OBJECT FATE ANALYSIS – A VIRTUAL OVERLAY METHOD FOR THE CATEGORISATION OF OBJECT TRANSITION AND OBJECT-BASED ACCURACY ASSESSMENT

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ABSTRACT:

Land use often changes considerably due to shifts in political and societal systems. The border zone between Austria and Hungary (the former Iron Curtain zone) is an outstanding example for these socio-politically driven changes of land use patterns. This paper discusses a methodology to assess temporal changes, which occurred in three 2500 ha test sites near Lake Fertő between 1985 (t_0) and 2000 (t_1), regarding altered arrangements of agricultural fields. By using Landsat TM and ETM+ imagery, changes were evaluated and quantified field-specific, i.e. comparing the spatial characteristics of t_0 and t_1 fields and categorizing their 'fate' through time. Object fate analysis has been used to examine spatial changes of the t_0 fields by investigating the topological relationships between t_0 and t_1 fields. Two indices, object loyalty (*OL*) and interference (*I*), were introduced as field-specific measures to characterise field stability.

1. INTRODUCTION

1.1 Changing landscape patterns

In many areas of the world, socioeconomic and political factors have a high influence on existing land use and land cover structures, and thus may cause changes in the predominant spatial pattern in the landscape (Croissant, 2004). This study focuses on a part of the former Iron Curtain zone that represents one of the most inconsistent regions of Europe as far as ecological balance and land use, social and economic structure as well as agricultural and industrial development is concerned. In some remote areas along the border line changes occur in a wide dimension; thus long-term monitoring and change detection is particularly required (Howarth and Wickware, 1981). The progress during the last 15 years towards a common Europe can be measured by an increase of bilateral cross-border co-operations; moreover it can be analyzed by the landscape patterns being observed. Acute changes in land cover are commonly associated with human land-use activities (Lunetta, 2002; Lunetta et al., 2004) and in most parts resulting in shifting cultivations. The main influencing factor of human activity causes changes in landscape patterns, which in turn can be analysed by looking at where these changes occur, as well as the kind of changes, and the degree and rates of these (Southworth et al., 2004). Change detection maps are an important prerequisite, but the understanding of temporal and spatial dynamics of the landscape is likewise crucial (Turner, 1990).

Landscape are complex mosaics showing spatial heterogeneity caused by a specific arrangement of patches of a certain class (Riitters et al., 1995; Croissant, 2004). This mosaic can be characterized in terms of landscape composition (i.e. percentage of classes) and configuration (i.e. spatial arrangement of patches) (Turner et al., 2001). Landscape metrics (i.e. quantitative structural measures) can be used to analyse landscape patterns and study the behaviour of the metrics through time (Wickham et al., 1997; Petit and Lambin, 2002; Hudak et al., 2004; Narumalani et al., 2004; Corry and Nassauer, 2005). In the context of landscape monitoring, landscape metrics have been used as structural indicators to highlight pattern-related changes in the landscape, which are considered to cause a significant shift of underlying processes (Langanke and Lang, 2004). Other approaches characterize changes by investigating the topological relationships among corresponding patches.

1.2 Spatial change detection

Automated change analyses usually rely on the use of spatial implicit measures like percentage of changes. Several techniques for digital change detection have been presented and used for different applications, but unfortunately, few spatial change detection techniques to highlight pattern-related changes in the landscape are available. Since nature is various, a method should be capable of detecting both quantitative changes of landscape elements and changes in the patterns (object transition). Most studies clearly focus on quantification of changes, but neglect to a certain degree the specific spatial implications of changes of single units or the entire pattern. Tools for spatial explicit object-based change analysis which may represent the specific 'fate' of an object are rare. Common ways to solve this problem are map-to-map comparisons using raster overlay techniques, which are site-, but not object-specific (i.e. they refer to pixels). Vector overlay and intersections on the other hand produce complex geometry with sliver polygons. Finally, visual comparisons are powerful but highly subjective and time-consuming.

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Spatial representations and relations are discussed in the light of geographical information science since several decades; important recent studies were done by Mark (1999) and Hornsby and Egenhofer (2000). In the remote sensing community first approaches to characterize changes by investigating the topological relationships among corresponding patches are discussed by e.g. Raza and Kainz (2001) and Blaschke (2005). A typology of object geometry changes may include four basic categories, namely existence-related, size and shape-related and location-related changes. However, in reality a combination of all of these basic types of geometric changes must be tackled with.

1.3 Limitations of point-based accuracy assessment

Point-based accuracy assessment (site-specific accuracy assessment according to Congalton and Green, 1999) evaluates the thematic assignment on specific sites (i.e. point or pixels, respectively). Under the premises of site-specific assessment this is a adequate and sound method. On the other hand the appropriateness of object generation is much more difficult to assess. Object-based accuracy assessment requires both thematic and geometrical accuracy. But the latter is also depending on scale and data material being used. Any reference data set is quite likely to be captured under different conditions than the result to assess. For example, classification can be compared with a visual interpretation (Koch et al., 2003; Hölbling et al., 2005) or delineations on the ground via GPS. Either of them are conducted in specific scales and under specific conditions, which have to be considered when being used for geometrical assessment of the objects generated.

2. STUDY AREA AND DATA

The study site (see figure 1) is situated along the border between Austria and Hungary. The area is dominated by the lake Fertő, a unique steppe lake in Central Europe. The lake spreads to 315 km², of which 240 km² are located on Austrian and 75 km² on Hungarian territory. The attractiveness of the study area lies in the unique pattern along the border, where neighbouring countries can be recognized and separated visually. After the fall of the former Iron Curtain in the year 1989 the border became increasingly fuzzy. To perform the studies on changes in the land use pattern, three distinct sub-sites have been selected, all of them 2500 ha in size and bearing typical cross-border characteristics.

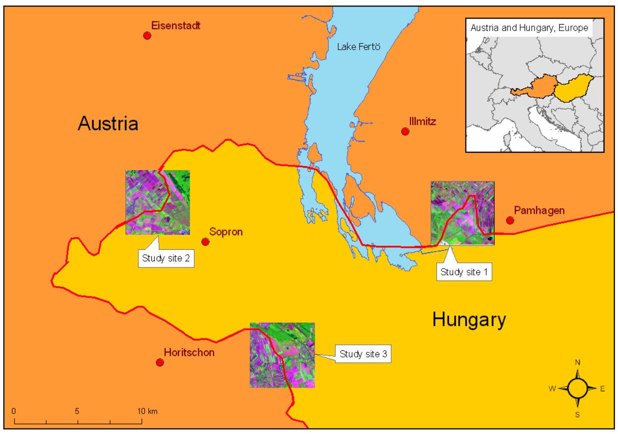

Figure 1. Location of the study site; boxes show specific study sub-sites.

Multi-temporal satellite imagery, a Landsat TM from 1985 and a Landsat ETM+ from 2000, were selected for the time series analysis. The Landsat ETM+ scene was used as the master image to co-register the Landsat TM satellite image to a ground sample distance (GSD) of 30 meter in UTM zone 33N (WGS-84) by using a second degree polynomial transformation and nearest neighbour resampling. Co-registration was done in Erdas Imagine 8.7 with an RMS error of 0.47. Afterwards the geo-referenced images were cropped to the three sub-sites of 5000 m by 5000 m along the border.

For the analysis of the dynamics of the landscape patterns, the field boundaries were needed. Instead of manually delineating these, we used image segmentation (Haralick and Shapiro, 1985), which manages to capture the field structure in an automated way. The algorithm used is a region-based, local mutual best fitting algorithm (Baatz and Schäpe, 2000) as implemented in eCognition 4.0. The images from 1985 (Landsat TM) and 2000 (Landsat ETM+) were segmented for each study site in independent working steps. For the two dates the same scale parameter has been used. This was optimized for field boundary delineation in both dates: coarse enough that in 1985 the larger fields were captured, and fine enough to reflect the higher heterogeneity in 2000. Additionally a refinement of the objects by manual fusion and manual cutting of the objects were performed to generate borders of the agricultural fields at best. The resulting image objects were exported in a non-splined vector format and re-imported into a GIS environment. The segmentation approach being used is optimized for very high spatial resolution data (e.g. one-meter satellite imagery or sub-meter aerial photographs) and radar imagery; thus aliasing and the presence of 'stepped' boundaries had to be tackled with.

3. METHOD

3.1 Object fate analysis

Since nature bears high spatial variability studies should pay more attention on the spatial arrangements rather than merely focusing on the history of changes in LULC (Crews-Meyer, 2004). We present and discuss a method for analyzing spatial object changes. The approach implies enhancements in the context of investigating spatial relationships among corresponding objects. This correspondence can be seen both as a product of object transition (change over time) or as an outcome of different object representations or delineations. Since spatial relations are various and appear in reality in different combinations there is a demand for ready-to-use solutions which are able to structure and categorize these.

A tool called LIST (Landscape Interpretation Support Tool) was developed and programmed as an extension for ESRI's ArcView 3 and ArcGIS 9 by Lang et al. (in press). The tool performs object quantification, complements visual interpretation and includes a method for object-based change analysis and object-based accuracy assessment. Following the concept of parent-and-child themes two vector layers represent the specific 'fate' of corresponding objects (the term was introduced by the authors). 'Object fate' may reflect different time slices of data capturing (change analysis) or different methods for object generation (i.e. different segmentation algorithms, heterogeneous data material, visual vs. machine-based interpretation, reference data sets from other sources, etc.). So the comparison of two data sets can also be utilzed for object-based accuracy assessment, as generated objects can be compared with visually delineated ones.

When comparing two segmented images, the corresponding boundaries of delineated land use patches do not necessarily coincide due to differences in data material or segmentation algorithms (ibid.). Even if no visible change has occurred, spatial boundaries may not be fully congruent. We utilize a method for investigating spatial relationships by performing a virtual overlay. For considering spatial uncertainty in image object generation (spatial overlay strictness, SOS), a buffer zone is introduced. The size of the buffer, either specified by the user or dynamically according to object size, controls the allowed spatial difference of spatially coinciding and corresponding fields. SOS also reflects the degree of overlap of invading objects, expressed by a percentage values. By virtual overlay we manage to characterize the specific object fate over time without modifying its geometry.

LIST investigates spatial relationships for three generalised states of transition. In this particular case, it is assumed that t_0 (*before*) objects are larger than t_1 (*after*). Object fate can be expressed by three possibilities when comparing objects from t_0 and t_1, i.e. (1) 'good' objects falling completely into the buffered outline of a t_0 object; (2) 'expanding' objects exceeding the original boundary to a certain degree; and (3) 'invading' objects (see figure 2). A special case of (1) occurs, when only one 'good' object is recorded, i.e. the t_0-object remains stable. This allows both to characterize the development of a t_0-object and to categorize objects being produced in t_1.

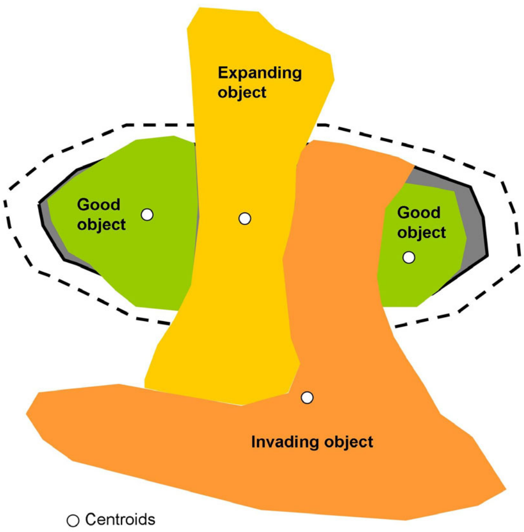

Figure 2. Schematic illustration of different kinds of object fate implemented in LIST.

This concept is a straight-forward solution to characterizing the development of each t_0-object ('parent object') and additionally enables unique categorization of every 'child object'. To characterise overall object stability two object-specific measures were introduced. The first index, 'offspring loyalty' (*OL*), is calculated by:

$$OL = \frac{n_{good}}{n_{good} + n_{exp}} \qquad (1)$$

where n_{good} = number of good objects
n_{exp} = number of expanding objects

A value of 1 indicates that no expanding objects are among the t_0 object. The second index, 'interference' is defined by:

$$I = \frac{n_{inv}}{n_{all}} \qquad (2)$$

where n_{inv} = number of invading objects
n_{all} = number of all intersecting t_1 objects

The smaller the value, the smaller the number of invading objects that interfere with the t_0 object.

Both indices *OL* and *I* can be aggregated by calculating the respective average values for measuring object fate of an entire data set by a single measure on the landscape level.

For the study the following SOS parameters were chosen: (1) dynamic buffer generation, and (2) 10% overlap for the definition of invading objects. That means, if a t_1 object overlaps with less than 10% with the t_0 object, it will be neglected. Usually, the overall number of expanding and good objects will be equal to the number of child objects. But it has to be noted that, working with stepped boundaries of relatively small parcels on Landsat imagery, some centroids may fall exactly on the field boundary between two neighbouring fields. In this case centroid ambiguity occurs, i.e. the sum of the numbers of t_1-objects in each category will exceed the actual number of t_1-objects.

3.2 Classification and accuracy assessment

Classification of the Landsat ETM+ from 2000 (study site 1) was done using ISODATA (iterative self-organizing data analysis) clustering algorithm, as implemented in Erdas Imagine 8.7 with maximum 20 iterations and a 0.98 convergence threshold to generate 40 spectral classes. The classification pre-results were visually evaluated and the individual signatures were grouped to the final classes (dense crop, arable bare soil, scrubland, meagre grassland, rich grassland and open water). Because of the relatively coarse grain of the data (900 m²), there was no possibility to classify on a finer level including more discriminations of classes.

For site-specific accuracy assessment of the classification results in the study site we applied an automatically stratified random distribution of 100 points with a minimum of 10 points for each class using the software Erdas Imagine 8.7. The reference values are based on ground truth data and ancillary data of the reference area. Moreover visual interpretation of Landsat ETM+ image in different band combinations was used to provide highest correctness. The overall accuracy was 85.00 % and the Kappa index was 0.8175, which can be considered as a moderate degree of accuracy.

The following analysis is on a preliminary stage and aims at illustrating the potential of object-based accuracy assessment. To this end we used the LIST extension and performed the following steps:

(1) A regular grid with 450 m raster cell size has been produced.
(2) Out of that, five raster cells (test cells) were selected by a random generator. The classification result intersected with these cells.

(3) The cells were visually interpreted and digitized according to the classification scheme. The produced polygon themes were further used as parent themes.
(4) The accuracy has been assessed both spatially implicit and explicit, i.e. based on (a) the percentages of the classes occurring in both themes and (b) object stability.

4. RESULTS

Object fate analysis has been performed by using both offspring loyalty (*OL*) and interference (*I*) (see figure 3). Object fate analysis has revealed that *OL* ranges between 0 and 1 in all three study sites, which was used for classifying the stability (i.e. < 0.6, 0.6-0.8 and >0.8). Taking into account the t_0 objects that have generated at least one good child object, in figure 4 the respective number of child objects are shown in three specific ranges of *OL* (< 0.6, 0.6-0.8 and >0.8). The other metric, *I*, reflects the degree of interference between corresponding objects. The values of *I* range from 0 to 1, but mainly occur between 0 and 0.6. Interference, therefore, can be considered moderate for all three study sites with high occurrences in the range >0-0.6 in study sites 1 and 3 as opposed to study site 2.

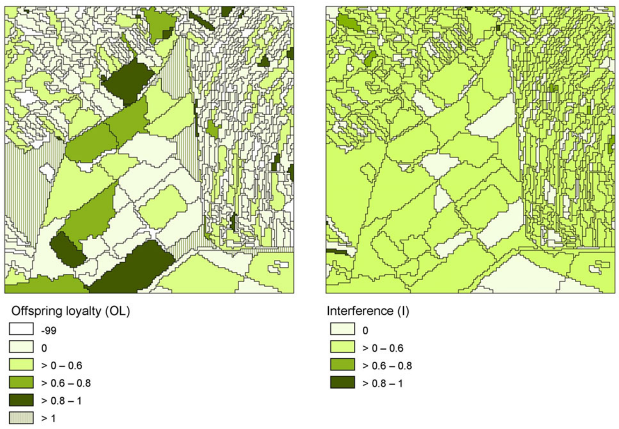

Figure 3. Spatial distribution of two variables calculated for each object t_0 in study area 1. Left: Offspring loyalty (*OL*). Values of -99 occur if neither good nor expanding objects exist, values higher than 1 indicate centroid ambiguity. Right: Interference (*I*).

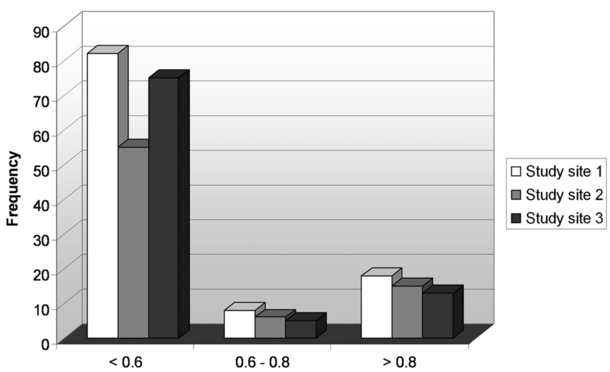

Figure 4. Histogram of offspring loyalty in three ranges (< 0.6, 0.6 - 0.8 and > 0.8) for the three study sites.

The diagram in figure 5 shows the comparison of the percentages of each class between the classified and digitized test cells. From this (spatial implicit) point of view, the congruence seems to be high. However, regarding object stability only two polygons were identified as being *stable* for altogether 20 polygons observed in the test cells.

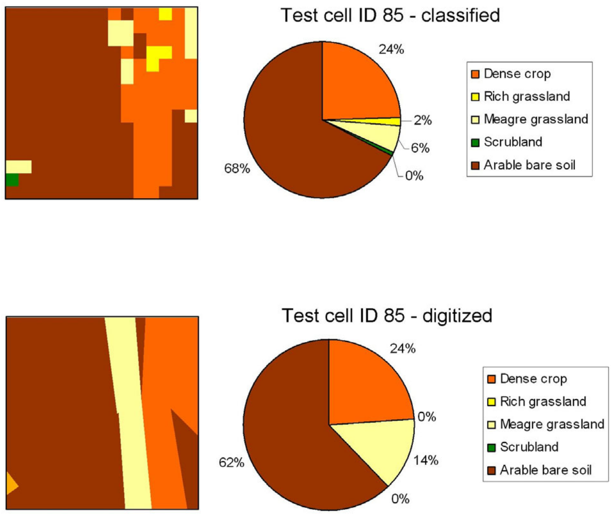

Figure 5. Diagram showing the percentages of each class (top: classified evaluated cells, bottom: digitized reference cell)

5. CONCLUSIONS

In order to fulfil the requirements for new approaches to tackle with temporal and spatial complexities, the application introduces a method called object fate analysis. Three different spatial relationships of object transition are considered. There is a demand to come up with a ready-to-use solution which generalises and categorizes the variety of spatial relations, which appear in different combinations over time. Consolidation and extension of the introduced concept is envisaged. In general, the integration of GIS concepts of representing relationships as discussed by Langran (1992), Egenhofer (1994), Mark (1999) and Hornsby and Egenhofer (2000) is challenging to be adapted to LULC change detection applications. Remote sensing methods need to integrate spatial concepts; the pixel-based neighbourhood concept is limited. An object-based approach instead makes use of spatial analysis methods dealing with polygons.

Object fate analysis relies on a straight-forward and operable concept of spatial relationships among corresponding image objects. These objects can be obtained from any two different sources, such as two time slots, different ways of field delineation, multi-scale representations of a single scene, etc. It has some built-in flexibility using the scale-dependent SOS concept with different possibilities of parameterisation. But the dependency of the results on these parameters has yet to show and the sensitivity has to be proven. Limitations mainly are related to the quality of the generated objects, which very much depends on the specific data material and segmentation algorithms. Nevertheless this approach clearly demonstrated that the interpretation of land use changes overcomes the restrictions of a mere comparison of classification results based upon pixel classification.

In general, the integration of GIS concepts representing spatial relationships offers a new dimension of change interpretation for land use/land cover related studies. The spatial explicit comparison of objects may overcome the limitations of a mere comparison of classification results based upon pixel classification. Differences in scale and representation we take into account by introducing the SOS factor; however, the parameterization of SOS is crucial for telling real changes from data-induced one.

This also applies to object-based accuracy assessment. By explicitly focusing on the spatial accuracy we go beyond traditional point-based assessment methods, since the spatial delineation of the image object may be even more significant for validating the overall quality of the classification. As it has been shown, t_1 may represent the result of automated object generation and t_0 the result of a visual interpretation. A measure, which shows the total accuracy of spatial change, is to be developed in the future. The comparison of the visual vs. automated delineation in a narrow sense contradicts the premise of Congalton and Green (1999) that reference and evaluation data records geometrically exactly one fit above the other. The segment-based approach used in this paper follows the pixel boundaries. By this, even on higher hierarchical level, the aggregated segments are only scale-adapted. The visual delineation, however, is scale-specific. The results are also influenced by parameterization of SOS, which depends on scale and resolution.

We believe that only by spatial explicit change and accuracy assessment we can link the observed pattern to landscape ecological processes. These changing spatial arrangements could further be assessed by applying other spatial measures from the toolbox of landscape metrics.

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