TOWARDS A FRAMEWORK FOR CHANGE DETECTION BASED ON IMAGE OBJECTS

T. Blaschke

Z_GIS: Centre for Geoinformatics University of Salzburg
Hellbrunner Str. 34, A-5020 Salzburg, email: thomas.blaschke@sbg.ac.at

ABSTRACT

With the advent of high resolution satellite imagery and airborne digital camera data approaches that include contextual information are more commonly utilized. One way to include spatial dimensions in image analysis is to identify relatively homogeneous regions and to treat them as objects. Although segmentation is not a new concept, the number of image segmentation based applications is recently significantly increasing. Concurrently, new methodological challenges arise. Standard change detection and accuracy assessment techniques mainly rely on statistically assessing individual pixels. Such assessments are not satisfactory for image objects which exhibit shape, boundary, homogeneity or topological information. These additional dimensions of information describing real world objects have to be assessed in multitemporal object-based image analysis. In this paper, problems associated with multitemporal object recognition are identified and a framework for image object-based change detection is suggested. For simplicity, this framework breaks down the *n*-dimensional problem to two main aspects, geometry and thematic content. These two aspects can be associated with the following questions: did a certain classified object change geometrically, class-wise, or both? When can we identify an object in one data set as being the same object in another data set? Do we need user-defined or application-specific thresholds for geometric overlap, shape-area relations, centroid movements, etc? This paper elucidates some specific challenges to change detection of objects and incorporates GIS-functionality into image analysis.

Keywords: Image processing, change detection, context information, GIS, object-based classification.

1 INTRODUCTION

Changes in landscapes and their components can occur in a variety of ways and at a variety of rates. Spatially, they may occur in isolation or unevenly and need to be aggregated in order to be efficiently interpreted. If early warnings or advice to land managers such as farmers and planning officers is to be given so that management practices can be modified, it is essential that the design of the surveillance system can be related to the drivers of change [1]. Changes in land-cover (LC) and land use (LU) composition and status are important landscape characteristics that affect ecosystem condition and function. LC data are increasingly used as primary data sources to calculate landscape-based indicators for regional to national scale assessments [2] although problems with the calculation of landscape metrics exist and the assumptions for using LU/LC as super indicators for processes which are of interest but cannot be measured directly for certain areas are not always clear. Though related, there is a clear distinction between land use and land cover. While land cover refers to the biophysical earth surface, land use is shaped by human, socio-economic and political influences on the land [3]. In essence, "land use links land cover to the human activities that transform the landscape" [4] (p. 12).

The use of satellite-based remote sensor data has been determined to be a cost-effective approach to document changes over large geographic regions [5], [6]. Optical systems are still widely used for remote sensing due to the simplicity with which these data can be processed and probably also because they are visually appealing and intuitively understandable. New data sources include Laserscanning data which unravel three-dimensional structures in vegetation, resulting in huge amounts of data. The users and especially the potential users of remote sensing data are not interested in the data as such, but rather in information. Image classification has been developed further over the last thirty years or so and more recently research emphasizes pre-classification of images, feature extraction and automated information retrieval.

There are many techniques available to detect and record differences (e.g. image differencing, ratios or correlation) and these might be attributable to change [7], [2], [8]. However, the simple detection of change is rarely sufficient in itself: information is generally required on the initial and final land cover types or land uses—the ‘from–to’ analysis described by [9]. Furthermore, the detection of image differences may be confused by problems with phenology and cropping, and such problems may be exacerbated by limited image availability and poor quality in temperate zones, and the difficulties in calibrating poor images. Post-classification comparisons of derived thematic maps go beyond simple change detection and attempt to quantify the different types of change. The degree of success depends upon the reliability of the maps made by image classification [10].

The ecological processes in landscapes can be studied at different spatial and temporal scales [11], [12]. In this sense, it has required new methods to identify spatial patterns, compare them, quantify significant differences, and determine relationships between functional processes and landscape patterns [13]. Indexes of landscape richness, evenness, and patchiness have been used widely by means of the size and distribution of the patches in the landscape. These characteristics may be of particular importance for species or vegetation communities that require habitat patches of a minimum size or specific arrangement. Patch size and arrangement may also reflect environmental factors, such as topography or soil type.

In many landscape studies one main objective is to obtain homogeneous landscape units on which one can apply spatial statistics and, to assess the superficial changes observed through time-establishing relationships with the ecological parameters such as the interannual variability of vegetation over a large scale, animal species occurrence, or habitat suitability studies. The common denominator of the various approaches in computer vision, pattern recognition, image analysis etc. and the approaches in landscape ecology, environmental monitoring is the search for tangible objects. Technically, feature extraction tools and approaches permit the analyst to identify relevant features and their outlines by post processing digital imagery to enhance and isolate feature definition. Approaches to be used and quality of results depend on quality and characteristics of available images and on nature of feature extraction / recognition problem.

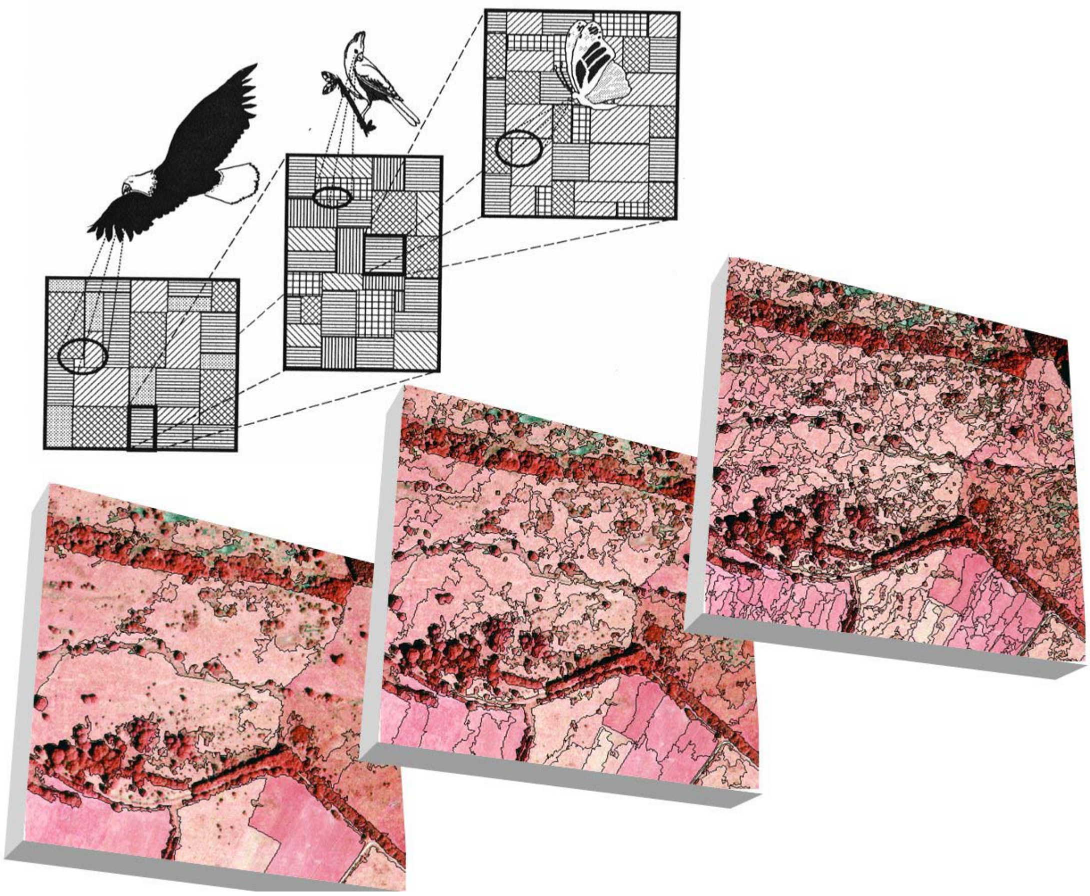

Figure 1. Demand for tangible landscape objects at several scales which are internally relatively homogeneous expressed by the different taxa levels juxtaposed to the delineation of landscape objects at three different scales for a pasture dominated landscape in Central Germany, Biosphere Reserve Rhoen (adopted from [14]).

2 METHODS AND MATERIAL

2.1 LAND USE CHANGE AND CHANGE DETECTION TECHNIQUES

There is a legion of change detection techniques. Recent overviews can be found in [15] or [8]. While much land cover change analysis is performed using the fairly simple technique of post-classification comparison [15], alternative procedures can be used [16], [17], [18]. For instance, rather than using land cover classes as the basis for change detection, Normalized Difference Vegetation Index (NDVI) values can be used [19]. In contrast, [20] used remotely sensed imagery to derive landscape metrics (generated through texture and context analysis) as a means for identifying land cover change, or [12] assessed the temporal persistence of LU/LC through incorporating landscape pattern metrics. Rather then comprehensively discussing the multitude of possibilities in change detection, the reader is referred to two recent overviews.

In [21], the authors identify four main categories of LU/LC change detection: traditional post-classification, Cross-correlation Analysis (see also [16]), Neural Networks, and Image Segmentation based Classification. Not so widespread, cross-correlation Analysis is a change detection method that measures the differences between an existing land cover image and a recent single date multispectral image [16]. The benefit of this technique is that it eliminates the problems associated with radiometric and phenological differences that are so readily experienced when performing change detection. Cross-correlation works by using the class boundaries from the base land cover image to derive an expected class average spectral response [21]. These authors conclude in a comparison study that there is merit to each of the land use change detection methods studied, and that there appears to be no single best way in which to perform change analysis.

While most typologies of change detection focus on the processing status of the data – change based on original pixel values vs. classified data - [8] define three main groups of approaches according to the level of image processing. According to [22] they suggest a three level categorization system that differentiates these methods by introducing the notion of *pixel*, *feature*, and *object* level image processing. *Pixel level* refers to numerical values of each image band, or simple calculations between corresponding bands such as image differencing or rationing. In general, it is not possible to attach any symbolic meaning (e.g. a decrease in total forest canopy) from the pixel level without further analysis. The *feature level* is a more advanced level of processing, which involves transforming the spectral or spatial properties of the image (e.g. principal components analysis (PCA), texture analysis, or vegetation indices), thus the enhanced feature may have real-world meaning (e.g. vegetation indices in the radiometric domain, or lines/edges in the spatial domain) or may not (e.g. principal components in the radiometric domain). The *object* is the most advanced level of processing. All levels can involve symbolic identification in addition to pixel or feature change detection.

To identify and compare objects of two different images of the same area we have to break down the complexity of the task to the two main steps: object building in each of the data sets and comparison of the resulting objects. Methodologically, success in isolating particular features depends on establishing a set of conditions that uniquely mark that feature. Another motivation to develop techniques for the extraction of image objects stems from the fact that most image data exhibit characteristic texture which is neglected in common classifications. The texture of an object can be defined in terms of its smoothness or its coarseness. One field of image processing in which the quantification of texture plays a crucial role is that of industrial vision. These systems are used to assess characteristics of products by measuring the texture of their surface. Most methods are based on the statistical properties of an image as well as the spectral or Fourier characteristics of airborne data, radar or VHR-satellite data which are playing an increasing role in remote sensing. But how to include neighbourhood information across several spectral bands for a pixel-based analysis? Several research groups tried to achieve this by using pre-defined boundaries (‘per-parcel classification’ or ‘per-field classification’). This classification technique is applicable for agricultural lots or other pre-defined, spatially discrete land cover classes. Only recently, [23] presented a change detection approach based on an object-based classification which is classifying not single pixels but groups of pixels that represent already existing objects in a GIS database. The approach is based on a supervised maximum likelihood classification. The multispectral bands grouped by objects and different measures that can be derived from multispectral bands represent the n-dimensional feature space for the classification. The training areas are derived from the GIS database.

2.2 IMAGE SEGMENTATION AND THE MSS/ORM APPROACH TO DECOMPOSE SPATIAL COMPLEXITY

Segmentation is clearly not new [24]. Although there has been a lot of development in segmentation of grey tone images in the aforementioned field and other fields, like robotic vision, there has been limited progress in segmentation of multi-band imagery. Especially within the last five years many new segmentation algorithms as well as applications were developed, but not all of them lead to qualitatively convincing results while being robust and operational. From the legion of segmentation algorithms available only a few of the existing approaches lead to qualitatively convincing results when applied to remote sensing data while being robust and operational. One reason is that the segmentation of an image into a given number of regions is a problem with a huge number of possible solutions. The high degrees of freedom must be reduced to a few which are satisfying the given requirements [25].

As the commercial software system *eCognition* is becoming more popular, so too are object-oriented processing techniques. As opposed to most other pattern recognition algorithms which operate on a pixel-by-pixel basis, *this approach* segments a multispectral image into homogeneous objects, or regions, based on neighboring pixels' spectral and spatial properties. Image segmentation can be performed at different levels of resolution, or granularity. A knowledge-based approach is used to classify objects into information categories, using Fuzzy Logic based on attributes of image objects and their mutual relations. This classification actively utilizes different levels of segmentation and different classification hierarchy levels (class depths). Although more than 300 scientific papers are listed at the company's website (www.definiens-imaging.com) only a few of these papers are based on a sound methodology of object-oriented image processing.

One technical solution to overcome the pixel view is image segmentation. In this paper, I build on a recently developed multiscale segmentation / object relationship modelling (MSS/ORM) methodology suggested by [26] which performs image segmentation as a first step and bases any further analysis or classification on derived image objects. Based on the delineation of image objects at several levels, a semantic network is built. A segmentation algorithm generates objects at several user-defined levels. It generally allows generation of image objects on an arbitrary number of scale-levels, taking into account criteria of homogeneity in colour (reflectance values in a remotely sensed image) and shape. Thereby, a hierarchical network of image objects is generated, in which each object knows its neighbouring objects in the horizontal and vertical direction. The aim of the segmentation is to generate the most meaningful objects possible. This means that the shape of each object should be represented by an image object. This shape, combined with further derivative colour and texture properties, can be used to initially classify the image by classifying the image objects. Thereby, the classes are organized within a class hierarchy.

In a second step, additional semantic information can be used to improve the image classification. With respect to the multi-scale behaviour of the objects, a number of small image objects can be aggregated to form larger objects, constructing a semantic hierarchy. Likewise, a large object can be split into a number of smaller objects. The semantic network and modelling approaches built upon it allow for the derivation of geographical models capable of representing both observational data and (higherlevel) semantic abstractions that can be derived from that data and an external expert knowledge describing the classes. The main difference of this integrated GIS/remote sensing approach is that topological relationships—information on size, orientation, or distribution of objects—are intrinsically obvious and can be used directly in the formulation of rules. [27] provides a table of examples of successful applications of this approach in various ecological situations.

MSS/ORM is designed to utilize information from different scales within a single image and to integrate external information from auxiliary data sets. It can provide various representations of the image content in a flexible manner by offering candidate discretizations of space. Still, a main research challenge lies ahead of us: to validate image objects derived from imagery.

3 CHANGE DETECTION BASED ON OBJECTS

As described earlier, object-based image analysis is becoming more widespread. This is often associated with the commercial success of the software *eCognition*. Several of these applications are dealing with land use / land cover change. But most applications described in scientific literature do not encounter independent dissections of the image data under consideration. Typically, they force new dissections to obey existing boundaries either derived from imagery or existing geospatial data sets.

In [28], the authors propose an oo-approach to model land-use changes based on object-oriented concepts and a formulation of cell complexes based on Unified Modeling Language. Each land use is considered as an object. Detailed land use is recorded at the parcel level, while general land use does not require parcel information. An object-relational approach is employed to achieve the model at the logical level. These authors demonstrate how SQL can be used for spatiotemporal queries. Although they assume the underlying spatial objects (i.e., the parcels) to be geometrically stable, the model is already rather complex.

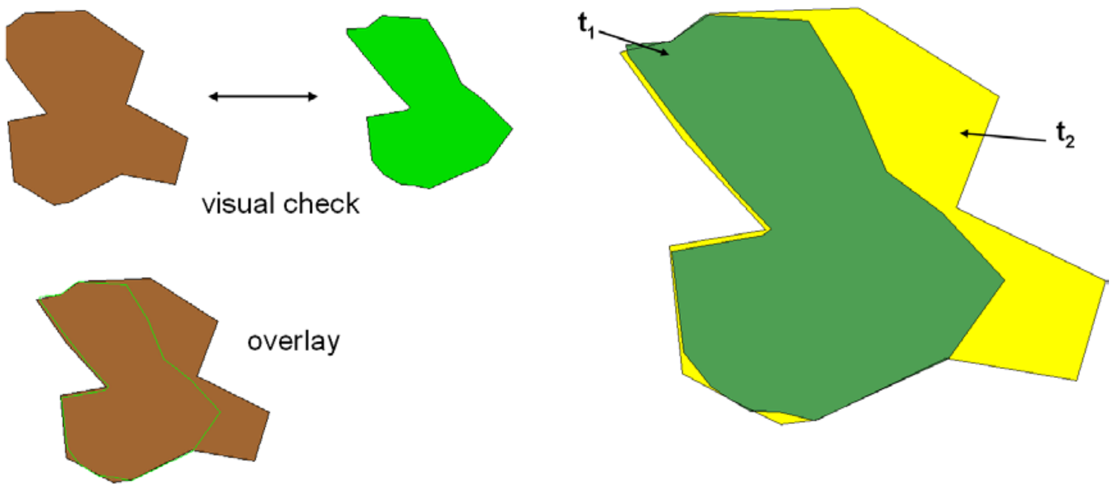

Figure 2. Visual comparison and overlay of two polygons for times t1 and t2 which are considered to be the same object. The close-up look (right) illustrates that next to a clear shrinkage to the East more geometric changes occurred which may be interpreted as being spatial inaccuracies.

For a homogeneous feature to be detected, its size generally has to be significantly larger than the resolution cell. If the feature is smaller than this, it may not be detectable as the average brightness of all features in that resolution cell will be convolved. When comparing objects the problems of data set mis-registration are more complex than in per-pixel analysis. Major problems associated with data set registration have, for example, been observed in studies of change detection that are commonly undertaken within GIS [29]. These studies typically aim to identify thematic changes that have occurred over time, sometimes involving temporal interpolation between the specific periods represented by the data sets used [30]. Such studies clearly require the data sets to be co-registered, but this is difficult. The resulting mis-registration can have a significant impact on the analyses and interpretations made. For example, [31] shows how, when using a temporal sequence of remotely sensed imagery, mis-registration errors can act significantly to exaggerate or alternatively mask thematic change. Figure 2 illustrates for just one object how difficult it is to distinguish between real change and geometric inconsistencies which can be due to inaccuracies in co-registration but can also imply object changes.

In Figure 3, I suggest a framework which categorises the geometric changes which may occur between the same object in two different data sets. It immediately becomes clear that object-based change detection is much more a GIS task than a remote sensing task if we consider post-classification analysis. It involves a much smaller number of objects compared to pixels which are subjected to change detection. However, in contrast to geometrically predefined pixels we are faced with a much more complex task. While a usual real world data set based on Ikonos-like to Landsat-like resolutions typically results in the range of 10^5 to 10^6 objects the combination of the two data sets would result in 10^7 objects.

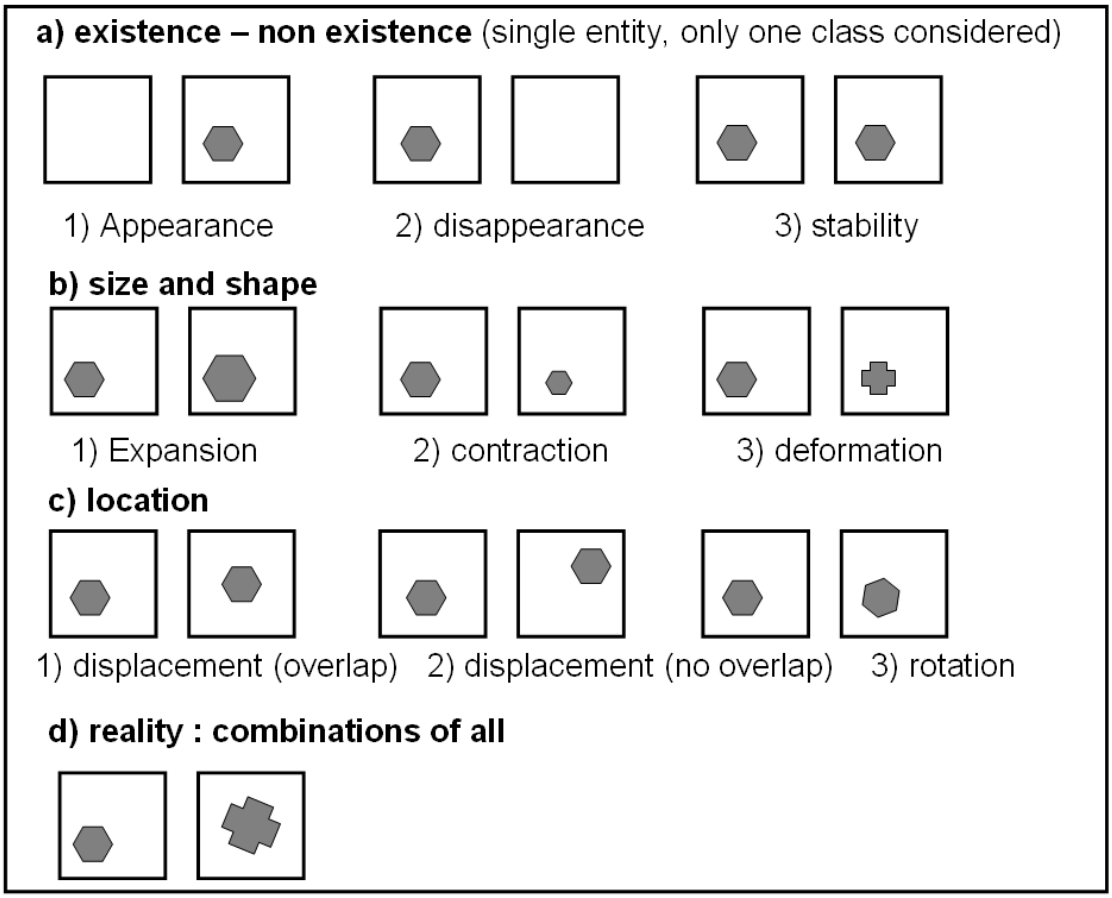

Figure 3. A typology of objects geometry changes

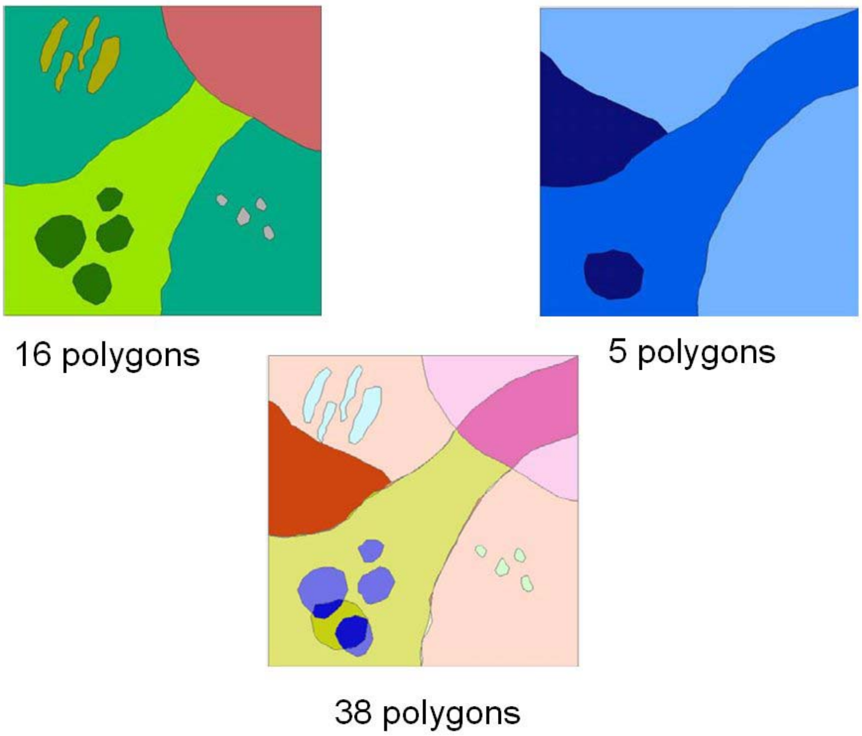

Figure 4. Illustration of the GIS overlay (*see text for explanations*)

Figure 4 demonstrates the identification problems for two small subsets for the same area. The two data sets were classified independently. Through GIS overlays and the calculation of perimeter/area ratios for all resulting areas the "sliver polygons" could be clearly distinguished from the "real" changes in the data set. The latter range between 1 and 3.1 in such an index. The slivers fall into a range of 8.1 to 25 and consist of a total area of 0.4% of the overlay result.

4 DISCUSSION

The field of landscape ecology is based on the recognition of the strong linkage between spatial pattern and ecological process [13], [32], [11]. GIS, image processing and spatial pattern analysis provide analytical methods to create a spatio-temporal analysis framework that facilitate the main underlying task to map relatively homogeneous areas. This paper builds on recent developments in image processing which would theoretically support the monitoring tasks related to discrete objects in the landscape. While many recent papers highlight the potential of image segmentation approaches for high resolution data [33] there seems to be a methodological gap. Firstly, image processing based on objects needs theories dealing with scale and hierarchy and methodologies beyond pixel-by-pixel multivariate statistics. Secondly, accuracy assessment and change detection based on objects need new methods. This short paper concentrates on change detection for two snapshots in time only. It turns out that we have methodological difficulties with even the simplified problem of comparing two data sets (Dx and Dx+1) and corresponding questions (e.g. whether or not objects Ox{Dx} and Oy{Dx+1} are the same objects).

Progress in image processing over the last years, a significant increase in computing power and an integration of remote sensing and GIS in desktop computer environments lead to an increase in applications and to more acceptance of remote sensing applications. Most image classification techniques are based on the relatively simple and straightforward concept of per-pixel information analysis. Although sophisticated methods have been added to overcome limitations of this concept, only relatively recently have integrated GIS/remote sensing approaches [34] gained momentum (for an overview see [25], [33]). Although conceptually not new, object-based image processing has been gaining in popularity since the advent of the above-mentioned commercial software product, in 2000.

The lack of semantic / methodological spatio-temporal data models greatly affects operational information update as there is an inevitable gap in the information chain. An appropriate theory-based methodology is needed, one that is relatively abstract but more accurate, that directly reflects domain objects and concepts. In [26] such a framework called MSS/ORM was suggested. It can be used to define both the structural and behavioural characteristics of geoinformation. Structure is defined in terms of objects, attributes, relations between objects and between attributes/classes and behaviour in terms of query and transaction information. Several applications demonstrate the applicability of this methodology to analyse, describe and to model image information and other kinds of spatial information (for an overview see [27] [25]). It is believed that this methodology is especially suitable to deal with multiresolution information. This paper demonstrated that it is problematic to meet the needs of change detection for independently derived dissections of the underlying data. This paper paves the road for the development of a methodological framework for object-based change detection by breaking down the complexity in the two main dimensions, namely thematic change and spatial change. Clearly, a number of important issues are not addressed, for instance the temporal scale [35].

The advent of object based image analysis techniques provides a new thrust to remote sensing, greatly expanding the inferential capabilities of such research. While ecological systems are characterized by dynamics, disturbance, and change, and landscapes are seen as shifting mosaics, analyses of spatial heterogeneity have often been conducted in a static framework [32]. Future research must explicitly consider how best to expand the temporal dimension of such research. Although this paper underpins unsolved problems and current methodological deficits, it is believed that object based analysis offers great potential for identifying and characterizing LU/LC change processes. Remote sensing and image analysis shall exploit object- and process-oriented methods and support decision support systems and uncertainty management strategies. Data volume and computing complexity are often said to be the main challenges for remote sensing. It is concluded that for unravelling spatial complexity through a (multiple) dissection strategy we are mainly concerned with semantic and ontological problems of class definition and the spatial definition of objects. We are on the way to overcome some immanent limitations of the per-pixel approach but apparently with the price of more complexity in image processing. Conversely, these developments pave the road to a theoretical/methodological debate on information extraction from images. There are neighbourhood-based methods of testing accuracy that show potential for extrapolation to patch-based analysis. However, these methods would have to adjust for unequal size of patches (versus the regularly sized neighbourhoods) in order to ensure statistical validity of the accuracy assessments [36], [2].

While the elementary spatial unit of per-pixel image analysis is predefined, object-based image classification requires some a-priori knowledge about the type of elementary objects one is looking for, either from externally defined requirements or knowledge, or from information mining. While data mining is popular in various fields of applications it is not common in Earth observation and geospatial analysis.

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