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# Segmentation of Remotely Sensed Imagery: Moving from Sharp Objects to Fuzzy Regions

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## 1. Introduction

The increasing availability of remotely sensed imagery data with high spatial resolution is demanding more efficient, and more accurate methods for image analysis. Traditional per-pixel classifiers focus on analysing spectral characteristics of single pixels and ignore contextual properties from surrounding pixels (Townshend et al., 2000). This inability to integrate neighbourhood information triggered the need of developing image analysis algorithms able to go 'beyond pixels' and take also into account spatial information (Jensen, 2005).

New approaches for land cover characterization from high spatial resolution images include object-based image analysis (OBIA), also referred to as geospatial object based image analysis (GEOBIA) (Blaschke, 2010). OBIA uses segmentation techniques to group pixels into discrete image objects as a first stage of the image analysis process. By analysing image objects rather than individual pixels, it is then possible to include spatial and/or textural properties of image objects into the process (Blaschke et al., 2006). Recent research demonstrates that this segmentation based approach for image classification produces higher thematic accuracy than the traditional per-pixel methods (Blaschke et al., 2006; Lang et al., 2006; Platt & Rapoza, 2008; Thomas et al., 2003).

The OBIA approach is based on the assumption that image objects produced by segmentation can be unambiguously linked to the geographic objects of interest and has proven valuable in a number of applications, see, for example, Shackelford & Davis (2003); Wei et al. (2005); Zhou et al. (2007). However, it can not be considered to be a silver bullet: when classes overlap spectrally, high classification accuracy is still difficult to achieve (Platt & Rapoza, 2008). The aim of creating meaningful image objects may be affected by blurring and distortion problems inherent to the image acquisition process (Bezdek et al., 1999).

A central stage of OBIA is the segmentation stage. Standard image segmentation usually requires considerable parameterisation effort to find the right sizes and homogeneity criteria that produce meaningful image objects for a given scene and application. In many situations, image segmentation becomes a time consuming task which requires iterative processing, and may not always succeed (Lang et al., 2006; Schiewe et al., 2001a). Depending on the complexity of the landscape, the quality of the image and the parameterisation procedure, image segmentation may produce image objects that represent real-world objects, part of

objects or just noise. Such image segmentation approach is a subjective and user driven task which essentially prevents automated processing of large data sets.

The traditional image segmentation looks for delineating discrete image objects with sharp boundaries. The underlying assumption of this hard segmentation is that it is always possible to determine spatial boundaries between land cover classes. However, many geographic objects, both natural and man made, may not appear clearly bounded in remotely sensed images. Therefore, a fuzzy segmentation approach which takes into account the fuzziness of the real world and the ambiguity of remote sensing imagery is potentially more appropriate than a hard segmentation to resolve the spectral and spatial confusion which characterizes urban landscapes.

Over the last decades, geographic information systems (GIS) researchers have applied fuzzy concepts to deal with the vagueness and imprecision widespread among geographic objects (Burrough, 1989; Burrough & Frank, 1996). Remote sensing researchers have applied per-pixel fuzzy classification to study geographic phenomena that are continuous and lack sharp boundaries (Fisher & Pathirana, 1990; Foody, 1992; Wang, 1990). However, fuzzy concepts have not been applied yet in the segmentation process for environmental remote sensing image analysis. As remote sensing applications include a wide spectrum of geographic phenomena ranging from discrete objects to continuous fields, a fuzzy segmentation approach can be potentially useful for land cover characterization on natural and man-made landscapes. This chapter proposes a method for land cover characterization based on fuzzy image segmentation. It argues that, in order to handle uncertainty of real world landscapes, image segmentation should output fuzzy image regions rather than sharp image objects.

The chapter has been structured in two parts. In the first part, basic principles and assumptions of OBIA are explained. It is highlighted that a successful application of OBIA depends on the quality of the discrete image objects produced at the segmentation stage. In the second part, a fuzzy image segmentation approach is proposed in more detail.

## 2. Traditional Object-based image classification

A basic assumption underlying traditional object-based image classification is that it is always possible to identify groups of pixels that can be related to geographic objects. These groups of pixels with meaning in the real world are referred to as image objects (Schneider & Steinwender, 1999). Thus, image objects are basic entities, composed of similar digital values, and possessing intrinsic sizes, shapes and geographic relationships with the real-world scene they model (Hay et al., 2001).

The standard object-based image analysis (OBIA) approach for image classification can be represented as shown in Figure 1 using a three stage workflow (Benz, 2001):

1. image segmentation which creates *meaningful* image objects;
2. feature analysis which measures spectral, spatial, and contextual attributes of image objects; and
3. classification which allocates image objects to target classes

Image segmentation, the first stage, outputs image objects that hopefully represent, completely or partially, the structural properties of the geographic objects under study. Feature analysis, the second stage, aims to select a set of attributes (also referred to as a feature vector) able to differentiate the classes of interest (i.e. the target classes). This stage requires users to establish correspondence between the image objects and the real-world objects (classes), and also to determine which properties can be relevant for the problem under

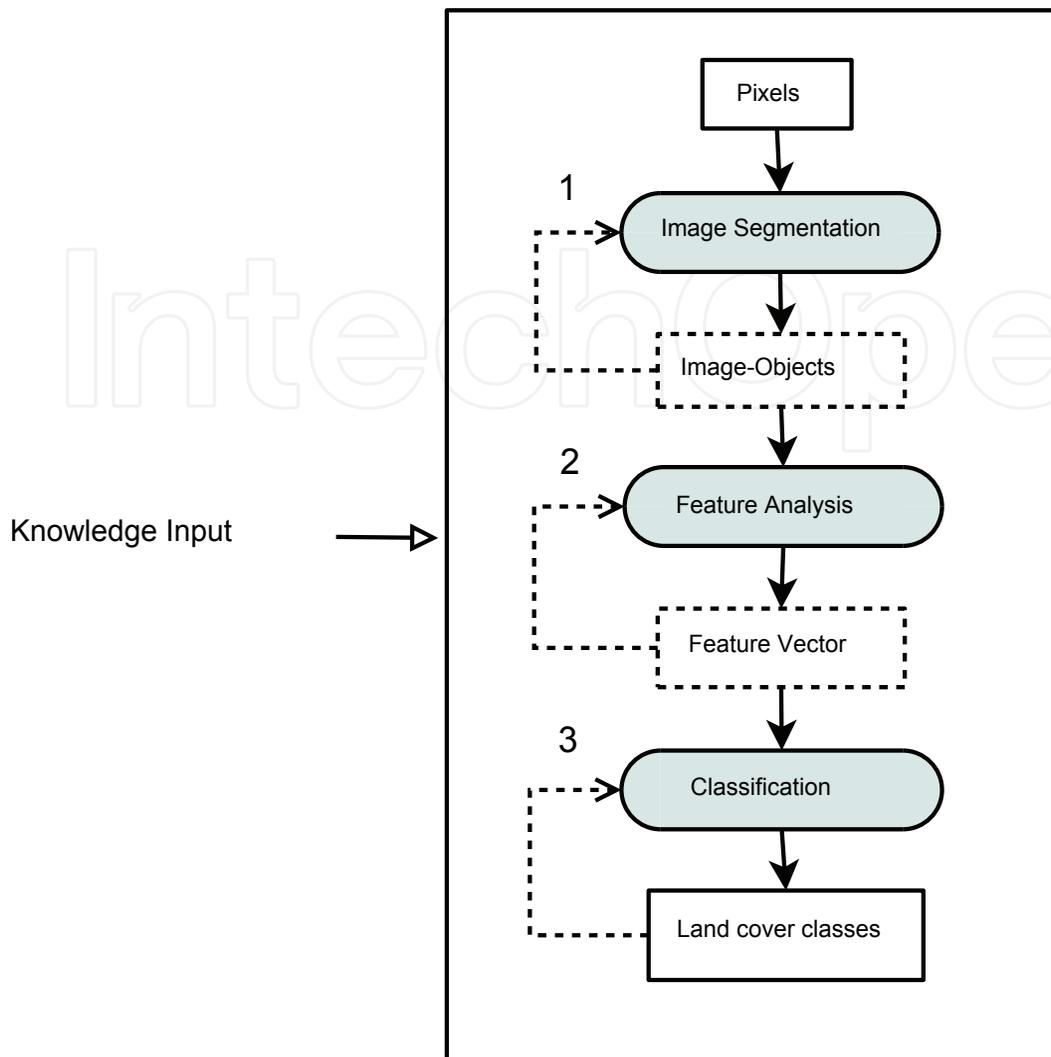


Fig. 1. Flowchart of the OBIA image classification process.

study. Classification, the last stage, assigns classes to image objects applying appropriate classification rules which can be set up automatically or manually. This classification may be conducted using conventional (e.g. maximum likelihood or minimum distance to mean) or non-conventional techniques (e.g. neural networks, fuzzy logic, nearest neighbor) (Gao, 2009; Jensen, 2005). The final outcome of the process are digital objects representing the categories of interest. The OBIA process is iterative rather than linear and strictly subsequent, and knowledge input may occur at any stage of the process (Lang, 2008).

### 2.1 Image segmentation

Image segmentation is recognized as the critical step of the OBIA approach because its results affect directly all the subsequent tasks (Carleer et al., 2005; Neubert et al., 2006; Rekik et al., 2007). Image segmentation aims to partition the image into a set of regions which are distinct and uniform with respect to some intrinsic property of the image, such as grey level, texture or color (Freixenet et al., 2002). The selection of an appropriate segmentation technique depends greatly on the type of data being analyzed and on the application area (Pal & Pal, 1993).

A successful segmentation produces image objects which can be unambiguously linked with ground objects. Typically, the segmentation stage is not concerned with the thematic identity

of the image objects as they are class labelled later in the classification stage (Rosenfeld & Kak, 1992).

The result of image segmentation is determined by the purpose of the study, the grouping strategy and specific decisions about the desired levels of homogeneity and (or) the expected size of the resulting segments (Pal & Pal, 1993). Image segmentation is therefore a highly subjective task which has to be adapted to the specific interest of users and the spatial and spectral constraints of the available images (Bock & Lessing, 2002). This poses significant problems for the transferability of image segmentation methods and the development of automated classification rules (Bock & Lessing, 2002).

Traditional image segmentation can be referred to as crisp or hard segmentation because it produces image objects with clearly defined boundaries. In a crisp segmentation, it is assumed that the image can be partitioned into spatially continuous, disjoint and homogeneous groups of pixels which represent the relative homogeneity of geographic phenomena (Blaschke et al., 2006). However, real-world landscapes are comprised by objects of different sizes which may exhibit internal heterogeneity (Herold et al., 2003). As single scale segmentations may not suffice to capture such complexity, it has been suggested that image segmentation be conducted in a nested hierarchy of scales modeling relationships between sub-objects, objects and super-objects (Burnett & Blaschke, 2003). While it is an appealing approach, it can bring further complications to the classification stage due to the additional need for user-driven individual parameterization.

### 2.1.1 Image segmentation in computer vision

Computer vision is concerned with the theory for building artificial systems that obtain information from images. The image data can take many forms, such as a video sequence, views from multiple cameras, or multi-dimensional data from medical scanners (Azad et al., 2008). As opposed to multispectral remote sensing, computer vision deals mainly with single band data sets, i.e. greyscale images.

Image segmentation is an active field of research in computer vision and 'hundreds of segmentation algorithms have been proposed in the last 30 years' (Freixenet et al., 2002) (p. 408). This proliferation of algorithms shows how elusive a satisfactory segmentation is. There is an almost infinite number of ways an image can be sub-divided, they are all technically correct, but most of them are not what users want (Shi & Malik, 2000).

Comprehensive reviews of image segmentation techniques have been published in the last two decades in the computer vision literature, including, for example Freixenet et al. (2002); Haralick & Shapiro (1992); Pal & Pal (1993).

In computer vision, image segmentation is the process of extracting objects from background or separating the image into several regions which are considered to be coherent and meaningful (Pal & Pal, 1993). Generally, image segmentation is a process of clustering pixels in an image based on some rules, e.g. pixels with similar attributes should be together (Pal & Pal, 1993).

In general terms, image segmentation techniques may be divided into two basic categories: edge-based and region-based (Pal & Pal, 1993). Edge-based segmentation methods look for detecting image discontinuities. In this category, the assumption is that boundaries of regions are sufficiently different from each other and from the background to allow boundary detection based on local discontinuities in grey level intensity. On the other hand, region-based segmentation methods are based on partitioning an image into regions that are similar according to a set of predefined criteria such as grey level, shape or texture.

Two common approaches for region-based segmentation are either merging individual image objects (bottom-up approach) or recursively splitting regions starting from the whole image (top-down approach) (Pal & Pal, 1993).

Although the edge and region approaches are considered to yield good results, some researchers have argued the impossibility of extracting complete information of either aspect of the image independent of the other and have proposed hybrid approaches which integrate boundary and region information (Moigne & Tilton, 1995; Pal & Pal, 1993). One example of these approaches is the watershed algorithm which sees an image as a topographic surface and, after identifying maxima (ridges) and minima (valleys), attempts 'flooding' the terrain to obtain catchment regions (Dam, 2000).

### 2.1.2 Image segmentation in remote sensing

Image segmentation is a relatively recent field of research in environmental remote sensing, despite the fact that it has been applied extensively in neighboring disciplines such as computer vision and medical imaging (Carleer et al., 2005). The main problem was the inability of computer vision algorithms to process color or multiband image data sets. However, in the last decade, the remote sensing community has adapted and enhanced the computer vision segmentation approach for dealing with multispectral data sets. A number of operational software tools are now available to conduct segmentation-based image classification for remote sensing. This includes *Definiens Developer*, previously known as *eCognition*, ENVI's *Feature Analysis*, ERDAS's *Objective*, and IDRISI's *Segmentation*. Although all of these programs offer a number of similar functionalities, *Definiens Developer* implements the most advanced algorithms and is a popular choice in OBIA applications (Blaschke et al., 2006) and will therefore be reviewed as example for current standard 'crisp' OBIA implementations.

*Definiens* implements the *fractal net evolution* algorithm which provides multiresolution segmentation capabilities 'applicable and adaptable to many problems and data types' (Baatz & Schape, 2000) (p. 1). Multiresolution segmentation is a bottom up, region-merging technique which starts building one-pixel image objects which grow by merging adjacent objects based on heterogeneity criteria (Yan et al., 2006). These objects may be extracted from the image in a number of hierarchical levels and each subsequent level yields image objects of a larger size by combining objects from a level below, which represents information on different scales simultaneously (Baatz & Schape, 2000).

Image object heterogeneity can be spectral heterogeneity,  $h_{spectral}$ , or shape heterogeneity,  $h_{shape}$  (Baatz & Schape, 2000). Spectral heterogeneity is a function of user-assigned layer weights, number of pixels comprising the objects, and standard deviation of pixel values within each layer. Shape heterogeneity is based upon the change in object shape before and after an eventual merge. Object shape is described in two ways: (i) compactness and (ii) smoothness.

Compactness  $C$  is measured as indicated in Equation 1:

$$C = s_n * l_n / b_n \quad (1)$$

where  $s_n$  is the size of each image object,  $l_n$  is the perimeter of the image object and  $b_n$  is the perimeter of a minimum box bounding each image object.

Smoothness  $S$  is measured as indicated in Equation 2:

$$S = s_n * l_n / \sqrt{s_n} \quad (2)$$

Spectral and shape heterogeneity are summarized by a single *fusion value* ( $f$ ), which indicates the potential merge between two image objects given by Equation 3 (Zhang, 2006):

$$f = (1 - w) * h_{spectral} - w * h_{shape} \quad (3)$$

where  $w$  is the weight associated with shape heterogeneity (Definiens, 2007).

Throughout a single segmentation step, the underlying optimization procedure minimizes the heterogeneity of resulting image objects weighted by their size. A segmentation step is finished when every original image object is assigned to the optimal higher level image object. To achieve adjacent image objects of similar size and thus of comparable quality, the procedure simulates the growth of objects over a scene in each step and also for the final result (Yan et al., 2006).

Other alternatives to multiresolution segmentation are provided by *Definiens*. The chessboard algorithm produces a regular grid of segments with a predefined size. The quadtree segmentation splits an image domain into squares, and then into smaller squares, until the spectral heterogeneity of every image object falls below a user-defined threshold. The spectral difference segmentation merges adjacent image objects that do not exceed a user-defined threshold for a weighted spectral difference (Esch et al., 2008).

An approach to address the problems associated with multi-level segmentation is the move from multi-level to single-level segmentation approaches (Corcoran & Winstanley, 2006). This approach is advantageous due to two main reasons. First, it looks for conducting segmentation in a way closer to human visual perception. Second, it helps to solve practical problems for evaluation of multi-level segmentation such as complex hierarchical classification schemas and complicated quality evaluation procedures. In fact, it has been argued that a robust set of intensity and texture features could be extracted and integrated to represent urban land cover in a "true form" with just one level segmentation (Corcoran & Winstanley, 2006).

In summary, the traditional approach for image segmentation is problematic due to the following reasons: (i) remotely sensed images portray an ambiguous representation of geographic objects which often prevents the formation of meaningful image objects; (ii) the current implementations of such segmentation are highly dependent on complicated parameterisation procedures which are both labour intensive and time consuming; (iii) linking image objects to real world classes, and identifying appropriate attributes, are not trivial tasks, and usually require a trial and error approach. This means that the effectiveness of crisp segmentation for land cover classification is at least partly depending on effort and skill of the individual user.

### 2.1.3 Segmentation quality

Image segmentation can be seen as an improvement of the analysis process of remotely sensed imagery. It provides an alternative means to conduct image classification. However, it has been observed that object-based image classification also has limitations (Song et al., 2005):

- classification accuracy depends on the quality of the image segmentation (i.e. if objects are extracted inaccurately, subsequent classification accuracy will not improve);
- classification error could be accumulated due to error in both image segmentation and classification process; and
- once an object is mis-segmented, all pixels in this object will be misclassified.

Image segmentation is therefore the critical stage in OBIA, but it is also viewed as an *ill-posed problem* in the sense that it has no unique solution: a minor change of the homogeneity measure leads to different segmentation outcome (Hay & Castilla, 2008).

However, not all segmentation methods are good enough for a particular type of images and users of each application have to evaluate the quality of the image output from a given segmentation algorithm. Thus, the problem is to ensure that the evaluation of the segmentation results is an objective process. A common approach, in computer vision applications, is to create a vector of comparison measures between the segmented image and a 'ground truth' segmentation (Pal & Pal, 1993).

A simple way to evaluate the quality of segmentation, provided that such ground truth segmentation is available, is to use an overlapping area matrix (OAM) and the following metrics (Ortiz & Oliver, 2006):

- percentage of correctly grouped pixels (CG);
- percentage of oversegmentation (OS); and
- percentage of undersegmentation (US).

In the field of environmental remote sensing, similar concepts have been proposed to evaluate segmentation quality. A good segmentation is achieved when the overall differences between the segmentation results and the associated reference objects are as low as possible (Meinel & Neubert, 2004; Neubert et al., 2006). In general, the quality of image segmentation may be evaluated using both qualitative and quantitative methods. Qualitative measures are visual evaluations of general criteria such as the delineation of varying land cover types, the segmentation of linear objects, or the occurrence of faulty segmentation. Quantitative measures make a comparison between clearly defined reference areas (varying in location, form, texture, contrast, land cover type) and segmentation results using geometric properties such as area  $A_i$ , perimeter  $P_i$ , and shape index  $S_i = P_i/4\sqrt{A_i}$  of the image object  $i$  (Meinel & Neubert, 2004; Neubert et al., 2006).

As presented, all of the methods proposed for quantitative evaluation of segmentation quality of remotely sensed images rely on a reference segmentation. A main issue is how to define such ground truth or reference segmentation. Some researchers have suggested adopting a library of reference images with their corresponding segmentation reference image, as computer vision community does, in order to evaluate different segmentation algorithms (Corcoran & Winstanley, 2006). Using that approach, a group of researchers have evaluated the performance of different segmentation algorithms using a common set of remotely sensed images and measures (Neubert et al., 2008). However, this initiative is just a first step on the path to well established criteria and methods for judging the quality of segmentation for remote sensing applications.

For practical purposes, users need to build the reference segmentation suitable for their own applications by visual interpretation. In this case, expert humans partition the image into spectrally homogeneous regions, adjust them to accommodate spatial or contextual characteristics and, then, use that ideal segmentation to evaluate segmentation results. A problem with this approach is that the whole process of image classification becomes more dependent on visual interpretation and harder to automate.

Segmentation evaluation becomes more complex with multiscale segmentation which produces a number of segments at different scales. It seems impractical to define an ideal reference segmentation for each scale. A sensible approach in this case would be a qualitative evaluation through visual inspection of each segmentation level. However, a subjectivity

problem may arise with visual evaluations. This problem suggests that, while multi-scale segmentation seems valuable to capture both the coarse and the fine scales of real world objects (Benz, 2001), it may demand intensive user interaction to validate the consistency of the different segmentation levels.

An additional issue could emerge as a by-product of changing the classification paradigm from pixels to image objects. Although quality assessment of pixel-based classes can be done without many problems using proven techniques based on the well known mis-classification or error matrix, it could be not entirely right for objects obtained using the object-based approach. It could be necessary to build a new framework for assessing the quality of ground objects derived from remotely sensed data. In that direction, Zhan et al. (2005) have proposed adopting a so-called per-object method of quality assessment able to measure spatial or contextual attributes of the object-classes not just the label assigned to each pixel.

In summary, the objective evaluation of segmentation quality remains problematic. As an example, a detailed evaluation of four different segmentation algorithms (i.e. optimal edge detector, watershed segmentation, multilevel thresholding, and fractal net evolution) concluded that the 'miraculous segmentation' method which segments in a correct way for all types of landscape does not exist (Carleer et al., 2005).

#### 2.1.4 Uncertainty in image segmentation

A useful model for understanding uncertainty in image analysis is the *image chain approach* which considers the remote sensing process as a chain linking subsequent stages from image collection to the final thematic mapping (Schott, 1997). In such a view, image analysis is only as strong as the weakest link in the chain and limitations existing at each step affect the entire process (Woodcock, 2002).

In the case of object-based image analysis, image segmentation is not only the weakest link in the chain but also the earliest one. Understanding uncertainties associated with the image classification process may be useful to propose alternative ways for conducting image segmentation.

Atkinson & Foody (2002) suggested dividing uncertainty between ambiguity and vagueness. Ambiguity is the uncertainty associated with crisp sets, for example, when hard classification is conducted to allocate pixels to one of several possible land cover classes. Vagueness, on the other hand, is expressed by the degree of incompleteness of land cover classification schemas or the eventual fuzziness needed to deal with borderline cases (e.g. the dividing line between a sprawling shrub and a woody vine which is indefinite).

Such ambiguity intensifies in urban areas, where mixed pixels occur in images with different spatial resolution (Herold et al., 2003; Mesev, 2003). This ambiguity is due to the complex composition of urban landscapes where the same materials may be present in different land cover classes, as for example in roads and rooftops made of asphalt and concrete. In such cases, any attempt to produce crisp image objects representing one or another land cover class can fail easily. As a simple illustration, Figure 2 shows eight crisp segmentations obtained from a high spatial resolution image over an urban area. In this example, image segmentation was conducted using a watershed segmentation algorithm which needs three parameters as input: (i) denoising factor (conductance of an anisotropic diffusion filter), (ii) scale (size of the image objects), and (iii) dissimilarity criteria (threshold value to merge the image objects). A visual assessment of the resulting image segmentations suggests that none of these single level segmentations produces meaningful image objects. Moreover, it demonstrates that parameterisation of a meaningful segmentation is really a complicated and hard task. This

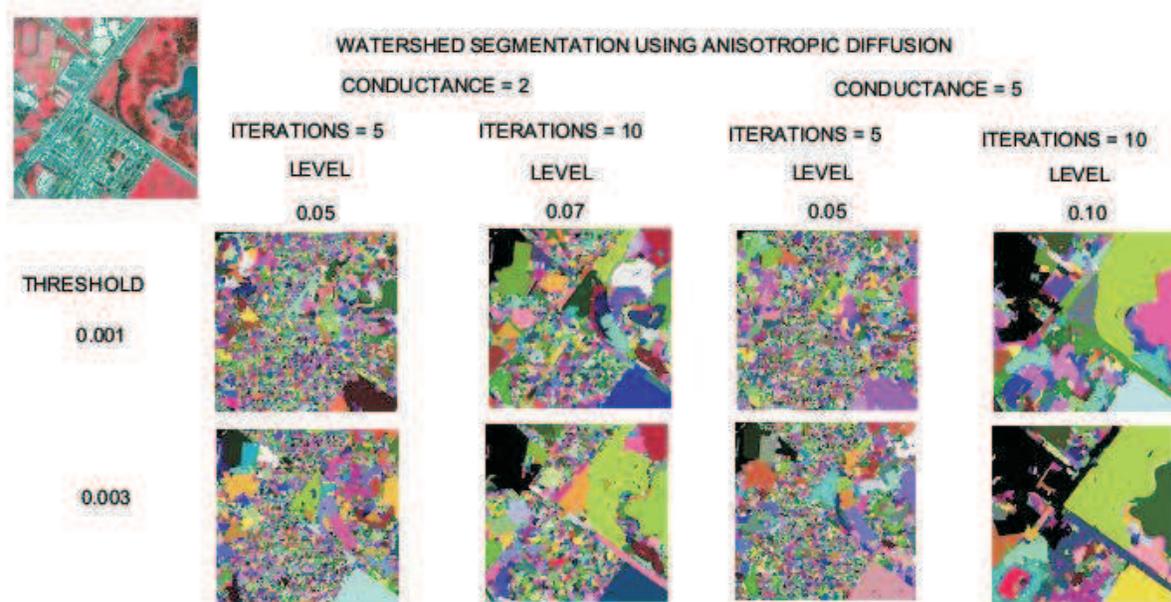


Fig. 2. Examples of crisp image objects produced by a hard image segmentation of a multispectral image using the watershed algorithm and different combinations of parameters

example illustrates that, very often, a discrete image segmentation does not help to resolve the ambiguity present in urban image data sets.

On the other side of uncertainty is vagueness, a component which refers to the application of fuzzy sets concepts, for example, when fuzzy classification is used to establish degrees of membership to natural land cover that varies continuously (Atkinson & Foody, 2002). This topic is reviewed in the next section.

## 2.2 Fuzzy sets and image classification

Fuzzy classification attempts to address the fact that geographic information is imprecise, meaning that the boundaries between different phenomena are fuzzy, or there is heterogeneity within a class, perhaps due to physical differences. A fuzzy classification takes into account that there are pixels of mixed composition, that is, a pixel cannot be definitively assigned to one or another category (Fisher & Pathirana, 1990; Wang, 1990).

A *hard* classification algorithm is based on classic set theory, which requires precisely defined set boundaries for which an element (i.e. a pixel) is either a member (true = 1) or not a member (false = 0) of a given class. In contrast, a *fuzzy* classification allows degrees of membership of image objects to each of the different classes. A main advantage of fuzzy classifiers is that they provide a more informative and potentially more accurate alternative to hard classification (Atkinson & Foody, 2002). Thus, a fuzzy classifier is a realistic way to take into account the ambiguity problem described in the previous section.

Fuzzy approaches for per-pixel image classification have been proposed since 1990 (Foody, 1996; Wang, 1990; Zhang & Foody, 1998). It has been argued that, because of mixed pixels, remotely sensed images provide an ambiguous representation of the landscape (Fisher, 1997). As a consequence, identification of thematic classes from images can not be achieved with a high level of certainty (Molenaar & Cheng, 2000). Hence, a hard classification of images into well-defined classes has been evaluated as inappropriate and inaccurate (Doan & Foody, 2007). A fuzzy or soft image classification can be obtained by using either a per-pixel or a per-field approach (i.e. using existing boundary data) (Aplin & Atkinson, 2001; Zhang &

Stuart, 2001). A fuzzy classification is especially useful for analyzing and detecting changes in complex landscapes (Burrough & Frank, 1996; Fisher et al., 2006).

Pixel-based fuzzy classification is typically conducted using three main stages:

1. *fuzzification*, in which membership functions to classes are established for a number of features,
2. *fuzzy rules definition*, in which different membership functions are combined into a rule set base and used for classification, and
3. *defuzzification*, in which the fuzzy classification result is discretized to produce the eventual crisp allocation/classification.

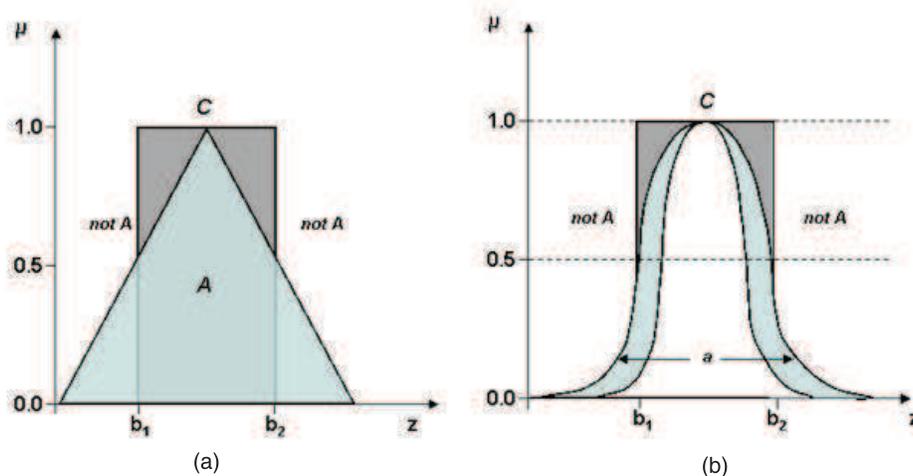


Fig. 3. Crisp (rectangular) and fuzzy (i.e. triangular and normal) membership functions for feature  $z$ .

*Fuzzification* is a term used to describe the transition from crisp (classic) sets to fuzzy sets. In a fuzzy system, every class is represented as a fuzzy set and memberships take values anywhere in the range  $[0, 1]$  (Zadeh, 1965). Figure 3 shows that, for a particular feature  $z$ , the membership value  $\mu$  to a given class can be defined by either a crisp membership function as the rectangular function or by a fuzzy membership function such as the triangular or the bell-shaped functions. In a crisp function, such as the rectangular one, the membership value  $\mu$  is full (1.0) if  $b_1 \leq z \leq b_2$ , or null (0.0), otherwise. In a fuzzy function, such as the triangular in (a) or the normal in (b), the membership value  $\mu$  can be any value between 1.0 and 0.0, depending on the value of  $z$  and the specific nature of the selected function.

The second stage is the definition of fuzzy rules, i.e. *if-then* rules in which, if a condition is fulfilled, an action takes place. Referring to Figure 4 the following rules apply: If the value of feature  $z$  is below 25, then the pixel has a full membership to a given land cover class (e.g. class A). If the value of feature  $z$  is 50, then the pixel has 0.5 membership to class A and 0.5 membership to class B. A fuzzy rule base produces a fuzzy classification which consists of discrete return values of membership of pixels for each of the output classes.

In *defuzzification*, the last stage of the process, every pixel is assigned to one of the classes of interest. A common way of defuzzification is to assign each pixel to the class with the highest membership degree value. If this value is below a certain threshold (e.g. less than 0.50), no classification is performed to ensure a minimum reliability of such allocation.

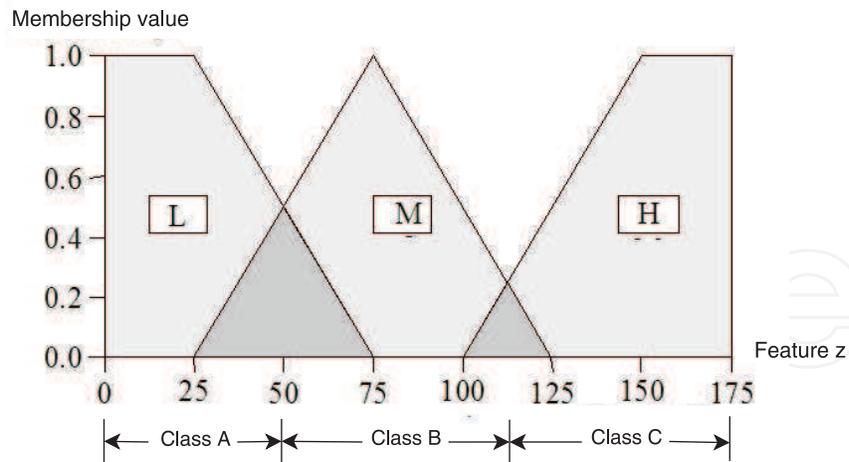


Fig. 4. The fuzzy membership functions for feature  $z$  define the fuzzy set  $L$  (low),  $M$  (medium), and  $H$  (high) of membership to classes A, B and C.

It should be noted that the use of fuzzy sets techniques in the context of conventional OBIA is not new. However, fuzziness has not been considered at the segmentation stage but later in the process chain, that is, at the classification stage. In this stage, the richness of fuzzy sets concepts is used to handle the uncertainty carried by sharp image objects and hopefully to increase the final thematic accuracy (Benz et al., 2004). Fuzzy classification is, however, the last stage of the process, and it may be too late to take into account uncertainty. As an example, *Definiens* software provides capabilities for fuzzy classification of image objects. However, in such implementation users need to manually select fuzzy membership functions and experiment with classification rules. This particular setup of the defuzzification step leads to time consuming trial and error experiments which add significant effort to the whole classification process.

Fuzzy sets concepts have been implemented in the segmentation stage of OBIA only very recently (Lizarazo & Elsner, 2009). This chapter links into this work and pursues the argument that a much more natural way for dealing with uncertainty is to apply fuzzy set concepts at the very beginning of the OBIA process, that is in the segmentation stage. By doing that, the earliest (and regularly weakest) link could be strengthened and therefore the entire classification process be improved.

In the next section, a general framework for object-based image classification based on fuzzy segmentation will be proposed.

### 3. Geographic objects and image objects

In the previous section, 'image objects' were introduced as the core spatial units for conducting object-based image analysis (OBIA). As segmentation, the OBIA's critical stage, produces such image objects which aim to identify real world objects, it is important to review how geographic objects are conceptualised in digital environments.

At its most basic level, geographic objects can be modeled as discrete objects or continuous fields, depending on a number of considerations, including purpose and scale of analysis (Couclelis, 1992; Goodchild, 1992; Goodchild et al., 2007).

Discrete objects are non-overlapping partitions of the geographic space which can be used to conceptualise sharply bounded objects like buildings, roads or real estate units. Continuous

fields are functions that map locations to a given property (attribute) which may serve to conceptualise spatially variant phenomena like elevation, soil type, agricultural suitability or flood risk. For some applications, a given geographic object can be modeled simultaneously as being a field and an object, e.g. an agricultural parcel can be conceptualised as an enclosed area of land whose soil acidity varies continuously (Bian, 2007; Goodchild et al., 2007).

Thus, geographic objects can be represented using three main categories: (i) geo-objects for discrete objects, (ii) geo-fields for continuous fields, and (iii) field-objects for spatial regions with internal heterogeneity (Goodchild et al., 2007). All categories can be derived from the concept of a geo-atom which associates a point location in space-time and a property. In formal language, a geo-atom is a tuple  $\langle x, Z, z(x) \rangle$  where  $x$  defines a point in space-time,  $Z$  identifies a property and  $z(x)$  defines the particular value of the property at that point.

A geo-object is therefore an aggregation of points in space-time whose geo-atoms have uniform values for certain properties. A geo-object can have either natural (also known as *bona fide*) boundaries or cognition-induced (also known as *fiat*) boundaries (Goodchild et al., 2007). Examples of *bona fide* boundaries are buildings, roads, or rivers. Examples of *fiat* boundaries are county borders or property-lines.

In geo-fields, the values for a particular property of geo-atoms are allowed to vary. A *scalar* geo-field describes a single property such as elevation; a *vector* geo-field describes both magnitude and orientation of continuous phenomena such as wind or temperature. A field-object is a mixed object which describes the variation of a continuous property across an areal geo-object such as changes on biomass in a forest. In current GIS practice, geo-objects can be represented in the two dimensional space using points, lines and polygons. Geo-fields are commonly represented by raster grid cells or triangular irregular networks (Goodchild et al., 2007). Field-objects, however, are not very well represented yet in GIS systems (Bian, 2007).

In the realm of OBIA, the segments output by standard 'hard' segmentation procedures can be related to geo objects. However, segmentation could be defined in a broader way to be compatible with other types of geographic objects as well. Such a more generic view of the image segmentation process would allow it to produce *image regions* able to resemble both discrete geo-objects and continuous geo-fields.

It is proposed here that image segmentation should be understood as the process of grouping pixels either spatially or thematically. In the first case, spatial segments can be identified as crisp *image objects* which are discrete groups of pixels with clearly delimited boundaries but no thematic description. These are the geo-object type segments that are produced by current standard OBIA approaches. In the second case, segments can be conceptualised as *image fields*, whose pixels store individual values to a given property. Image fields are not single layer output such as the spatial segments of standard OBIA approaches. Rather, image fields consist of as many layers as properties of interest, e.g. target land cover classes, exist. A set of image fields representing respective membership to a given set of thematic categories and individual image fields can be understood as continuous *image regions*.

Figure 5 illustrates both spatial and thematic image segmentation: (a) an example of spatial segmentation with four discrete image objects labelled as 1,2,3, and 4; (b) three layers of continuous image regions, identified as target land cover classes A, B, and C. In (c), the hypothetical thematic categories A, B, and C, are shown for reference. Typically, discrete image objects, or spatial segments, are crisply bounded, have individual identity but lack any thematic description. Crisp image objects are created using intrinsic homogeneity criteria which usually do not refer to thematic similarity. Thus, discrete image objects are simply *crisp*

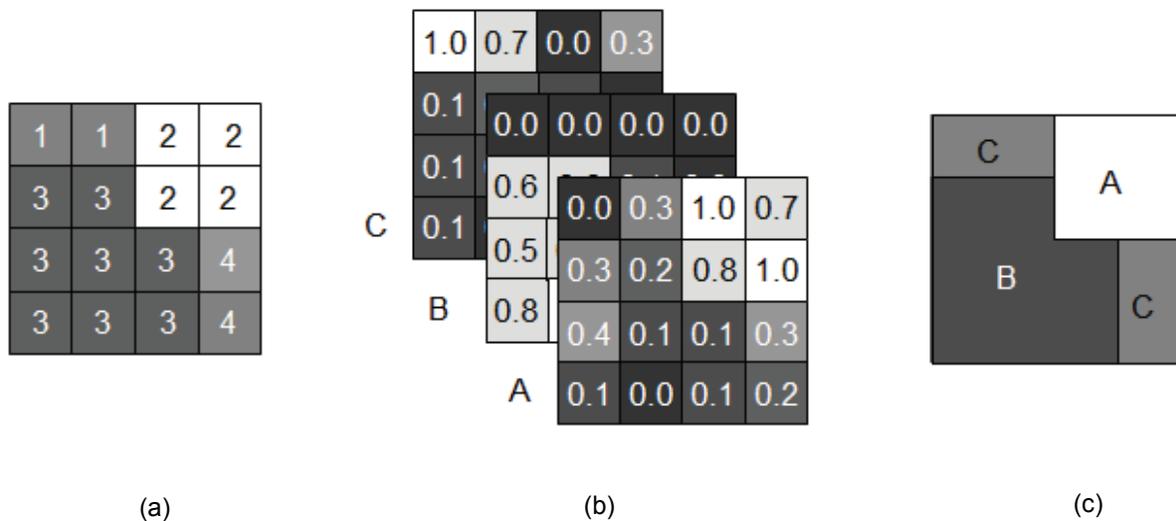


Fig. 5. Two different types of segments output by image segmentation: (a) discrete image objects with crisp boundaries but no thematic description; and (b) continuous image regions with indeterminate boundaries but thematic description. Three hypothetical thematic categories A, B and C are shown in (c) for reference.

regions whose spatial and spectral properties need to be analysed at a later stage of the OBIA process to produce an eventual thematic allocation.

Continuous image regions, or thematic segments, on the other hand, are a set of image fields with no spatial boundaries but holding a membership value to a given set of thematic categories. Thematic segments have no sharply defined boundaries, thus they can be considered as fuzzy or vague regions. As illustrated in (b), there are as many layers of image regions as target classes exist. Each pixel in a image region holds membership values to every one of target classes A, B and C. A given pixel, for example the one to the top right corner, holds the following membership values: 0.7 to class A, 0.0 to class B, and 0.3 to class C (in this example, it is assumed that membership values add up to 1.0 which is not always the case).

### 3.1 Spatial image segmentation and sharp image objects

Spatial or crisp image segmentation that is undertaken in traditional OBIA analysis can formally be described as follows. Let  $R$  represent the entire geographic region occupied by an image. Spatial segmentation can be seen as a process that partitions  $R$  into  $n$  homogeneous sub-regions  $R_1, R_2, \dots, R_n$  such that:

$$\bigcup_{i=1}^n R_i = R. \tag{4}$$

$$R \text{ is a connected set, } i = 1, 2, \dots, n. \tag{5}$$

$$R_i \cap R_j = \emptyset \text{ for all } i \text{ and } j, \quad i \neq j. \tag{6}$$

$$Pred(R_i) = TRUE \text{ for } i = 1, 2, \dots, n. \tag{7}$$

$$Pred(R_i \cup R_j) = FALSE \text{ for any adjacent regions } R_i \text{ and } R_j. \tag{8}$$

In equations 4 to 8,  $Pred(R_k)$  is a logical predicate defined over the points in set  $R_k$ , and  $\emptyset$  is the null set. The symbols  $\cup$  and  $\cap$  represent set union and intersection, respectively. A region is a connected set of pixels. Two regions  $R_i$  and  $R_j$  are considered adjacent if pixels lying on their boundaries are neighbours. A pixel may have either 4 neighbours (i.e. two *horizontal* and two *vertical*) or 8 neighbours (when the *four* diagonal neighbors are also considered). Equation 4 indicates that every pixel is allocated to a region. Equation 5 requires that pixels in a region be 4- or 8- connected. Equation 6 indicates that the regions must be disjoint (i.e. they have no pixel in common). Equation 7 indicates what properties must be satisfied by the pixels in a segmented region—for example,  $Pred(R_i) = TRUE$  if all pixels in  $R_i$  have their intensity level within certain interval. Finally, equation 8 denotes that two adjacent regions  $R_i$  and  $R_j$  must be different in the sense of predicate  $P$ .

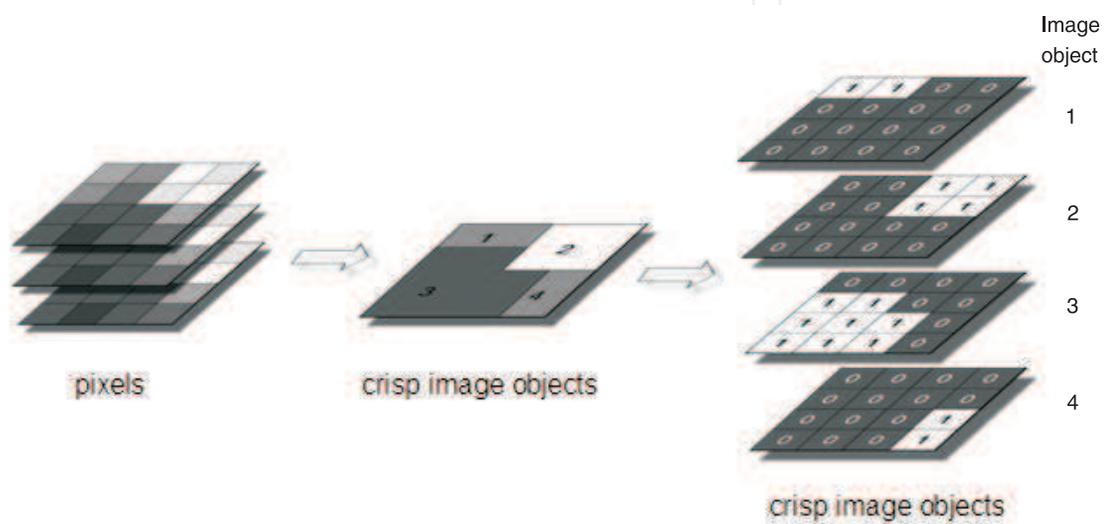


Fig. 6. Spatial or crisp image segmentation produces one single image composed of sharp image objects with clearly defined boundaries. In a field representation of sharp image objects, as the one depicted to the right, pixels hold full or null membership to image objects. In a *perfect* segmentation, discrete image objects can be unequivocally associated to target land cover classes.

Discrete image segmentation divides an image into a set of non-overlapping regions or image objects whose union is the entire image (Haralick & Schapiro, 1992). Figure 6 illustrates that crisp image objects are discrete structures with clearly defined boundaries which cover the totality of the imaged geographic area. Image objects are an aggregation of (raw or pre-processed) pixels whose digital values, located at one or several spectral bands, meet one or several homogeneity criteria defined by predicate  $P$ . Pixels aggregated as image objects satisfy predicate  $P$ —which usually involves properties of single pixels but may also include constraints related to the segment under construction like minimum or maximum size. As outlined earlier, the definition of predicate  $P$  is a subjective decision which usually entails a trial and error parameterisation procedure in established OBIA workflows.

However, Figure 6 demonstrates that such image objects can be expressed as well in the field view of thematic segmentation. This is done as three image regions in which the membership of pixels to image objects 1 to 4 is expressed in the binary 0/1 membership to each individual region. In a *perfect segmentation* each image object 1, 2, 3, and 4 can be unequivocally linked

to the target classes A, B, and C (as shown in Figure 5). This demonstrates that the spatial segments can also be conceptualised as extreme examples of thematic segmentation.

### 3.2 Fuzzy image segmentation and fuzzy image regions

Thematic segmentation offers the opportunity to widen the binary crisp membership attributes that are inherent in the spatial segmentation approach by allowing not just membership values of 0 or 1 but also any value in between, i.e. expressing fuzzy membership values. This is the central paradigm of the proposed *fuzzy image segmentation* approach. Figure 7 shows vague (or fuzzy) image regions output by a fuzzy segmentation. In this hypothetical example, the input image is a multispectral image composed of  $n$  spectral bands. The output of the fuzzy classification is a set  $X$  composed of  $m$  image regions, where  $m$  is defined by the number of target land cover classes of the OBIA process. In the example of Figure 7,  $X_m$  comprises of three land cover classes A, B, and C. Partial membership values  $\mu(X_m)$  are represented by continuous values ranging from 0.0 (no membership) to 1.0 (full membership).

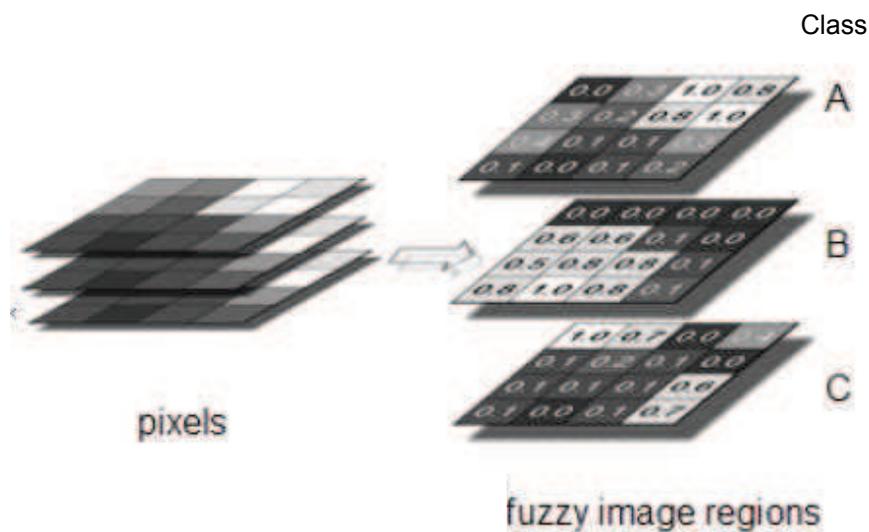


Fig. 7. Thematic or fuzzy image segmentation outputs fuzzy image regions holding multiple membership values to target thematic categories A, B, and C. Fuzzy image regions are continuous or thematic segments which take into account the inherent ambiguity of remotely sensed images.

A fuzzy segmentation partitions the image  $R$  into overlapping image fields with indeterminate boundaries and uncertain thematic allocation. This means that equations 5, 6 and 8 that apply to discrete segmentation do not hold for continuous or thematic segmentation. Instead, there is no condition of spatial connectedness (Equation 5); each pixel belongs to all  $m$  fuzzy image regions with varying degrees of membership (Equation 6); and there is no condition of dissimilarity between regions (Equation 8). In addition, membership values can be anywhere in the range from 0.0 to 1.0.

The concept of a fuzzy image region can be further extended in order to allow pixels to store not only a single membership value per class (a scalar) but a multi-valued membership per class (a vector). This extension may be useful to store, for example, minimum, mean and maximum estimated values of membership. This additional type of fuzzy image region can be referred to as a *composed* fuzzy image region. A composed image region can be seen as a

finite set of possible realizations of a fuzzy image-region where each realization is the value inferred using one specific processing technique.

Once fuzzy image regions have been established, there are two alternative approaches for conducting the subsequent OBIA classification process:

- *direct* discretization which transforms fuzzy image regions into discrete objects or classes skipping the feature analysis stage (i.e. using a similar approach to traditional pixel-wise fuzzy classification), or
- *object-oriented* discretization which introduces a feature analysis stage in which fuzzy image regions properties are measured before proceeding to the defuzzification/classification stage.

### 3.3 A general workflow for image classification

A general framework to conduct fuzzy segmentation-based image analysis is proposed in Figure 8. The image classification process can be understood as the sequential development of three distinct and interrelated stages: (i) *fuzzy segmentation* in which  $n$  spectral bands are transformed into  $m$  fuzzy image regions, (ii) *feature analysis* in which properties of fuzzy image regions are measured to build a set of relevant features, and (iii) *defuzzification* (or classification) in which fuzzy image regions are allocated to one of  $m$  land cover classes.

#### 3.3.1 Fuzzy segmentation

In this stage, fuzzy image regions are created from raw or pre-processed pixels. As outlined in the previous section, fuzzy image-regions have membership values in the range  $[0, 1]$ . Such values represent degrees of belongingness of every pixel to the classes under study. Fuzzy segmentation can be understood here as a supervised regression task in which, training samples are used to infer membership values to classes for the whole image. Thus, following such a concept, any statistical technique able to fit a supervised regression model may be used to produce fuzzy image regions. Once a set of membership grey-level images has been produced, there will be one fuzzy image region available for each target class.

#### 3.3.2 Feature analysis

This stage aims to define, select and extract a relevant set of image regions' properties and relationships suitable to be used as a feature vector to infer appropriate decision rules to resolve the spectral ambiguity of land cover classes. An example metric is the absolute normalized difference index (ANDI) defined in Equation 9:

$$ANDI = |\mu_i A - \mu_i B| / (\mu_i A + \mu_i B) \quad (9)$$

where  $\mu_i A$  and  $\mu_i B$  are the membership values of the  $i^{th}$  pixel to the classes  $A$  and  $B$ , respectively. The *ANDI* value is an indicator of the overlap existing between two specific fuzzy image regions. *ANDI* values range in  $[0, 1]$ . *ANDI* values close to 0 represent areas of thematic confusion.

Another metric is the sum of logarithms index (SOL) defined in Equation 10:

$$SOL = \ln \mu_i A + \ln \mu_i B \quad (10)$$

where  $\ln$  is the natural logarithm. The *SOL* index measures the overlap between two fuzzy image regions  $A$  and  $B$  and highlights areas exhibiting high membership values to more than one target class.

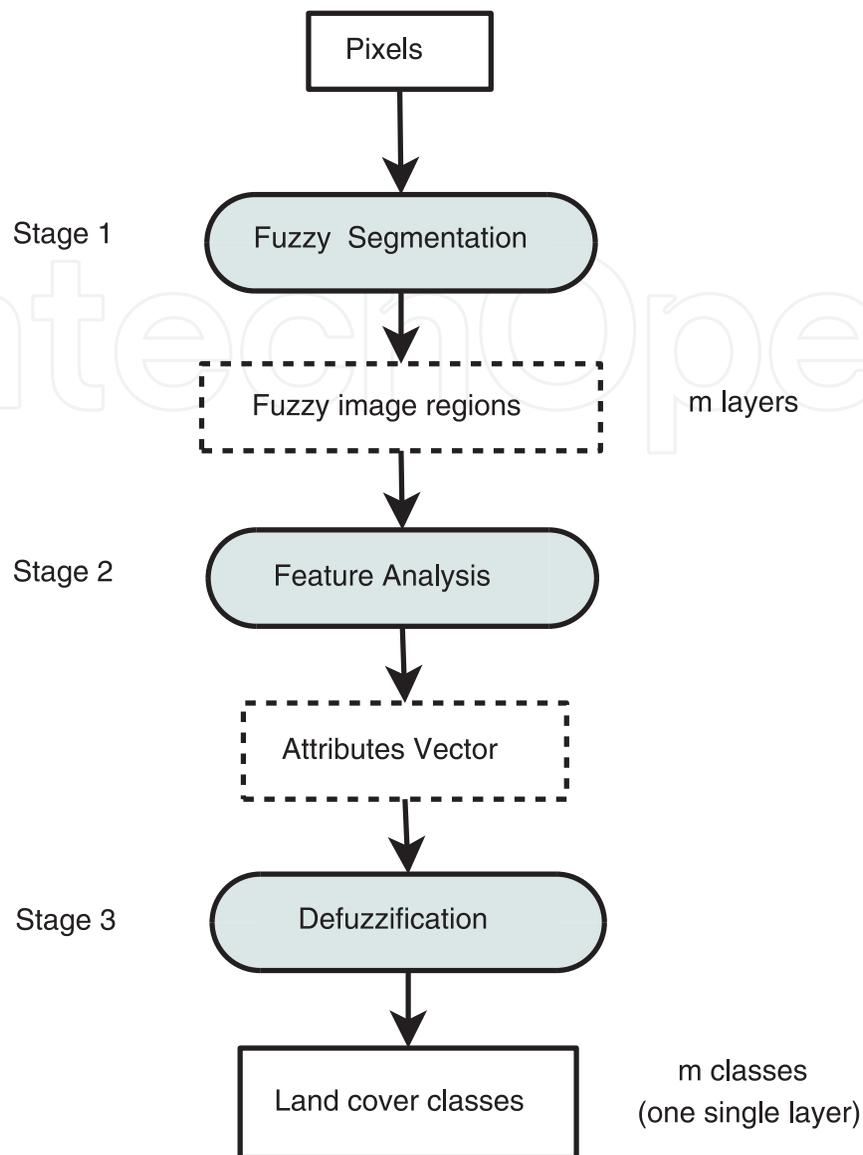


Fig. 8. A general workflow for image classification based on fuzzy segmentation.

### 3.3.3 Defuzzification

This stage aims to infer (and apply) appropriate decision rules to assign either full membership from the fuzzy image regions to the target land-cover classes (in the case of categorical qualitative analysis) or compositional values representing proportion of land cover classes at every pixel (in the case of quantitative analysis).

For *qualitative* analysis, a common defuzzification technique used in fuzzy applications is the allocation using the maximum membership values (Wang, 1990), which has been applied in per-pixel classification in the last two decades. Other approaches include the centroid method, the weighted average method and the mean max membership method (Ross, 2004). However, all these established techniques do not exploit the potential richness of information carried by fuzzy image regions (and quantified in the feature analysis stage). Thus, in the approach proposed here, the process of defuzzification is addressed as a problem of supervised learning in which a variety of non parametric classification algorithms could be applied.

For *quantitative* analysis, the defuzzification task can be understood as a supervised regression problem in which appropriate training samples are used to infer compositional land cover values for the whole image (in this case, fuzzy image regions need to add to 1.0). For solving such a problem, a double regression is conducted: one for the fuzzy segmentation, and the other one for the final classification.

### 3.4 Application of the proposed framework

The proposed framework has been applied to qualitative and quantitative land cover analysis. The following sections summarize main results of applying the fuzzy image segmentation approach for classification of a number of remotely sensed urban datasets.

#### 3.4.1 Categorical land cover analysis

Lizarazo & Elsner (2009) applied the fuzzy segmentation method to classify the *University* image, a hyperspectral dataset of the University of Pavia (Italy) that was collected by the Hysens project on 8<sup>th</sup> July 2002 (Gamba, 2004).

The University data set size is 610x339 pixels. Spatial resolution is 1.2 m. There are 112 hyperspectral channels ranging from 400 to 1260 nm. This data set was chosen because it was used in a previous OBIA study using crisp image segmentation (Aksoy, 2006).

Seven spectral channels which roughly correspond to the center wavelength of Landsat Thematic Mapper (TM) channels were selected as input for the image classification experiment. The *University* data set includes training and testing samples for nine land cover classes: asphalt, meadows, gravel, trees, (painted) metal sheets, bare soil, bitumen, self-blocking bricks, and shadow. The training sample comprises 3921 pixels and the testing sample 42762 pixels.

For this experiment, the fuzzy segmentation stage was conducted using the generalized additive method (GAM) which output nine fuzzy image regions (i.e. one image region per target land cover class) from the seven spectral channels. For the feature analysis stage, the ANDI indices were calculated for the following pairs of classes as they were visually identified as potential source of spectral confusion: asphalt and gravel, asphalt and bitumen, asphalt and bricks, meadows and trees, and meadows and bare soil. For the final defuzzification stage, a support vector machine (SVM) was used to output the intended land cover classification. The overall classification accuracy reported by Lizarazo & Elsner (2009) was a 0.95 confidence interval of KIA (Kappa Index of Agreement) equals to [0.764, 0.784].

The performance of the proposed fuzzy segmentation method was evaluated by using an earlier classification of the *University* data set (Aksoy, 2006) as benchmark. In that work, a three stage crisp segmentation OBIA procedure was applied. Input to the crisp segmentation comprised of 24 bands as follows: 8 linear discriminant analysis (LDA) bands, 10 principal components analysis (PCA) bands, and 16 Gabor texture bands. The feature analysis step used a feature vector of 4 values for each image object by clustering spectral statistics from the 24 input bands and from 10 shape attributes. The final classification was based on Bayesian classifiers. The overall classification accuracy reported by Aksoy (2006) was a 0.95 confidence interval of KIA equals to [0.788, 0.814].

It is apparent that the work of Aksoy (2006) achieved slightly higher accuracies. However, it also required significant user input and has very limited potential for automation. Fuzzy segmentation-based OBIA as implemented by Lizarazo & Elsner (2009) required very little user-input and could easily be automated for the analysis of large data sets.

### 3.4.2 Quantitative land cover analysis

The traditional OBIA methods, based on crisp segmentation, are mainly used to delineate and classify land cover efficiently (Duveiller et al., 2008). As crisp segmentation deals with the delineation of meaningful sharp image objects, it is clear that its main advantage relies on its ability to produce qualitative land cover units. The OBIA approach focuses on qualitative interpretation of remote sensing images. Often, however, it is preferable to use a continuous representation of land cover (i.e. a quantitative analysis) rather than a discrete classification (i.e. a qualitative classification). In a continuous representation of land cover, the different compositional classes vary continuously not only in space but also in time. By contrast, in the discrete representation of land cover, each spatial unit is represented by a single categorical value which is stable over time (Lambin, 2000). Quantitative land cover classification is of particular relevance where a individual land surface characteristic is of interest, e.g. the fraction of impervious surface in each pixel, or the percentage of tree cover at each location.

Lizarazo (2010) applied the fuzzy segmentation method for estimation of impervious surface area (ISA) values in Montgomery County, Maryland, USA, from Landsat-TM orthorectified images. The Landsat images, collected in 1990 and 2000, comprised of seven spectral channels with pixel size of 28.5 m at 50 m root mean square error (RMSE) positional accuracy. As part of an extensive study on urbanization in the Chesapeake Bay Watershed, Jantz et al. (2005) obtained accurate ISA maps and qualitative land cover maps for the study area. These maps were used as ground reference for training sample collection and accuracy evaluation.

The estimation of quantitative land cover involved four main stages: (i) pre-processing for relative radiometric normalization of the two Landsat-TM scenes, (ii) fuzzy segmentation, (iii) feature analysis, and (iv) final regression. For the fuzzy segmentation stage, a supervised regression SVM model was fitted using land cover class memberships as a response variable and six independent analysis components (ICA) as predictor variables. Training sample comprised 1000 randomly selected pixels representing 0.27% of the study area. As a result of this stage, the following five fuzzy image regions were created: water, urban, grass, trees, and bare soil. For the feature analysis stage, ANDI indices were calculated for the following pair of fuzzy image regions: urban and water, urban and grass, urban and trees, and urban and bare soil. For the final regression stage, the SVM regression technique was used to predict ISA values from the five vague image regions and the four SOL indices.

As a final step, the accuracy of the fuzzy segmentation method was evaluated by comparing the predicted ISA values with the ground reference data using the standard correlation index (Jensen, 2005). The correlation index between the predicted ISA images and the ground reference images were 0.75 for the 1990 date, and 0.79 for the 2000 date. The fuzzy segmentation method overestimated ISA values by 10% and 8% respectively. This estimation level can be considered to be a good approximation to the real impervious surface area. Minor misprediction problems were detected only after a careful visual assessment.

Unlike traditional OBIA methods, the fuzzy segmentation approach can therefore be used for both qualitative and quantitative land cover analysis. This characteristic of the proposed approach is clearly one of its central advantages. This potential is very important for remote sensing image analysis, as there is an increasing need to estimate biophysical parameters to better understand the environmental dynamics at local and national scales (Camps-Valls et al., 2009). In this context, there seems to be an urgent need for robust and accurate regression methods in order to overcome the challenges posed by the inversion of analytical models which are often considered as too complex, computationally intensive, or sensitive to noise (Camps-Valls et al., 2009; Kimes et al., 2000).

Consequently, the fuzzy segmentation approach can be included in the list of emerging methods which use empirical models to learn the relationship between the acquired imagery and actual ground measurements. Furthermore, the fuzzy segmentation approach can act as an unifying framework which contributes to bridging the gap between the two traditional branches of remote sensing analysis, i.e. those methods that study categorical variables and those methods focused on estimating continuous variables, which are often considered as opposite, and independent worlds (Liang, 2007).

#### 4. Conclusions

Fuzzy image regions can serve as a general conceptual framework for producing both accurate quantitative and qualitative characterizations of land cover. The application of the proposed method in several case studies illustrated that fuzzy image segmentation provides a robust, accessible and easy to use method for urban land cover analysis. The contribution of this chapter, which was discussed in last section, can be summarized as follows:

1. The potential of fuzzy sets concepts to extend the traditional perspective of image segmentation was evaluated.
2. The suitability of the fuzzy segmentation approach to produce both categorical and compositional characterization of land cover was tested.

The proposed method therefore enhances the range of OBIA alternatives and contributes to improving the remote sensing image analysis process. It addresses the concerns of Platt & Rapoza (2008) that traditional OBIA approaches commonly have difficulties dealing with spectrally overlapping classes. This is particularly true in urban landscapes which usually comprise objects of different sizes with high levels of within-class heterogeneity (Herold et al., 2007). In such landscapes, where spectral complexity is a common issue, the fuzzy segmentation approach represents a suitable alternative to the hard image segmentation approach, a trial and error process which may not always succeed (Frauman & Wolff, 2005; Lang et al., 2006; Robson et al., 2006; Schiewe et al., 2001b). In addition, in contrast to image classification based on hard segmentation, the proposed method is able to deal, throughout the whole process, with the inherent imperfections of remote sensing data such as sensor noise, local shading and highlights which often prevent the creation of meaningful image objects (Bezdek et al., 1999).

Lastly, standard *crisp* OBIA implementations require significant user input for the parameterization of segmentation models. This introduces significant subjectivity into the process and makes the eventual classification performance at least partly a function of individual user skill and effort. Fuzzy segmentation-based OBIA on the other hand requires very little user input. This makes the approach more robust, objective, and reproducible.

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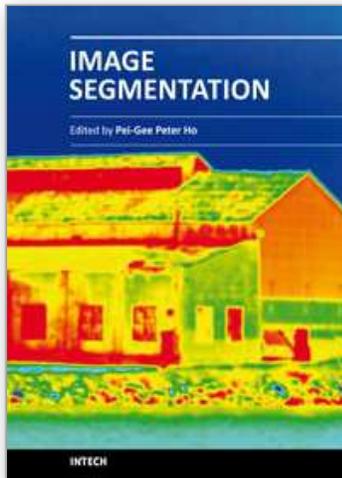
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## **Image Segmentation**

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It was estimated that 80% of the information received by human is visual. Image processing is evolving fast and continually. During the past 10 years, there has been a significant research increase in image segmentation. To study a specific object in an image, its boundary can be highlighted by an image segmentation procedure. The objective of the image segmentation is to simplify the representation of pictures into meaningful information by partitioning into image regions. Image segmentation is a technique to locate certain objects or boundaries within an image. There are many algorithms and techniques have been developed to solve image segmentation problems, the research topics in this book such as level set, active contour, AR time series image modeling, Support Vector Machines, Pixon based image segmentations, region similarity metric based technique, statistical ANN and JSEG algorithm were written in details. This book brings together many different aspects of the current research on several fields associated to digital image segmentation. Four parts allowed gathering the 27 chapters around the following topics: Survey of Image Segmentation Algorithms, Image Segmentation methods, Image Segmentation Applications and Hardware Implementation. The readers will find the contents in this book enjoyable and get many helpful ideas and overviews on their own study.

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