16 Defining Robustness Measures for OBIA Framework

A Case Study for Detecting Informal Settlements

Peter Hofmann

CONTENTS

16.1 WHY AUTOMATED DETECTION OF INFORMAL SETTLEMENTS FROM REMOTE SENSING DATA?

16.1.1 Informal Settlements in the Context of Worldwide Urbanization

According to estimations of UN-HABITAT (2011), the number of people living in urban areas worldwide will increase from 3.5 billion in 2010 to 4.9 billion in 2030. This is equivalent to an urbanization rate of 1.81% per year from 2010 to 2020 and 1.60% per year between 2020 and 2030, respectively. That is, on average, the number of people living in urban areas worldwide is increasing per year by 1.71%. The largest portion of urbanization will take place in developing countries: from 2010 to 2020, the rate will be at 2.21% per year and from 2020 to 2030, it will decrease to 1.92% per year. From the group of developing countries, the African continent will have the highest urbanization rates: 3.21% per year for the period from 2010 to 2020 and 2.91% per year from 2020 to 2030, of which the largest portion belongs to sub-Saharan Africa with 3.51% per year (2010 to 2020) and 3.17% per year (2020 to 2030). Irrespective of the reasons for such enormous migration movements, these numbers indicate that cities in the developing countries, especially the sub-Saharan countries, will face an enormous increase in population pressure. Following UN-HABITAT (2007), among the "nearly one billion people alive today one in every six human beings are slum dwellers, and that number is likely to double in the next thirty years." This number is estimated to be 2 billion by 2030. That is, besides a general increase in urbanization, the portion of the urban population living under slum conditions will increase from 28.57% from now to 40.82% in 2030. This means that by 2030 there will be 2 billion people in urban areas lacking access to safe water, improved sanitation, and secure tenure living in overcrowded and unsecure housing structures with environmental degradation. "Alarmingly, there is currently little or no planning to accommodate these people or provide them with services" (UN-HABITAT 2007). With this background, programs such as the "United Nations Millennium Development goal to improve the lives of at least 100 million slum dwellers by 2020" (UN-HABITAT 2007) were started. However, regarding the increase in rates of slum dwellers, it is obvious that global and local policies and instruments are necessary to improve the living conditions in informal settlements and to fight poverty at all. "Much more political will is needed at all levels of government to confront the huge scale of slum problems that many cities face today, and will no doubt face in the foreseeable future" (Anna Kajumulo Tibaijuka, Executive Director of UN-HABITAT, in UN-HABITAT 2007). The described situation makes it clear that there is an increasing need to detect informal settlements at least for inventory reasons but also for continuous monitoring, mapping, and finally upgrading in terms of providing a minimum standard of housing conditions.

16.1.2 Dynamics of Informal Settlements

Although established informal settlements and the cores of informal settlements show rather durable structures, the situation is different in reality at the informal settlements' borders. Due to their informal character, dwellings are relatively easily built, extended, or demolished, which allows the dwellings' residents to react very flexibly on changing living conditions and therefore either to move quickly and easily if necessary or to extend their dwellings if necessary and possible. This has an impact on the location and physiognomy of informal settlements including the footprints and general structure, which can change very rapidly. However, although alternating structures are observable in some cases, in most cases, peripheral growth takes place. That is, informal settlements located at a city's periphery in general grow faster than the centrally located ones. Moreover, informal settlements usually grow faster at their outer border than in the core areas (APHRC 2002; Sartori et al. 2002; Kuffer 2003; Weber and Puissant 2003; Radnaabazar 2004; Davis 2006). This growth has an impact on neighboring land coverage (Sliuzas and Kuffer 2008), be it settlement, agriculture, or uncultivated land with habitats for potentially invaluable species and their ecosystems. In some informal settlements, even vertical growth can be observed (Canham and Wu 2008; Sliuzas et al. 2008; UNESCO 2012). Because of these expeditious changes of informal settlements' shape, conventional methods of mapping fail. Feasible methods are rather implemented by integrating the settlements' inhabitants themselves. They can contribute to an up-to-date spatial data acquisition by volunteered mapping. The most prominent example of such an approach is the Map Kibera Project (MKP) (http://mapkiberaproject.org/). Besides the production of shared geo-information, MKP enforced community and neighborhood building. In this context, Veljanovski et al. (2012) report the supporting role of very-high-resolution (VHR) remote sensing data in conjunction with object-based image analysis (OBIA) methods, especially for population estimation. For ex post change detection, that is, monitoring of already elapsed periods, remote sensing data and appropriate analysis methods proved to be the only reliable data source. Such ex post approaches are the basis for estimating past population sizes and densities together with their development. This information can be used to project respective future population developments by comparing past and recent image patterns with socioeconomic data. This way, hot spots of urbanization within informal settlements are identifiable by means of remote sensing image analysis. But even if there is no accompanying ground mapping, remote sensing is a valuable instrument for monitoring the development of informal settlements (Kuffer 2003; Sliuzas et al. 2008).

16.1.3 Common and Different Patterns of Informal Settlement

As several authors (Sliuzas et al. 2008; Kit et al. 2012; Taubenböck and Kraff 2013) have pointed out, there is an increasing need for mapping and monitoring informal settlements globally. Although several individual approaches for detecting informal settlements from mostly VHR remote sensing data have been introduced so far, there is no unique standard method available to delineate or even analyze them from remote sensing data (Sliuzas et al. 2008). The reasons therefore are manifold and are explainable by the individual characteristics of informal settlements rather than by a lack of understanding of the phenomenon. That is, each informal settlement shows an individual fingerprint and simultaneously fits typical general characteristics of informal settlements (Hofmann 2005; Taubenböck and Kraff 2013). The latter can be defined as general slum ontology (GSO), as introduced by Kohli et al. (2012). The GSO acts as a top-level (Guarino 1997a,b) or canonical (Subieta 2000) ontology for informal settlements. For operational tasks (e.g., the definition of OBIA rule sets), the GSO can be reapplied, adapted, and extended as needed. The resulting ontology then reflects the individual characteristics of the informal settlement of concern. That is, there exists already a general description of what makes an informal settlement, namely, a dense and irregular network of usually unpaved roads and lanes and a dense and irregularly arranged grid of small shacks or small houses, just to name those that are detectable from remote sensing data. However, this description is rather fuzzy and the de facto pattern of an individual informal settlement depends very often on local criteria such as cultural background, available construction material, topography, existing infrastructure, and existing formal settlement structures. The degree of local influence factors on the deviation from the "ideal," that is, top-level or canonical, informal settlement is hardly predictable. However, the defined ontologies can act as input for the creation of an OBIA rule set, which needs to be adapted and extended according to the current situation. Therefore, recent methods of automated detection of informal settlements from remote sensing data still include a relatively high proportion of manual adaptation to local conditions (Hofmann, 2005; Hofmann et al. 2008a,b, Sliuzas et al. 2008).

16.2 AUTOMATION AND ROBUSTNESS IN THE CONTEXT OF OBIA

As stated by several authors (Blaschke and Strobl 2001; Hofmann 2001; Benz et al. 2004; Niebergall et al. 2008; Sliuzas et al. 2008; Veljanovski et al. 2012), OBIA has numerous advantages, especially in the domain of analyzing VHR remote sensing data, since it operates on image objects as aggregates of pixels rather than on single pixels. Thus, on the one hand, effects such as the salt-and-pepper effect (Blaschke and Strobl 2001) are avoided and, on the other hand, a large feature space can be used for further image object analysis (Benz et al. 2004). Sometimes, OBIA has been criticized due to its dependency on the image segmentation used (Hay and Castilla 2006; Smith and Morton 2008). In this context, many discussions have been held about the suitability and performance of different segmentation algorithms (Meinel and Neubert 2004; Van Coillie et al. 2008; Zhang et al. 2008) and how to assess segmentation quality (Neubert and Herold 2008; Neubert et al. 2008). However, OBIA is an iterative process, starting with arbitrary initial image segmentation and continuing with step-by-step, knowledge-based improvement of image segments according to the analysis task (Baatz et al. 2008). The resulting image objects can be considered as the image representatives of the real-world objects that are to be detected. With this background, a very important point when regarding the segmentation quality and representation capabilities of image objects is whether scale is represented reasonably by the image object hierarchy. That is, do sub- and superlevel image objects reflect the interscale relationships of the real-world objects they represent? And can these interscale relationships be expressed with sufficient quality?

For the case of detecting informal settlements, this means that, on a lower scale, typical structural elements, such as small buildings and shacks, shadows of small buildings and shacks, as well as small roads and lanes, need to be outlined well enough in order to indicate on a higher scale a high density of dwellings and an irregularly shaped network of small roads—one of the major properties of informal settlements. Automation of informal settlement detection increases with the robustness of the underlying rule set. That is, for a given rule set, the fewer the manual adaptations and interactions necessary to produce sufficient results in similar images, the more robust the rule set is considered to be. Consequently, a highly robust rule set increases the automation of informal settlement detection.

16.2.1 Different Image Data and the Need for Adapting Initial Segmentation Parameters

When developing OBIA rule sets, this is usually done using one or two reference images reflecting a subset of the image data to be used and depicting the objects of interest to be detected. That is, the rule set to be developed is generated for a relatively clear defined task concerning objects of interest and the type of image data to be used. For reapplying developed classification rules on different images, the initial image objects should be comparable in size and shape. However, the spatial resolution of VHR remote sensing data can vary from approximately 0.25 to 5 m. Different spatial resolutions lead to a varying number of pixels per real-world object to be represented. Thus, in order to produce comparable image objects, the initial segmentation parameters need to be adapted with respect to the different spatial resolutions used (Hofmann et al. 2008a). Besides, the radiometric resolution has an impact on image object generation, as it increases or decreases details of local contrast. For recent remote sensing images, the radiometric resolution can be of 8, 11, 12, or even 16 bits. That is, the radiation at a pixel's location is quantized in $2^8 = 256$, $2^{11} = 2{,}048$, $2^{12} = 4{,}096$, or $2^{16} = 65{,}536$ discrete values. When segmenting images of different radiometric resolution, more or less randomly shifted object borders can arise (see Figure 16.1). Last but not least, the spectral coverage of the sensors' bands lets objects of interest appear differently, and therefore they can have an impact on initial segmentation results as well.

16.2.2 Adapting Image Segmentation Parameters

Most segmentation algorithms directly or indirectly take local contrast into account. Changing the radiometric resolution has an impact on local contrast and thus on the generation of comparable image objects. Consider a spectral difference segmentation that agglomerates pixels to image objects if their mutual gray value differences are below a given threshold. Different quantization leads to different gray value gradients in the pixels' neighborhood. Consequently, in the image with higher radiometric resolution, object borders are generated at positions where they would not appear in the lower radiometric resolution. Vice versa,

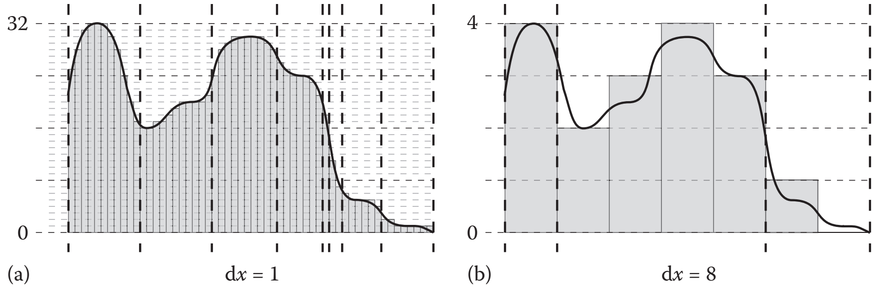

FIGURE 16.1 Different radiometric and spatial resolutions and their impact on object generation. (a) High resolution (32 gray values and 1 spatial unit). (b) Low resolution (4 gray values and 8 spatial units). Object borders are indicated by dotted vertical lines; scanning units are indicated by dotted horizontal lines. The original signal is indicated by the solid line; the scanned signal is given in gray bars.

existing gradients in the image with lower radiometric resolution get smoothed in the image with higher radiometric resolution. Consequently, local contrast is too low for generating an object border and the border disappears (see Figures 16.1 and 16.2). Hence, a generic segmentation adaptation for images with different radiometric resolutions is hardly feasible.

For region-growing algorithms taking the object size into account, the spatial resolution is relevant, too: the smaller the pixel size, the more pixels need to be agglomerated in order to create objects of similar size (Figure 16.1). For multiresolution segmentation (MRS), as introduced by Baatz and Schäpe (2000), Hofmann et al. (2008a) demonstrated a method for compensating different spatial resolutions. Different bandwidths are not compensable at all. But bands with bandwidths only existing in one image can be excluded from segmentation, while redundant bands can be merged into one band and similar bands can be used equally. Especially when working with pan-sharpened data, this issue can have an impact on object generation: for pan-sharpening, usually only those multispectral channels should be used that are covered by the spectrum of the panchromatic channel. But the latter can vary from sensor to sensor. Thus, pan-sharpened data from one sensor are not necessarily equal to that of another sensor.

16.2.3 Robustness of OBIA Rule Sets

The term robustness is applied in a variety of domains (Jen 2003). Constructions, for example, are considered to be robust if they function stable even beyond their specifications. Organisms are called robust if they are able to adapt to changing living conditions in terms of survival and reproduction (Kitano 2007). Societal structures can be seen as robust if they continue to exist under changing socioeconomic conditions (Berman 1997). Computer software is often called robust if it keeps functioning under conditions it was intentionally not made for, such as unexpected user behavior, invalid input data, or other stressful environmental

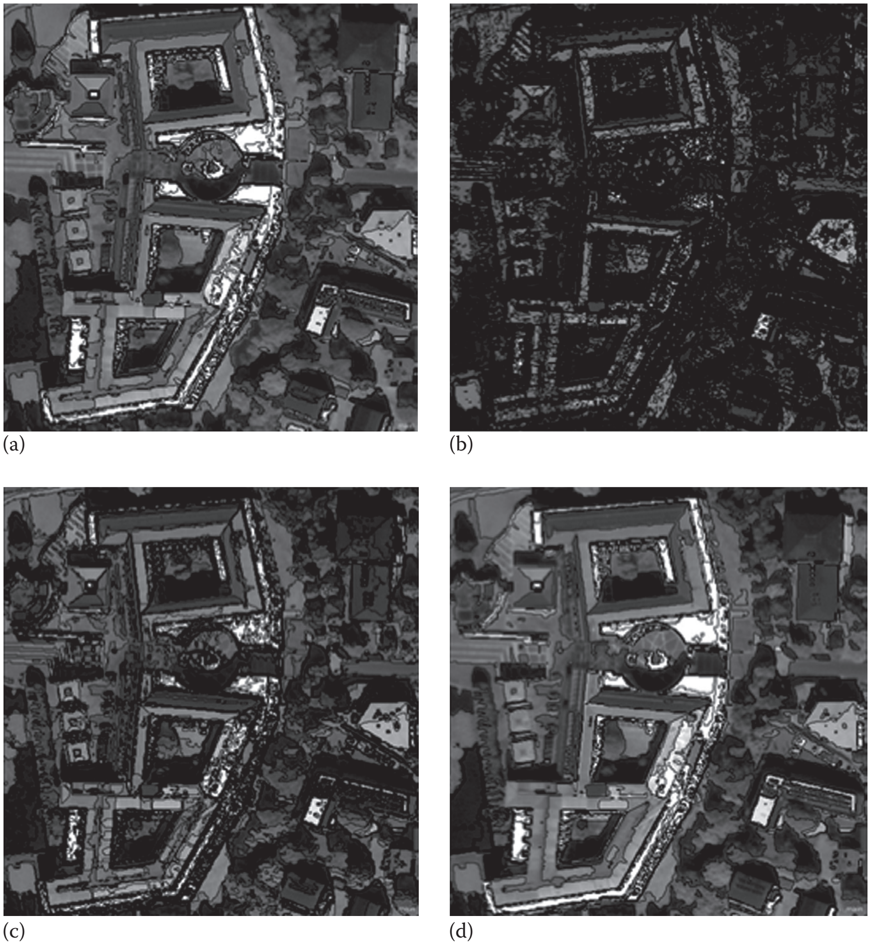

FIGURE 16.2 Different segmentation results (spectral difference) for different radiometric resolutions. (a) 8-bit, spectral difference threshold = 10. (b) 16-bit, spectral difference threshold = 10. (c) 16-bit, spectral difference threshold = 30. (d) 16-bit spectral difference threshold = 90.

conditions, for example, hardware faults (IEEE 1990; Kropp et al. 1998; Fernandez et al. 2005; Shahrokni and Feldt 2013). In the context of OBIA, rule sets can be considered robust if they produce similar results with similar quality on similar images with minimum adaptation effort (Hofmann et al. 2011). As we saw already in Section 16.2.2, different image properties have an impact on the initial segmentation results and therefore on the object quality. Thus, a prerequisite for a sensible rule set evaluation is comparable image objects. After a rule set has been adapted to an image and has produced acceptable classification results, the rule set's deviations in conjunction with the achieved classification accuracy can be investigated. Analyzing these deviations can be considered as the robustness analysis of a rule set. It becomes more reliable the more often it is applied on different varying but similar images. Classification rules are usually of the following form:

If <condition> is fulfilled then assign Object O to Class C

In OBIA classification, rules are used to assign image objects to respective classes. They can be nested, that is, objects which fulfill a variety of (pre)conditions can be selected for class assignment:

If <condition$_1$*> is fulfilled then*

If <condition$_2$*> is fulfilled then*

…

If <condition$_n$*> is fulfilled then assign Object O to Class C*

The conditions 1 to *n* can be pooled into one condition using a logical *AND* operator:

If <condition$_1$*> AND <condition*$_2$*> AND … <condition*$_n$*> are fulfilled then assign Object O to Class C*

When classifying, for all image objects the conditions are evaluated in terms of *TRUE* and *FALSE*. Thus, nested rules have the advantage of reducing computing time, since for the first condition to be *FALSE*, the evaluation of all following rules is skipped. Consequently, the number of objects to be fully evaluated is reduced to the number of objects fulfilling all conditions. However, conditions can also be combined with logical *OR* operators:

If <condition$_1$*> OR <condition*$_2$*> OR … <condition*$_n$*> is fulfilled then assign Object O to Class C*

In such cases, all conditions need to be evaluated per object, since the object is only not assigned to class *C* if all of the conditions 1 to *n* are *FALSE*. Classification rules as described earlier can also be considered as class descriptions. That is, class *C* is described by the conditions to be fulfilled per object in order to assign the object to class *C*. Elaborate class descriptions can consist of a variety of combined *AND* and *OR* conditions, as well as of explicit negations (*NOT* or ¬). In order to analyze the robustness of an existing rule set, it is necessary to measure its deviations if it is adapted and applied to similar images. Rule set deviations can be of the following forms:

1. Adding or subtracting classes to or from the rule set
2. Adding or subtracting single rules to or from class descriptions
3. Changing logical operators in rules
4. Changing relational operators in rules
5. Changing thresholds in rules

Enumerating these deviations is a first attempt to quantifying a rule set's robustness: the more the deviations, the less robust the rule set is. In the case that fuzzy classification rules (Benz et al. 2004) are applied, changes in the shape of each fuzzy membership function need to be considered, too (Hofmann et al. 2011), which is somewhat equivalent to points (4) and (5). Taking classification accuracy into account means comparing the accuracy that was achieved in the original image(s) the rule set was developed on with the accuracy achieved in all different images with respective adapted rule sets. For comparison reasons, the accuracy needs to be measured for the original rule set and all adapted rule sets identically, whereas the method used is indifferent but should be chosen adequately. Although there is a variety of accuracy assessment methods available (Van Rijsbergen 1979; Congalton and Green 1999), not all of them are suited for particular cases and not all of them produce equal values; therefore, for quantifying a rule set's robustness, normalizing the classification accuracy is necessary. Thus, measuring a rule set's robustness is always bound to the chosen method of accuracy assessment. For a rule set developed on one image and being adapted and reapplied on a similar image, we can formally describe the rule set's robustness r as follows:

$$r = \frac{q_2/q_1}{d+1} \tag{16.1}$$

with q_1 the accuracy achieved in the original image, q_2 the accuracy achieved in the image the rule set was reapplied on, and $q_1, q_2 \in \{0\ldots1\}$. d is the sum of all deviations of the rule set after adaptation as outlined under points (1) to (5) earlier. After a rule set is adapted and applied on several images, its mean robustness can be calculated easily. To determine the deviation for fuzzy rules (cases 4 and 5), the following points need to be considered: a membership function expresses the degree of membership μ with $\mu \in \{0\ldots1\}$ to a class regarding a value range vr with an upper bound v_u and a lower value bound v_l of a given property. A value of $\mu(v) = 0$ indicates for an object no membership concerning property value v. A value of $\mu(v) = 1$ in contrast means a full membership. The center value a of the membership function is given by $a = v_l + (vr/2)$ or $a = v_u - (vr/2)$. It indicates the crisp property value the membership function represents in terms of a classification rule. Fuzzy membership functions can be roughly categorized as depicted in Table 16.1.

In principle, fuzzy membership functions can have any kind of shape. However, in practice, three types have been established since they are easier to interpret and understand than complex shape functions. Nevertheless, membership functions can also be of linear shape, that is, without soft transitions at the extremes. Combining a fuzzy-lower-than with a fuzzy-greater-than function leads to a t-norm function, whereas v_u of the greater-than function is identical to v_l of the lower-than function. Both are identical to a of the created t-norm function. t-norm functions can also have a value range of $\mu(v) = 1.0$, which gives them a plateau-like shape. In the case where the slope of the membership function is at $\mu'(v) = 1.0$ for value v and the membership at this value is at $\mu(v) = 1.0$ or $\mu(v) = 0.0$, the membership function is called crisp,

TABLE 16.1
Principal Categories of Fuzzy Membership Functions

Category	Symbol	$\mu(v_l)$	$\mu(a)$	$\mu(v_u)$
t-Norm (triangular)		0.0	1.0	0.0
Fuzzy-lower-than		1.0	0.5	0.0
Fuzzy-greater-than		0.0	0.5	1.0

which is equal to threshold setting. If the function has only one property value v with $\mu'(v) = 1.0$ and $\mu(v) = 1.0$, the function is called a singleton, which is the same as the identity: $\mu(v) \equiv 1.0$. The deviation δF of a membership function after adaptation to a similar image is the sum of the membership function's shift δa and its stretch or compression δv:

$$\delta F = \delta a + \delta v \tag{16.2}$$

where $\delta a = 0$ if the function of concern is not shifted and $\delta v = 0$ if the function is neither stretched nor compressed. In the case where the membership function has been shifted in a positive direction along the v-axis, its deviation is given by $\delta a = 1 - (a_2/a_1)$. For a negative shift, it can be determined by $\delta a = 1 - (a_1/a_2)$. Analogously, the function's stretch or compression can be determined by $\delta v = 1 - (vr_2/vr_1)$ for stretching a function and $\delta v = 1 - (vr_1/vr_2)$ for compressing it. By systematically analyzing all possible rule set deviations as described earlier, critical rules can be determined automatically: rules that deviate in a wide range, that is, have a high value for δF, or classes that often have different descriptions have a high negative impact on the overall robustness of the rule set (see Table 16.3). For a good rule set design in terms of transferability, one should consider skipping or exchanging such rules or classes by other, potentially more robust (i.e., less deviating) rules.

16.3 OBIA RULE SETS FOR DETECTING INFORMAL SETTLEMENTS

16.3.1 Image Ontology for Informal Settlements

Developing an OBIA rule set in principle means to define rules that translate object properties into semantically meaningful real-world classes (Arvor et al. 2013). This is either done implicitly by sample-based classification mechanisms or explicitly by defining respective classification rules (Section 16.2.3). The latter has the advantage of being easily adapted to changing imaging conditions, if necessary, and allows formulating additional expert knowledge, such as spatial relationships. However, for being transferable, an OBIA rule set should reflect at least the underlying top-level ontology (Section 16.1.3). That is, the structure of the rule set, its classes, and

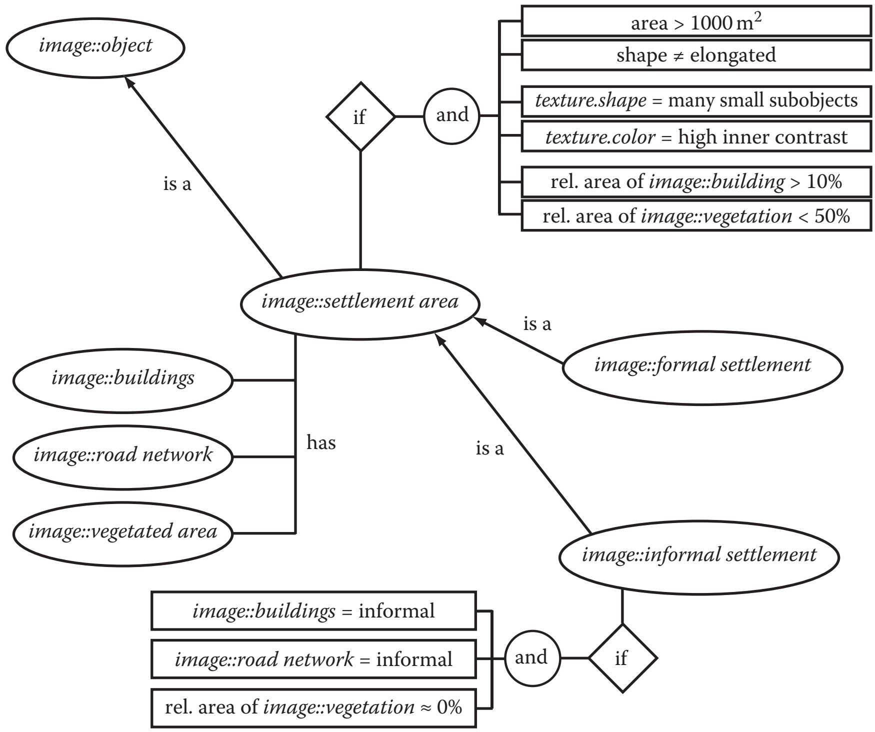

FIGURE 16.3 Top-level ontology for informal settlements, their components, and their appearance in remote sensing data (image::).

the classes' spatial dependencies together with some basic concepts should be similar to the respective ontology (Hofmann 2005; Kholi et al. 2012, Figure 16.3).

The domain description *image::* indicates that the ontology describes object classes as they can be observed in remote sensing data. Each *image::* class refers to a respective real-world class. The class *image::settlement area* is described by two principal characteristics: existence prerequisites of other object classes and physical object conditions. The former are described by the *has*-relations: *image::settlement area has image::buildings, image::road network, image::vegetated area*. The latter describe measurable thresholds in a fuzzy manner, such as *many small subobjects* or *shape ≠ elongated*. Consequently, if an image object cannot refer to building, road, or vegetation subobjects or if it is too elongated, it cannot be a settlement area at all. The class *image::informal settlement* is described as a subclass of *image::settlement area* by the *is_a* relation. Thus, it inherits the properties of *image::settlement area*. That is, the same prerequisites are valid for *image::informal settlement* but it distinguishes itself by its informal characteristics (*image::buildings = informal*, *image::road network = informal*, and *rel. area of image::vegetation ≈ 0%*). The rules that make *image::buildings = informal* and *image::road network = informal* are to be defined in separate ontologies. The same holds for the fuzzy concepts *elongated* or *high inner contrast*.

16.3.2 Transforming the Ontology into a Rule Set

For detecting informal settlements in VHR remote sensing images, a respective OBIA rule set has been developed, based on a pan-sharpened IKONOS scene depicting the so-called Cape Flats in Cape Town. The scene was captured on March 19, 2000. The rule set was adapted and reapplied on a pan-sharpened QuickBird scene showing the Ilha do Governador in Rio de Janeiro on May 14, 2002. As a development framework, the cognition network language (CNL) has been used, which is implemented in the software eCognition® (Trimble 2013).

16.3.2.1 Initial Segmentation Rules

The rule set starts with a two-level MRS, whereas on the top level, the average object size is at 5923 m^2 and on the base at 49 m^2. The segmentation parameters for the IKONOS scene were determined empirically by trial and error. Inspecting the segmentation results visually, the top-level segmentation depicts relatively good settlement structures at block level, including informal settlements. On the base level, small structures such as road segments, shacks, small buildings, and shadows are relatively well outlined. However, in many cases, the shacks and their shades are visually hardly distinguishable and neither is the segmentation. Nevertheless, with the two-level segmentation (see Figure 16.4) approach, the ontological relationships *image::settlement area has image::buildings*, *image::settlement area has image::road network*, and *image::settlement area has image::vegetated area* can be described as spatial-hierarchical sub- and superobject relationships. Similarly, the properties *texture.shape* and *texture.color* can be described by statistical parameters of the subobjects shape and color properties per superobject, such as the mean area of subobjects per superobject or the mean spectral difference of subobjects per superobject (Trimble 2012a). The segmentation of the QuickBird scene has been adapted according to the ratio between the sensors' pixel size (Section 16.2.1; Table 16.2) and applied with comparable results (Figure 16.5).

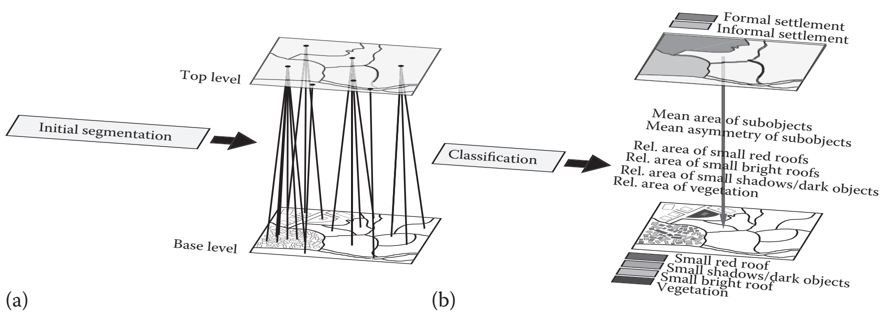

FIGURE 16.4 (**See color insert.**) Object-hierarchical relationships after segmentation (parameterization, see Table 16.2) and classification between top- and base-level objects. For detailed class descriptions, see Table 16.3. Every top-level object relates to its subobjects in the base level and vice versa (a). Relationships to subobjects can be used for classification of superobjects (b).

TABLE 16.2
MRS Parameters Used for Initial Image Segmentation

	IKONOS, Cape Town		QuickBird, Rio de Janeiro	
	Top Level	**Base Level**	**Top Level**	**Base Level**
Scale parameter	100	10	144	14
w_{color}	0.2	0.1	0.2	0.1
w_{shape}	0.8	0.9	0.8	0.9
Compactness	0.5	0.5	0.5	0.5
Smoothness	0.5	0.5	0.5	0.5

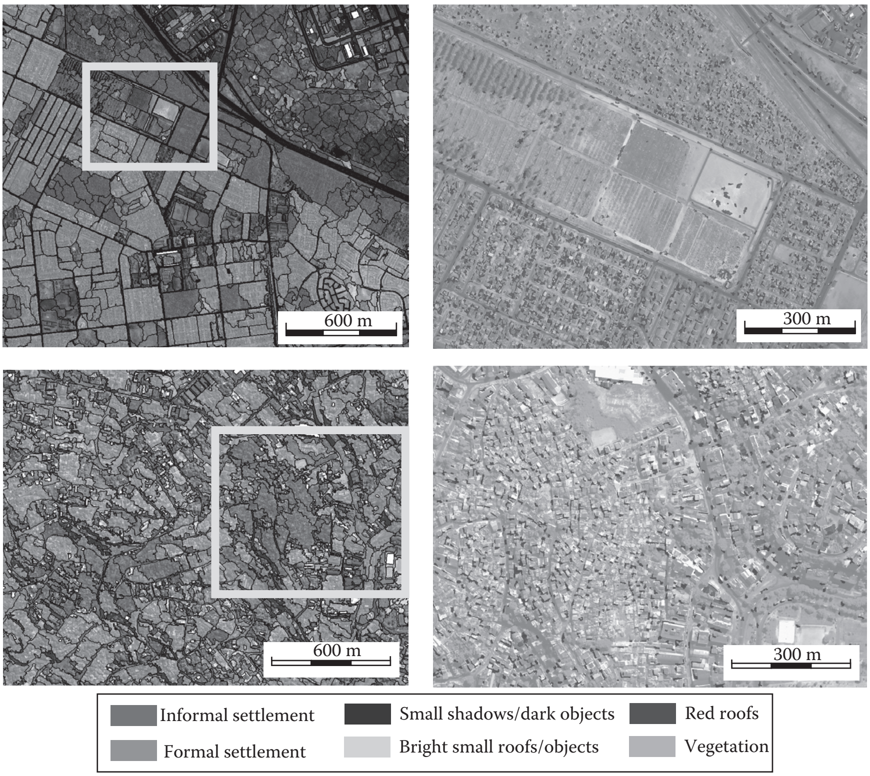

FIGURE 16.5 (**See color insert.**) Segmentation and classification results for IKONOS (top) and QuickBird (bottom). Left: top segmentation level with respective classes. Right: base segmentation level with respective classes. Blue rectangle in the left images indicates the location of the right images.

Since the initial segmentation result reflects informal settlement areas clearly, no further segmentation enhancements were performed.

16.3.2.2 Classification Rules

The classification rules were directly applied on the initially generated image objects, where the class descriptions intended to reflect the underlying ontology as well as possible. Respective classes described by fuzzy membership functions were developed, where the rule set initially consisted of three top-level classes: *settlement*, *informal settlement*, and *formal settlement*. *Formal settlement* and *informal settlement* are subclasses of *settlement* and therefore inherit its properties (see Section 16.3.1; Trimble 2012b: 95–111 and Table 16.3). The class *formal settlement* then acts as the inverse of class *informal settlement*. That is, objects fulfilling the criteria of *settlement* in general but not those of *informal settlement* are a *formal settlement* if they are fuzzy-greater than 1850 m^2. At base level, single shacks or other buildings with informal character (*image::buildings = informal*) are not undoubtedly identifiable. Thus, two classes were created indicating the settlement's structure in a rather fuzzy manner: *bright small roofs/objects* and *small shadows/dark objects*. While the former roughly outlines small square objects with bright roofs (e.g., shacks with roofs made from metal sheets), the latter just outlines dark objects that can be a shack or its shadow or both. The classes *red roofs* (*image::buildings ≠ informal*) and *vegetation* (*image::vegetation*) are rather clear: *red roofs* are simply determined by a high ratio of the red band to the green band in an object, while *vegetation* shows a high fraction of the near-infrared band in an object. At the top segmentation level, the ontological concepts for informal settlement *image::buildings = informal* is realized by pointing to the corresponding classes at base level, that is, evaluating the settlement structure. For this purpose, the following properties have been used: *area of subobjects (1), relative area of bright small roofs/objects subobjects (1), relative area of red roofs subobjects (1),* and *relative area of small shadows/dark objects subobjects (1)* (see Figure 16.4 and Table 16.3). The concept *image::road network = informal* is realized by the rule *asymmetry of subobjects: mean (1)*. Asymmetry measures how elongated an object is. The higher the asymmetry, the more elongated the object is. An irregular road network, such as that of informal settlements, leads to a relatively lower mean asymmetry within a settlement area. Accordingly, the *asymmetry of subobjects: mean (1)* of informal settlement areas must be lower than that of formal settlement areas. The concept *relative area of image::vegetation* ≈ 0% was directly implemented as a fuzzy membership function. For detailed class descriptions, refer to Table 16.2.

The class descriptions applied were all performed using the respective fuzzy membership functions (see Section 16.2.3). This approach has two advantages: (1) it allows to better express fuzzy concepts, such as *red* or *rectangular*, and (2) slight property variations in the data can be more easily captured. This is of advantage, especially for the detection of informal settlements, since even on a local level their patterns can be varied. Additionally, transitional forms of settlements are detectable by their membership degree to *informal settlement* and *formal settlement*, respectively. That is, a transitional settlement type has an overall membership to both classes by $\mu \neq 0$ and at least $\mu > 0.3$, which is the threshold set for defuzzification.

TABLE 16.3
Fuzzy Class Descriptions and Deviations for IKONOS (Cape Town) and QuickBird (Rio de Janeiro) Rule Set

Class	Property	Membership Function	Cape Town		Rio de Janeiro		Deviations		
			vr_1	a_1	vr_2	a_2	δv	δa	δF
Top level (level 2)									
Settlement	Area of subobjects (1)		3.00	43.50	3.00	51.50	0.00	0.18	0.18
	Asymmetry		0.01	0.96	0.01	0.96	0.00	0.00	0.00
	Average mean difference to neighbors of subobjects (NIR-channel) (1)		233.00	210.20	230.00	235.00	0.01	0.12	0.13
	Relative area of small shadows/dark objects subobjects (1)		0.00	0.01	0.00	0.01	0.00	0.00	0.00
	Relative area of vegetation subobjects (1)		0.10	0.45	0.10	0.45	0.00	0.00	0.00
Formal settlement	Area [m^2]		100.00	1850.00	100.00	1850.00	0.00	0.00	0.00
	Not informal settlement								
Informal settlement	Area of subobjects (1) [m^2]		2.00	40.00	2.00	37.00	0.00	0.08	0.08
	Asymmetry of subobjects: mean (1)		0.02	0.56	0.02	0.62	0.00	0.10	0.10
	Relative area of bright small roofs/objects subobjects (1)		0.01	0.04	0.01	0.06	0.00	0.71	0.71
	Relative area of red roofs subobjects (1)		0.0002	0.006	0.01	0.02	49.00	1.79	50.79

(*continued*)

TABLE 16.3 (continued)
Fuzzy Class Descriptions and Deviations for IKONOS (Cape Town) and QuickBird (Rio de Janeiro) Rule Set

Class	Property	Membership Function	Cape Town		Rio de Janeiro		Deviations		
			vr_1	a_1	vr_2	a_2	δv	δa	δF
	Relative area of small shadows/dark objects subobjects (1)		0.02	0.03	0.02	0.03	0.00	0.00	0.00
	Relative area of vegetation subobjects (1)			—	0.01				
Base level (level 1)									
Small shadows/dark objects	Area		5.00	37.50	5.00	37.50	0.00	0.00	0.00
	Ratio blue channel		0.13	0.26	0.13	0.32	0.00	0.20	0.20
Vegetation	Ratio NIR-channel		0.01	0.30	0.01	0.30	0.00	0.00	0.00
Red roofs	Ratio red channel/ratio green channel		0.01	1.10	0.05	1.28	4.00	0.16	4.16
Bright small roofs/objects	Area		20.00	50.00	20.00	50.00	0.00	0.00	0.00
	Brightness		25.00	762.50	25.00	762.50	0.00	0.00	0.00
	Shape index				0.10				
								$\sum\delta F$	56.35

Note: For detailed property descriptions, see Trimble 2012a.

Assuming that the developed rule set reflects the ontology for informal settlements at best, for each classified object it can be expressed to what degree (of membership) it fulfills the criteria of the informal settlement prototype. Vice versa, each image object is a gradual member of the class (concept) informal settlement or formal settlement of the ontology.

16.4 ROBUSTNESS ANALYSIS OF THE DEVELOPED RULE SET

16.4.1 Robustness Measurement

In order to analyze the robustness of the developed rule set, it was reapplied to the segmented QuickBird scene of Rio and single rules were adapted manually until acceptable classification results were obtained. The respective deviations were determined as outlined in Section 16.2.3 and displayed in Table 16.3. In both scenes, the classification accuracy has been generated by comparing each classification with a complete manual reference map. In the IKONOS scene, 215 ha (true positives) of informal settlements were classified correctly, whereas 50 ha were omitted by the classifier (false negatives) and 93 ha were mapped wrongly as informal settlement (false positives). This leads to precision *prec*, recall *rec*, and quality *qual* (Van Rijsbergen 1979; Heipke et al. 1997) as follows:

$$prec = \frac{\text{True positives}}{\text{True positives} + \text{false positives}} = \frac{2{,}151{,}138\,\text{m}^2}{2{,}151{,}138\,\text{m}^2 + 930{,}314\,\text{m}^2} = 0.70 \tag{16.3}$$

$$rec = \frac{\text{True positives}}{\text{True positives} + \text{false negatives}} = \frac{2{,}151{,}138\,\text{m}^2}{2{,}151{,}138\,\text{m}^2 + 499{,}624\,\text{m}^2} = 0.81 \tag{16.4}$$

$$\begin{aligned} qual &= \frac{\text{True positives}}{\text{True positives} + \text{false positives} + \text{false negatives}} \\ &= \frac{2{,}151{,}138\,\text{m}^2}{2{,}151{,}138\,\text{m}^2 + 930{,}314\,\text{m}^2 + 499{,}624\,\text{m}^2} = 0.60 \end{aligned} \tag{16.5}$$

As $prec \in \{0 \ldots 1\}$, $rec \in \{0 \ldots 1\}$, and $qual \in \{0 \ldots 1\}$, no normalization for robustness analysis is necessary. In the QuickBird scene, we could achieve accuracies of $prec = 0.52$, $rec = 0.68$, and $qual = 0.31$. Regarding the rule set deviation, in the present case, two rules were added to the QuickBird rule set: *relative area of vegetation subobjects* (1) for the description of informal settlements (for the Cape Town scene, this rule was not necessary) and *shape index* for describing the fuzzy class *bright small roofs/objects*. No classes were added or deleted and no logical or relational operators were added, deleted, or changed. That is, the rest of the deviations are changes of the fuzzy membership functions' values δF. According to Table 16.2, they sum up to

$\Sigma\delta F = 56.35$, which leads to an overall deviation of $d = 56.35 + 2 = 58.35$. Together with the achieved accuracies, we obtain a robustness of $r_{prec} = 0.012$ if we use precision, $r_{rec} = 0.014$ if we use recall, and $r_{qual} = 0.009$ if we use quality as the criterion. Considering that for $r > 1$, classification results are improving ($q_2 > q_1$) with little or no deviation ($d \approx 0$) and that for $r < 1$, the rule set was adapted ($d > 0$) but results did not improve ($q_2 \leq q_1$), the rule set must be seen as not very robust. Vice versa, if r was at ~1.0 or higher, the rule set would be very robust.

16.4.2 Interpretation of Robustness Measurement Results

Regarding the deviations of the fuzzy membership functions δF, there are some rules with no deviation ($\delta F = 0.0$), some with slight deviation ($0.0 < \delta F \leq 0.1$), one rule with higher deviation ($\delta F = 4.16$), and one rule with extreme deviation ($\delta F = 50.79$). While the rules with no and slight deviation can be interpreted as robust, the remaining rules seem to react more sensitively on image variations. In relation to the overall deviation $d = 58.35$, the impact of the extreme deviating rule on the rule set's robustness is very high (~87% of the overall deviation but only 1 rule out of 20). This indicates that the rule *relative area of red roofs subobjects (1)* is not easily transferable and should therefore be skipped or substituted, if possible. The impact of the rule *ratio red channel/ratio green channel* is comparably ~8.2% low although the sum of all other deviations equals 2.8%. Since the rule *relative area of red roofs subobjects (1)* indicates the density of small buildings with red roofs, the following considerations make the rule's high deviation plausible: while in South Africa the shacks' roofs are mainly made of plastic, iron sheets, or wood, in Rio, brick is more common. Thus, the *relative area of red roofs subobjects (1)* per informal settlement object must be higher in Rio. The deviation for the class *red roofs* could be explained by different construction material, too.

Excluding δF for *relative area of red roofs subobjects* (1) from the calculation of d, the robustness core parameters change to $\Sigma\delta F = 5.56$ and $d = 7.56$, leading to a slightly increased robustness of $r_{prec} = 0.09$, $r_{rec} = 0.10$, and $r_{qual} = 0.06$, respectively. If, additionally, the deviation for *ratio red channel/ratio green channel* of the class *red roofs* is excluded, overall deviations of $\Sigma\delta F = 1.4$ and $d = 3.4$ are produced, leading to a robustness of $r_{prec} = 0.17$, $r_{rec} = 0.19$, and $r_{qual} = 0.12$.

16.5 OUTLOOK TOWARD SEMIAUTOMATED TECHNIQUES OF MAPPING INFORMAL SETTLEMENTS

Although OBIA is a reasonable method for analyzing VHR remote sensing data, especially in the context of detecting and monitoring informal settlements, the design of rule sets is of core importance. For transferability and flexibility reasons, it should reflect the underlying ontology of the objects of concern. Simultaneously, it needs to take into account the imaging situation of the data used. This implies that there is no general rule set for the detection of informal settlements possible, but the effort for adaptation can be reduced if the rule set reflects the top-level ontology as well as possible. By measuring the robustness of rule sets, on the one hand, the suitability of a given rule set for a given application can be determined and, on the other hand, critical rules can be identified; that is, rules that might need to be adapted if the rule set is applied on similar data. As long as the ontology is not violated, such rules should be avoided or substituted. In the presented case, the rule set was applied directly on the initially generated image objects with relatively good results. As pointed out, a generic adaptation of initial segmentation parameters to varying image data is hardly feasible. However, classification results could certainly be improved if further dedicated (re)segmentation procedures were applied, generating optimal image objects. Especially the structural elements *buildings* and *road network*, which are key elements in identifying (informal) settlements, were described and detected in a fuzzy manner. Although robustness analysis has been applied only on two images, the results indicate a majority of robust rules in the developed rule set. Recent OBIA technologies allow creating solutions for highly automated image analysis. When reapplied on similar images, the necessary adjustments of a rule set can be performed even by a nonspecialist very easily. An example is given by eCognition Architect (Trimble 2013). For the present case, it would be easily possible to embed the developed rule set in a respective eCognition Architect environment. Necessary adaptations, especially those for critical rules, could be performed using respective slider widgets and/or buttons in a graphical user interface (GUI). This way, a variety of VHR images could be analyzed fast and as automated as possible.

ACKNOWLEDGMENTS

The author would like to thank Heinz Rüther of the University of Cape Town and Thomas Blaschke and Joseph Strobl of Salzburg University for their support, Space Imaging for providing the IKONOS scene, and INTERSAT for providing the QuickBird scene.

REFERENCES

African Population and Health Research Center (APHRC). 2002. *Population and Health Dynamics in Nairobi's Informal Settlements*. Nairobi, Kenya: African Population and Health Research Center.

Arvor, D., Durieux, L., Andrés, S., and M.-A. Laporte. 2013. Advances in geographic object-based image analysis with ontologies: A review of main contributions and limitations from a remote sensing perspective. *ISPRS Journal of Photogrammetry and Remote Sensing*, 82, 125–137.

Baatz, M., Hoffmann, C., and G. Willhauck. 2008. Progressing from object-based to object-oriented image analysis. In *Object Based Image Analysis*, eds. T. Blaschke, S. Lang, and G. Hay. New York: Springer.

Baatz, M. and A. Schäpe. 2000. Multiresolution segmentation an optimisation approach for high quality multi-scale image segmentation. In *Angewandte Geographische Informationsverarbeitung*, vol. XII., eds. Strobl, J. et al., pp. 12–23. Karlsruhhe: Wichman.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., and M. Heynen. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, 58, 239–258.

Berman, S. 1997. Civil society and the collapse of the Weimar Republic. *World Politics*, 49, 401–429.

Blaschke, T. and J. Strobl. 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *GIS Zeitschrift für Geoinformationssysteme*, 6, 12–17.

Canham, S. and R. Wu. 2008. *Portrait from above Hong Kong's Informal Rooftop Communities*, 2nd edn. Berlin, Germany: Peperoni Books.

Congalton, R.G. and K. Green. 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton, FL: Lewis Publishers.

Davis, M. 2006. *Planet of Slums*. London, U.K.: Verso.

Fernandez, J., Mounier, L., and C. Pachon. 2005. A model-based approach for robustness testing. In *Testing of Communication Systems, Lecture Notes in Computer Science 3502*, eds. F. Khendek and R. Dssouli, *Proceedings of 17th IFIP TC6/WG 6.1 International Conference TestCom 2005*, Montreal, Canada, May 31–June 2, 2005.

Guarino, N. 1997a. Some organizing principles for a unified top-level ontology. In *Proceedings of AAAI Spring Symposium on Ontological Engineering*. Stanford, CA: AAAI Press.

Guarino, N. 1997b. Semantic matching: Formal ontological distinctions for information organization, extraction, and integration. In *Information Extraction: A Multidisciplinary Approach to an Emerging Information Technology*, ed. M.T. Pazienza. Berlin, Germany: Springer, pp. 139–170.

Hay, G.J. and G. Castilla. 2006. Object-based image analysis: Strengths, weakness, opportunities and threats (SWOT). *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVI-4/C42. CD-ROM.

Heipke, C., Mayer, H., and C. Wiedemann. 1997. Evaluation of automatic road extraction. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 32(3-4W2), 151–160.

Hofmann, P. 2001. Detecting informal settlements from IKONOS image data using methods of object oriented image analysis—An example from Cape Town (South Africa). In *Proceedings of the Second International Symposium Remote Sensing of Urban Areas*, ed. C. Jürgens, Regensburg, Germany, pp. 107–118.

Hofmann, P. 2005. Übertragbarkeit von Methoden und Verfahren in der objektorientierten Bildanalyse das Beispiel informelle Siedlungen (Transferability of methods and procedures in object-oriented image analysis the example of informal settlements). Dissertation, University of Salzburg, Salzburg, Germany.

Hofmann, P., Blaschke, T., and J. Strobl. 2011. Quantifying the robustness of fuzzy rule sets in object-based image analysis. *International Journal of Remote Sensing*, 32(22), 7359–7381.

Hofmann, P., Strobl, J., and T. Blaschke. 2008a. A method for adapting global image segmentation methods to images of different resolutions. In *Proceedings of the Second International Conference on Geographic Object-Based Image Analysis*, eds. G. Hay, T. Blaschke, and D. Marceau, University of Calgary, Calgary, Alberta, Canada. CD-ROM.

Hofmann, P., Strobl, J., Blaschke, T., and H.J. Kux. 2008b. Detecting informal settlements from QuickBird data in Rio de Janeiro using an object-based approach. In *Object Based Image Analysis*, eds. T. Blaschke, S. Lang, and G.J. Hay. Heidelberg, Germany: Springer, pp. 531–554.

IEEE Std 610.12-1990, IEEE standard glossary of software engineering terminology, 1990.

Jen, E. 2003. Essays & commentaries: Stable or robust? What's the difference? *Complexity*, 8(3), 12–18.

Kohli, D., Sliuzas, R., Kerle, N., and A. Stein. 2012. An ontology of slums for image-based classification. *Computers, Environment and Urban Systems*, 36, 154–163.

Kit, O., Lüdeke, M., and D. Reckien. 2012. Texture-based identification of urban slums in Hyderabad, India using remote sensing data. *Applied Geography*, 32, 660–667.

Kitano, H. 2007. Towards a theory of biological robustness. *Molecular Systems Biology*, 3, 137.

Kropp, N.P., Koopman, P.J., and D.P. Siewiorek. 1998. Automated robustness testing of off-the-shelf software components. In *Proceedings of the Twenty-Eighth Annual International Symposium on Fault-Tolerant Computing*, Munich, Germany, June 23–25, 1998, pp. 230–239. IEEE Computer Society.

Kuffer, M. 2003. Monitoring the dynamics of informal settlements in Dar Es Salaam by remote sensing: Exploring the use of SPOT, ERS and small format aerial photography. In *Proceedings of CORP 2003*, ed. M. Schrenk. Vienna, Austria: Technical University Vienna, pp. 473–483.

Meinel, G. and M. Neubert. 2004. A comparison of segmentation programs for high resolution remote sensing data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXV-B4, 1097–1102.

Neubert, M. and H. Herold. 2008. Assessment of remote sensing image segmentation quality. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-4/C1. CD-ROM.

Neubert, M., Herold, H., and G. Meinel. 2008. Assessing image segmentation quality concepts, methods and applications. In *Object Based Image Analysis*, eds. T. Blaschke, S. Lang, and G. Hay. New York: Springer.

Niebergall, S., Loew, A., and W. Mauser. 2008. Integrative assessment of informal settlements using VHR remote sensing data: The Delhi case study. *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*, 1(3), 193–205.

Radnaabazar, G., Kuffer, M., and P. Hofstee. 2004. Monitoring the development of informal settlements in Ulaanbaatar, Mongolia. In *Proceedings of CORP 2004*, ed. M. Schrenk. Vienna, Austria: Technical University Vienna, pp. 333–339.

Sartori, G., Nembrini, G., and F. Stauffer. 2002. Monitoring of urban growth of informal settlements (IS) and population estimation from aerial photography and satellite imaging. Occasional paper, Geneva Foundation. http://vince.mec.ac.ke/publications/urban-growth-of-informal-settlements-is/ (accessed March 5, 2003).

Shahrokni, A. and R. Feldt. 2013. A systematic review of software robustness. *Information and Software Technology*, 55(1), 1–17.

Sliuzas, R. and M. Kuffer. 2008. Analysing the spatial heterogeneity of poverty using remote sensing: Typology of poverty areas using selected RS based indicators. In *Proceedings of the EARSel Joint Workshop: Remote Sensing New Challenges of High Resolution*, Bochum, Germany, pp. 158–167.

Sliuzas, R., Mboup, G., and de A. Sherbinin. 2008. Report of the expert group meeting on slum identification and mapping. Report by CIESIN, UN-Habitat, ITC. http://www.ciesin.columbia.edu/confluence/download/attachments/39780353/EGM_slum_mapping_report_final.pdf?version=1 (accessed March 7, 2013).

Smith, G. and D. Morton. 2008. Segmentation: The Achilles heel of object-based image analysis? *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-4/C1. CD-ROM.

Subieta, K. 2000. Mapping heterogeneous ontologies through object views. In *Engineering Federal Information Systems: Proceedings of the Third Workshop* (*EFIS 2000*), eds. M. Roantree, W. Hasselbring, and S. Conrad. Berlin, Germany: Akad. Verl.-Ges. Aka, pp. 1–10.

Taubenböck, H. and N.J. Kraff. 2013. The physical face of slums: A structural comparison of slums in Mumbai, India, based on remotely sensed data. *Journal of Housing and the Built Environment*. http://link.springer.com/article/10.1007/s10901-013-9333-x/fulltext.html (accessed March 5, 2013).

Trimble. 2012a. *eCognition® Developer 8.8 Reference Book*. Munich, Germany: Trimble Documentation.

Trimble. 2012b. *eCognition® Developer 8.8 User Guide*. Munich, Germany: Trimble Documentation.

Trimble. 2013. *Introducing eCognition 8.8*. http://www.ecognition.com/ (accessed March 2013).

UNESCO. 2012. New research about favelas is launched during international seminar in Rio de Janeiro. http://www.unesco.org/new/en/brasilia/about-this-office/single-view/news/new_research_about_slums_to_be_launched_during_international_seminar_in_rio_de_janeiro/ (accessed March 5, 2013).

UN-HABITAT. 2007. Slum dwellers to double by 2030: Millennium development goal could fall short. http://www.unhabitat.org/downloads/docs/4631_46759_GC%2021%20Slum%20dwellers%20to%20double.pdf (accessed March 5, 2013).

UN-HABITAT. 2011. Cities and climate change. Global report on human settlements 2011. United Nations Human Settlement Programme. Earthscan, London, U.K. http://www.unhabitat.org/documents/SOWC10/R1.pdf (accessed March 5, 2013).

Van Coillie, F.M.B., Pires, P.L.V.M., Van Camp, N.A.F., and S. Gautama. 2008. Quantitative segmentation evaluation for large scale mapping purposes. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-4/C1. CD-ROM.

Van Rijsbergen, C. 1979. *Information Retrieval*. London, U.K.: Butterworth-Heinemann.

Veljanovski, T., Kanjir, U., Pehani, P., Oštir, K., and P. Kovačič. 2012. Object-based image analysis of VHR satellite imagery for population estimation in informal settlement Kibera-Nairobi, Kenya. In *Remote Sensing Applications*, ed. B. Escalante-Ramirez. DOI: 10.5772/37869. http://www.intechopen.com/books/remote-sensing-applications/object-based-image-analysis-of-vhr-satellite-imagery-for-population-estimation-in-informal-settl (accessed March 6, 2013).

Weber, C. and A. Puissant. 2003. Urbanization pressure and modelling of urban growth: Example of the Tunis Metropolitan Area. *Remote Sensing of Environment*, 86(3), 341–352.

Zhang, H., Fritts, J.E., and S.A. Goldman. 2008. Image segmentation evaluation: A survey of unsupervised methods. *Computer Vision and Image Understanding*, 110(2), 260–280.