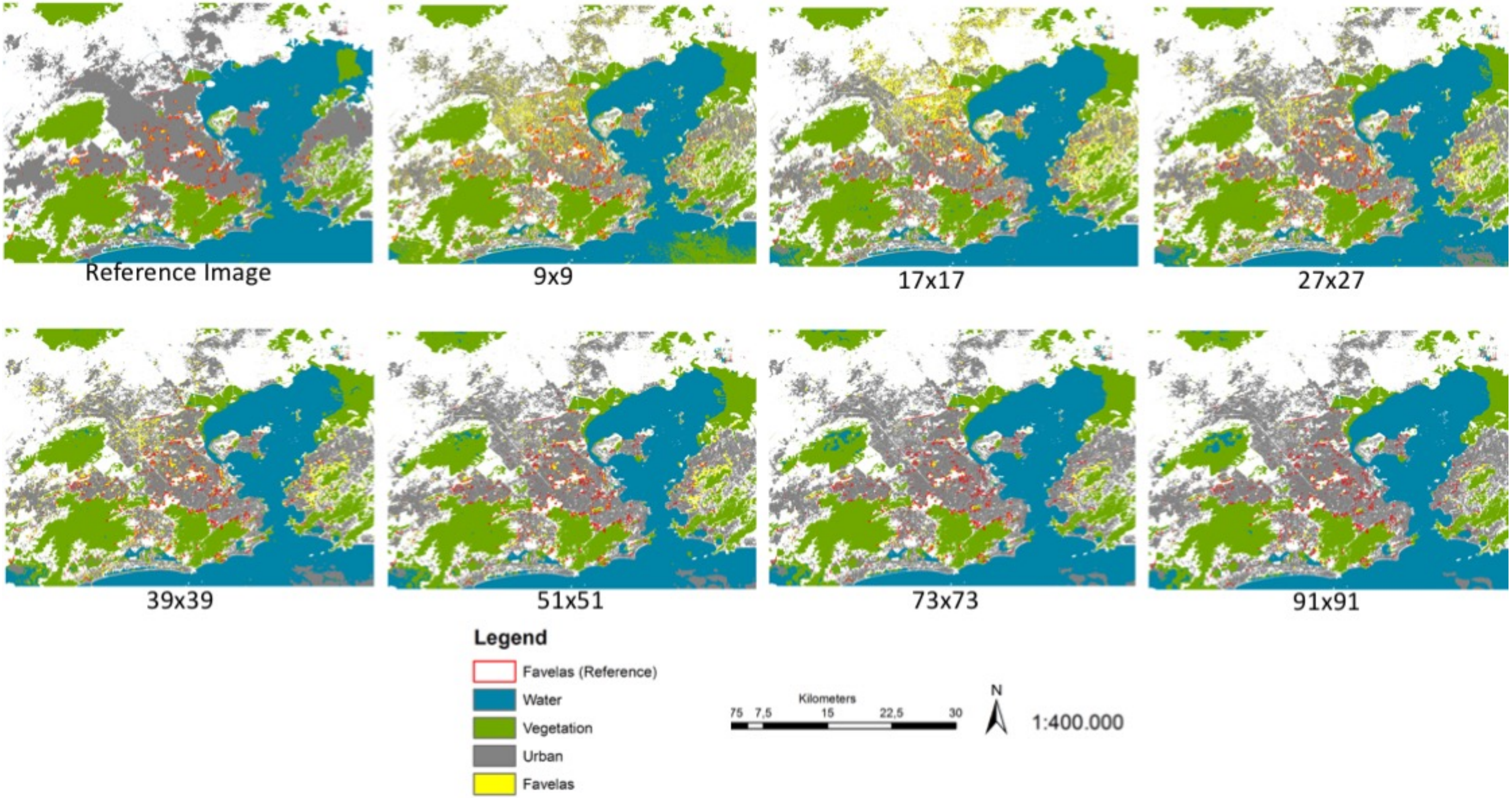
Rio de Janeiro – CBERS 2B

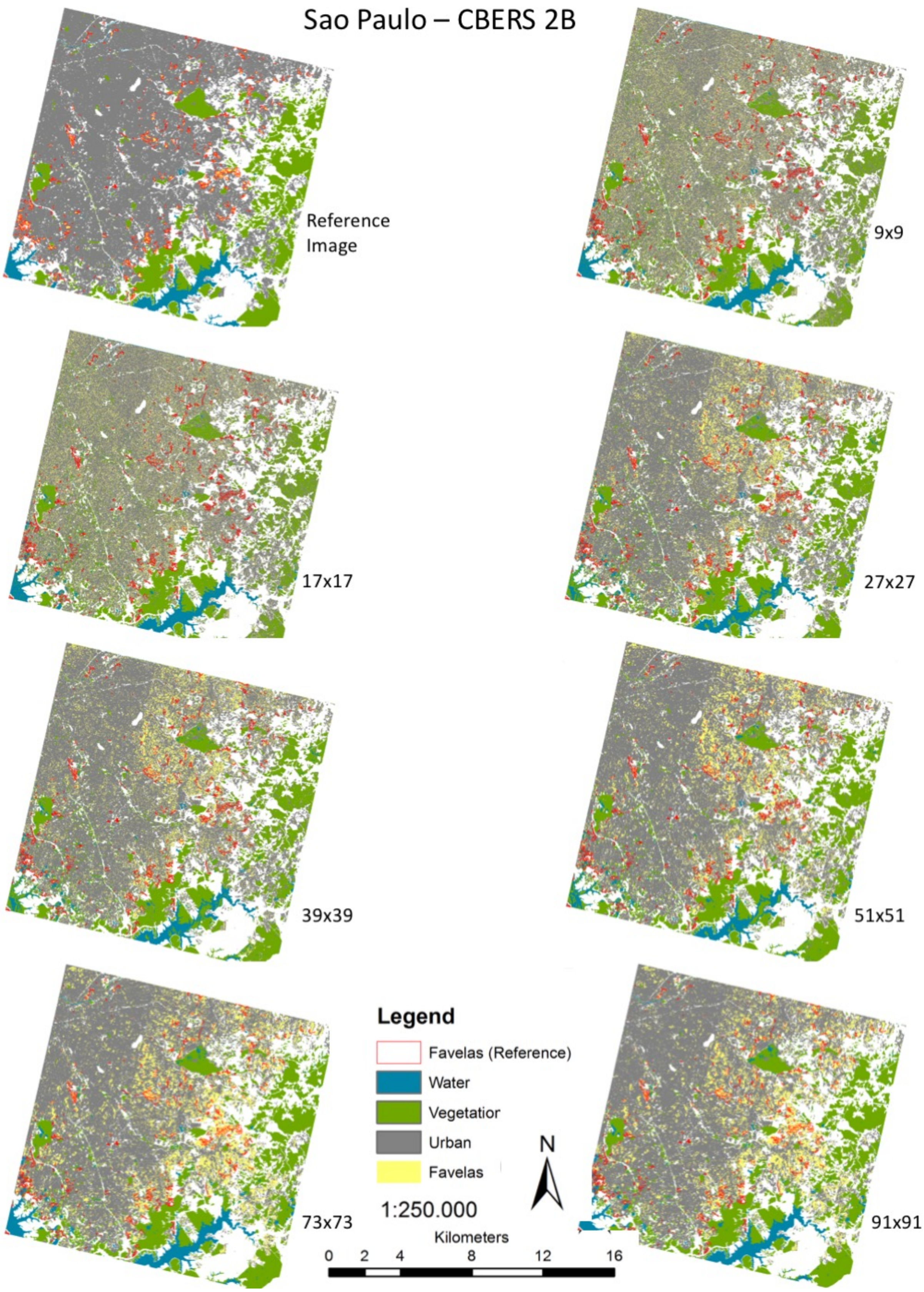


Rio de Janeiro – Orbview 3



Rio de Janeiro – Sentinel 2




Sao Paulo – CBERS 2B
Reference Image
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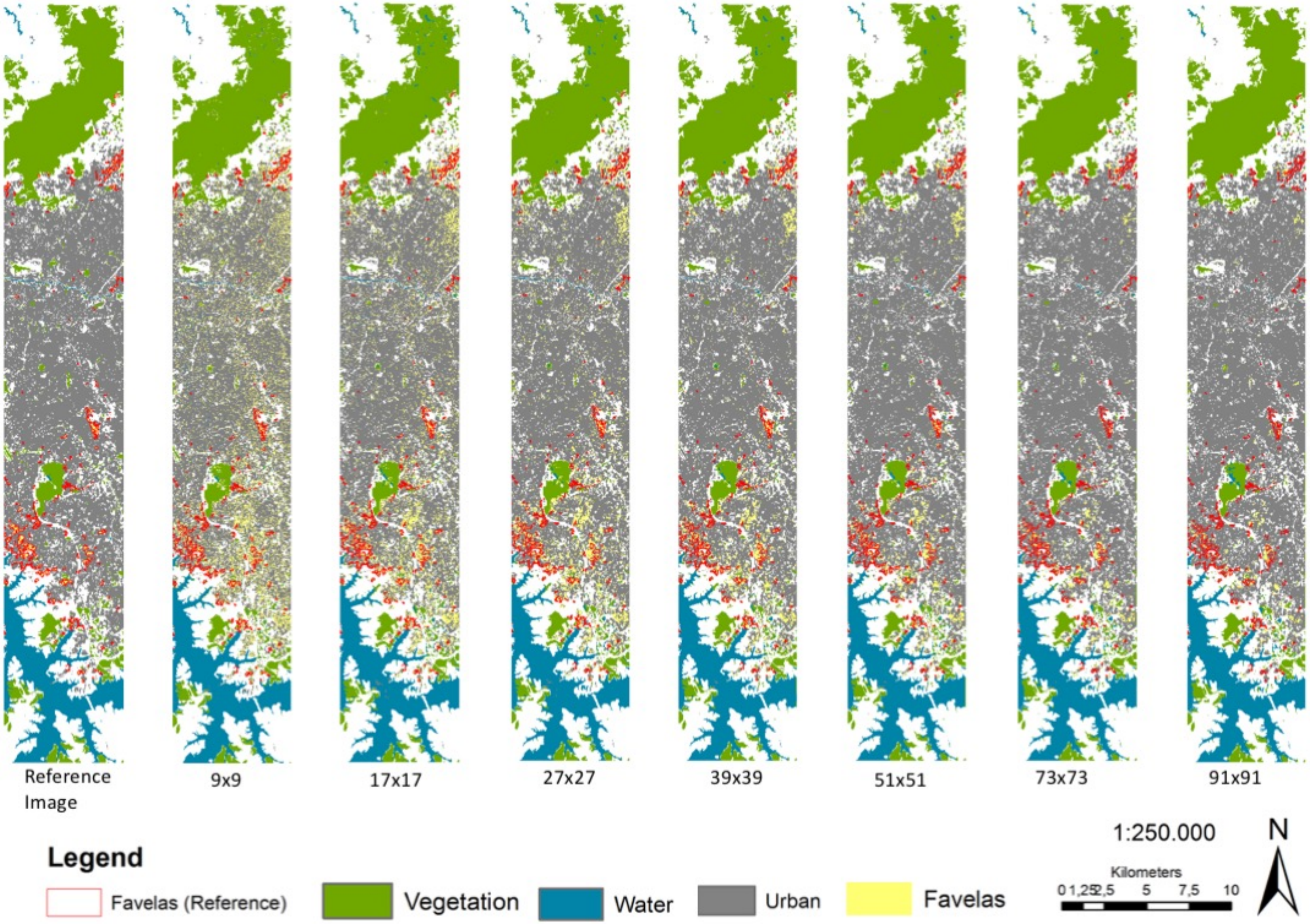
Sao Paulo – Orbview 3



Sao Paulo – Sentinel 2