CHANGE DETECTION BY OBJECT-BASED CHANGE INDICATIONS

P. Hofmann, P. Lohmann, S. Müller

IPI – Institute of Photogrammetry and GeoInformation, Leibniz Universität Hannover, Nienburger Str. 1, 30167 Hannover, Germany

{hofmann, lohmann, mueller}@ipi.uni-hannover.de

Keywords: Change detection, indicators, GIS, updating, mapping from satellites

ABSTRACT:

Within a current research project remote sensing imagery in the range of 5m spatial resolution like SPOT and IKONOS are used to derive a Land Use – Land Cover (LULC) database, which is regularily updated. The revision process includes a concept for an object-based change detection attempt to efficiently update existing geo-spatial data which is described in this paper. The change information needed is derived from recent satellite images using automatic image processing and analysis. The conceptual idea includes both, manual (applying visual interpretation) and automatic image analysis steps resulting in a change layer, which highlights those areas or objects which are suspect for change and gives an indication of the direction of change.

Different preprocessing steps have been implemented in order to avoid seasonal effects or changes due to different imaging conditions, such as atmospheric conditions, different sun angles, etc.. However not always ideal imaging conditions can be found which result in change indications, like shadows which becomes more dominant with increasing image resolution. Further pre-processing includes an automatic haze reduction and a shade correction using an appropriate DTM. Image coregistration and automatic cloud and shade-of-clouds detection is performed in the standard processing and thus will not be discussed here. However the attept presented uses additionally a priori knowledge of potential change for the specific object classes as input to control the subsequent image processing.

The concept of the change detection starts by setting up a focusing step to selectively initiate the following steps only for those objects which are considered as changed. Thereafter all changed objects are classified either visually (manually) or by an automatic procedure depending on the type of change detected. The decision which classification procedure is used depends on a transition-probability-matrix which indicates for each class the degree of likelihood of possible and impossible class-transitions respectively in combination with a table of available classification operators which can be applied to validate the predicted change. The transition-probability-matrix is generated manually and contains assumed possible changes from one class to another. If an automatic classification is indicated, the procedure then consists of two parts: First it is evaluated if the object's geometry is changed or if the object is changed as a whole. If a change in geometry is detected, the object of concern has to be re-segmented and re-classified. If not, the object has to be re-classified only. If a manual classification is indicated, changes will be mapped respectively. At the end the results of the visual/manual classification and the automatic classification are joined into one change layer, which holds for each changed object besides its change

indication information, the objects' historical classification and its new classification. This layer can then be directly used as input for updating existing GIS databases.

This paper concentrates on the first part of the process chain, namely the focusing module. The focusing module has two tasks: First, objects have to be found in the GIS data which are affected by change. Second, the focusing module has to decide, whether the changed objects subsequently can be processed automatically or must be processed manually.

Different pixel based change indicators are implemented based on a comparison of the input satellite data of two different dates. The decision if a change is apparent in many cases is dependant on the threshold or threshold function used. Approaches avoiding crisp thresholding and using fuzzy membership indicators at the desired object level will be discussed in this paper. The obtained results of the proposed object-based change detection process chain are compared to change detection results obtained by completely visual interpretation. Finally all results are assembled to a resultant change indication map.

1 DECOVER BACKGROUND AND CONTEXT

In the context of GMES (Global Monitoring for Environment and Security), a joint initiative of European Commission and European Space Agency, several services are developed to provide spatial information in support of the monitoring and reporting obligations of European directives (Overview at www.gmes.info, Example Water Framework Directive Dworak et al 2005). These implementations take place with strong participation of German authorities, researchers and service providers. Current developments at the European level support a new European-wide land cover data set (Core Service Land Monitoring). This data set must be seen as a European consensus and will solely contain thematic land cover data information supporting European reporting obligations. Its geometric and thematic resolution will only partly support national and regional needs. DeCOVER (Büscher, et al., 2007) will complement and extend these developments at the national and regional level for German users.
A set of geo-information services has been designed to support national and regional users in their monitoring and reporting obligations. The DeCOVER service concept is divided into core and additional services. The DeCOVER core service has two main focal points. First, the provision of national harmonized land cover data supports the German spatial data infrastructure (GDI-DE) in providing selected and validated geo-information and second, the development and application of change detection and interoperability methods to sustain existing data bases (namely ATKIS, CLC and BNTK). The project is co-funded by the Federal Ministry of Economics and Technology (BMWI) via the German Aerospace Center (DLR) and implemented by a consortium of 11 partners (see Table 1) each using its own expertise and specialized skills.

Partner	Expertise
EFTAS GmbH	Coordination, Agriculture
GAF AG	Validation, Forestry
DELPHI IMM GmbH	Interoperability, Link to INSPIRE
IPI, LUH	Innovation, Quality Control
Infoterra GmbH	Spec. Core Service, Economics, Link GMES
RapidEye AG	Implement. Process. Chain
GDS GmbH	Change Detection, SAR-Appl., Urban Areas
Definiens AG	SW support, Object Based Image Analysis. & Classific. of Water Areas
RSS RemoteSensing Solutions GmbH	Nature Landscape conservation
Jena.Optronik GmbH	SAR-Optical Co-Registration
DLR Assoc. Partner	Support. Urban, SAR-Proc.

Table 1: Consortial Partners, Expertises and Skills.

The overall structure of the project is shown in Fig. 1. In a coordinated attempt the processing (segmentation & classification of the satellite data is being done according to rules and directives as demanded by European and National directives and policies. Much effort has been put into the consideration of user requirements, which directly influence the service definition and design of the DeCOVER database and its production chain which has a strong feedback to user demands. The methods developed and strategies used are being implemented for the creation of the core service and have direct impact to the processing chain, quality control and data revision, considering at each stage the specification and standards as demanded by the interoperability task. An initial user requirement analysis has shown real synergies between (thematically) different user needs. Parallel to the user requirement analysis, potential of interoperability between the identified land cover classes has been analyzed in order to optimize synergies between existing data sets and newly collected information. The currently tested object catalogue of the core-service includes 39 land cover (LC)/land use (LU) classes arranged in a hierarchical order. The detailed object catalogue and mapping guide can be found in the user portal of the DeCover homepage (see DeCOVER, 2008).

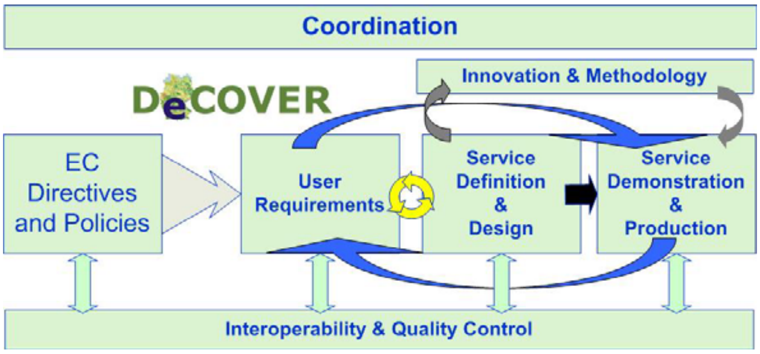

Figure 1: DeCOVER Organisation

There are three major areas of innovative research and development in the project, where methodologies are developed, namely

- the area of semantic interoperability
- change detection
- data fusion of optical and SAR images

In the following this paper will focus only to the second part, the change detection.

2 THE CONCEPT OF DECOVER CHANGE DETECTION

Change detection (CD) algorithms can be classified either into the comparison of classes following an interpretation at different dates (post-classification) or to image differencing (Singh, 1989). The former focuses on the comparative analyses of independently produced interpretations from different times, the latter comprises simultaneous analysis of multi-temporal data. Because a second classification of the whole area results in costs, far too expensive for most of the users another procedure is envisaged here. CD in this case is regarded not as a change mapping but rather as a “notification/indication” of change with a possibility to indicate geometric and attributive change occurrences (i.e. class transition(s)). Therefore, the output of the DeCOVER change-detection procedure is a GIS-data-layer (change-layer), which holds the geometry of detected changes (change-objects) plus information about the assumed changes together with indications for the plausibility of these assumptions. Thus, it relates to objects as part of an existing database but compares two images at different dates on a per-pixel level, giving a pixel- and segment-based indication of LU/LC change. Methods for the comparison of images from different dates may be grouped into those which use univariate image differencing alone (Singh, 1989, Fung, 1990), methods to compare vegetation properties like NDVI or Tasseled Cap Tranformations (Richards, 1993), or change vector analysis (Lambin, 1994, Bruzzone et al, 2002). A comprehensive overview of existing pixel based techniques, their advantages, disadvantages and resulting accuracies is given by Lu et al, 2004.

Relating pixel-based indications to objects means developing an approach for integrating these indications into an object based analysis. There are several ways to implement such a procedure as has been shown by different authors (Schöpfer, 2005, Busch et al., 2005 and Gerke et al., 2004). Because users of DeCOVER prefer some type of a "change notification", which might also be useful for their specific application, like updating of user operated databases (i.e. ATKIS) by proprietary techniques an attempt as described in the following chapters has been made to set up and realize a prototypical framework for CD. The framework is split into two main modules: a focusing module and a classification module. Both have been designed and realized in close cooperation between the company GeoData Solutions (GDS) and IPI.

2.1 FOCUSING MODULE

Within the CD-concept this module plays an important role, since it outlines potential changes by generating change-segments based upon per-pixel change indicators. Steps of pre-processing, necessary to render the two images comparable in both the spatial and spectral domains are included (co-registration, radiometric normalization). Fig. 2 shows an outline of the focusing module.

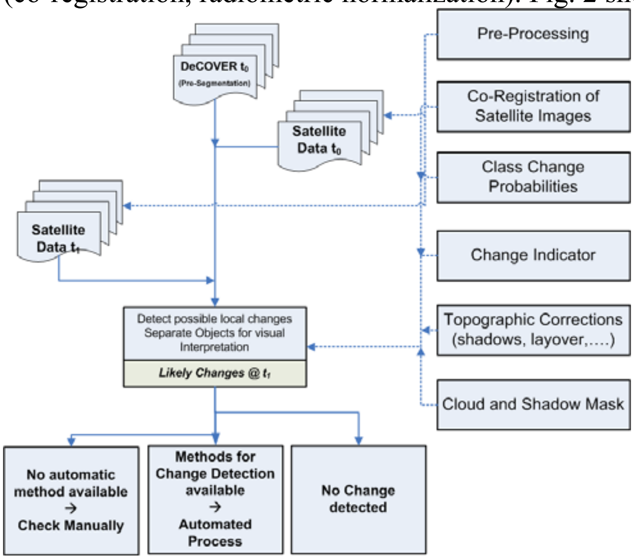

Figure 2: The Focusing Module.

With respect to the spatial domain miss-indications by displaced pixels in both images should be avoided. However, due to differences in illumination and view angles some "change noise" is still unavoidable. In order to outline changes indicated by a per-pixel comparison of the images within the focusing module, an image segmentation based upon one or more pixel-based change-indicators is applied. This way, not the changes themselves, but borders between different change indication-values are generated, which consequently leads to a spatial differentiation of change- (high indicator values) and no-change-areas (low indicator values) in terms of changes in signal. These segments can be subsequently handled as image objects (of change) which consequently offers the whole palette of object based image analysis (see Blaschke, T. et al, 2008; Schöpfer, E., 2005). Although all of these advantages of segmenting indicated changes, the typical drawbacks of this approach cannot be denied: the generated image objects should ideally represent true change-objects, which means: each change should be represented by only one image-object (no over- or under-segmentation). This in turn leads to the problem of finding suitable segmentation algorithms and parameterizations.Last but not least, comparing for each change-object its class assignment in the mapping of the GIS-database (DeCOVER t0), the a-priori probabilities (Pt) of change for this class and the statistics of the underlying (indicator-) images leads for each segment to an estimation, whether the segment outlines a change and if so whether the type of change, i.e. the new class can be determined automatically or manually. Vice-versa, each object of the DeCOVER-t0-mapping can be marked as changed as soon as it covers or overlaps a change-object.

2.2 SEGMENTATION AND CLASSIFICATION MODULE

Within the classification module in principle the last step of the focusing module is recursively applied for each change-object until the most plausible change, i.e. the most plausible class at the second point of time (t1) can be determined. In the worst case no such evidence can be given except that a change in signal has been detected, but its class-assignment in t1 remains unclear. In all other cases each change-object can be assigned to one or more classes with a certain degree of a-priori probability and an indicated type of change (e.g. increase or decrease of vegetation).

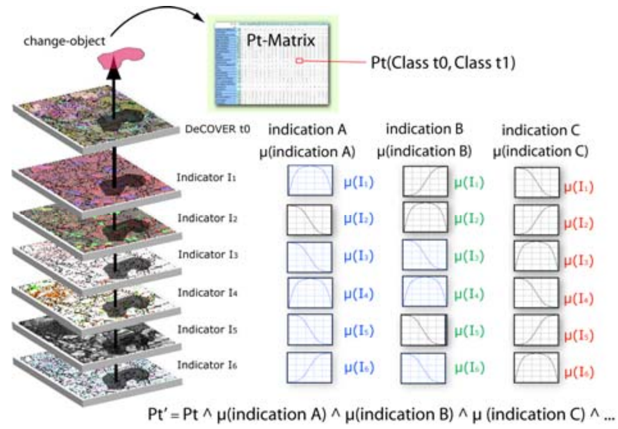

Figure 3: Illustration of determining plausible changes (Pt') for a segmented change-object by combining fuzzy-assignments to indication-classes (indication A to C) using different statistical parameters on a per-object basis for each indicator with a-priori probabilities of change (Pt). The segmentation is based upon one or more pixel-based change-indicators (I_1 to I_n)

Thereby, the a-priori probability is taken from a so-called transition-probability-matrix (Pt-matrix), which will be explained in chapter 3.1 in more detail, whereas the indicated type of change is given by the fuzzy-combination and -analysis of indicators (object-based statistics) and derived indicator-classes (see chapter 3.3). Thus, the combined analysis of a-priori probabilities of transition (Pt) together with fuzzy-membership-degrees (μ) to indicator-classes can be seen as a plausibility check of change, whereas the most plausible change (Pt') can be understood as the most likely change. Referring to the envisaged content of the change-layer, for each change-object its most plausible change (Pt'), together with its indications (membership-degrees to indication-classes) can be determined (see Fig. 3). Thus, after applying some generalization rules to the outlined change-objects the output of the classification module is exactly the desired change-layer.

Regarding the three-level-hierarchy of the DeCOVER-nomenclature (see DeCOVER, 2008) it is obvious that some changes can only be assigned in the first or second class-level automatically, while others are even assignable in the third level. Therefore, as soon as for a detected change no clear assignment can be given, it has to be determined manually or left as not assignable.

3. IMPLEMENTING THE CONCEPT

As described in chapter 2, besides the delineation of changes, each object of the change layer shall be given one or more likely classes for t1 and some tangible terms of expressing the plausibility for each assumed t1-class. A very central point in determining the plausibility of a detected change is the consideration of the a-priori probability of a class to exchange from the current (t0) class assignment to another in t1.

3.1 SETTING-UP THE PT-MATRIX

Assuming that the DeCOVER class-hierarchy and its nomenclature applies at the point of time t1 the same way, as it did in t0 and assuming that a change indicated by the comparison of the image data of t0 and t1 indicates a change of class assignment, then in principle such an indicated change simultaneously indicates a change from the class t0 to another out of the 38 possible classes at t1 at the indicated position. Since we know a-priori that some transitions or changes of an object are very unlikely or even impossible within a given time, e.g. such as from *dense urban area* to *glacier* within a period of two years, while others are relatively likely, e.g. from *arable land* to *sparse urban area* or *construction site* within the same period[1], we can assume that for an indicated change if there was *arable land* before the probability of being *sparse urban area* or *construction site* at the indicated position now is higher than being a *glacier* there. Thus, in all subsequent processes of analysis we can skip such procedures, which tend to verify unlikely transitions and focus on those which verify the most probable ones. For the given example: if at the indicated position or for the indicated (change-) object a decrease of vegetation is indicated and there was *arable land* in t0, it is more likely that in t1 there is *construction site* or *sparse urban area* to be found than *glacier*. The likelihood or probability of transitions within classes can be recorded in an n x n matrix whereas n is the number of classes. However, for some transitions reliable values are hard to determine without expert knowledge or analyzing historic mappings and statistics in detail. Thus, we decided to fill the Pt-matrix in collaboration with the experts of the DeCOVER consortium, whereas each Pt-value has to be below 1.0 and greater than 0.0. Additionally, the sum of each Pt-vector has to give 1.0 (normalization). Nevertheless, each Pt-value has to be seen as a heuristic value and does not claim to be 100% true.

In order to make the Pt-matrix and its values more usable in the change analysis, first all Pt-vectors are sorted according to the highest Pt-value. Then the sorted matrix is split into one table containing the sorted t1-classes for each t0-class and another table containing the appropriate (sorted) Pt-values. This way, each t0-class obtains an indexed vector of t1-classes, whereas index 1 indicates the most probable t1-class and index 38 indicates the less probable t1-class. This way, for each object of the DeCOVER-t0-mapping its sorted Pt-vector and the indexed t1-classes can be assigned.

3.2. Creating change-objects by segmenting per-pixel indicators

In order to keep the results based on the IKONOS- and SPOT5-data comparable, for all further investigations the IKONOS-1 (blue) and SPOT5-4 (swir) channels were skipped. As reported in Lohmann, P. et al., 2008 several pixel-based change indicators have been investigated regarding their suitability for a focusing module as described here. Therefore a comparison between the indicators and a manual change classification regarding the categories *Urban* and *Vegetation* has been undertaken. The results were relatively poor due to several reasons. One of them is the “change-noise” which is mostly caused by different illumination situations. However, it turned out in this investigation, that the principal components (PC) generated out of the channels of t0 and t1 and the (normalized) difference of corresponding channels (Diff_norm) show the best results. As the authors note, one of the reasons for the relative poor results lies in the reference used, which was a manual digitizing of recognizable changes. Respectively, objects were compared to pixels. This means changes and “change-noise” was compared to a noise-free reference, which leads to an overestimation of false-positives and false-negatives on a per-pixel-comparison.

In order to suppress “change-noise” and to obtain contiguous areas of change and no change respectively, an image segmentation based upon the per-pixel change indicators appears to be reasonable for the following reasons:

- The border of each change-object is generated along steep changes of change-indication depending on the thresholds of the used algorithms.
- Thus, the generated objects can be regarded as more or less homogeneous areas of change or no change given by the indicators used for delineation.
- Shape, texture and pixel statistics of each object can be used to analyze and classify it at least as change- or no-change-object.

[1] in Germany

Since the so called multi-resolution segmentation (MRS) described by Baatz & Schäpe, 2000 uses criteria of homogeneity in color (here in change-indication) and shape it seams to be adequate to generate reasonable change-objects based on the per-pixel indicators. This means the criterion of color-homogeneity of the MRS is generated by the per-pixel-indicator values, which finally leads to objects of homogeneous change-indication. As reported by several authors (Meinel, G., et al, 2001a; Meinel, G., et al, 2001b; Neubert & Meinel 2002a; Neubert & Meinel 2002b), a critical point of the MRS is its parameterization, i.e. to find a well balancing between over- and under-segmentation of the desired objects. To overcome this drawback, an over-segmentation - i.e. too small neighboring objects with similar indication values - can be merged according to their mutual difference of indication values if the difference is below a defined threshold. Thus, the resulting change-objects are generated in a first step according to their homogeneity of indication values and shape and in a second step according to their similarity of indication values.

Because of the results in Lohmann, P. et al., 2008 as a first mind it seams to be convincing to use the difference channels based upon the (normalized) green-, red- and nir-channel (Diff_norm) and the principal components of the t0 and t1 channels (PC) as input for the segmentation. However, regarding the information content in terms of change or no-change both indicators are relatively redundant - especially PC2 und PC4 are highly correlated to the differences of the three spectral channels (see Table 2). Additionally, the interpretation of PCs – especially of temporal PCs is relatively ambiguous so that the information content of each single PC is quite unclear. In the data present, regarding table 2 and table 3 in conjunction, it is quite unclear, whether PC4 reflects the difference in the red and green channels or just the content of the red and green channel at t0 and t1, which are highly correlated at each point of time. Consequently, when using the PCs as input for an image-segmentation, the results are hardly comprehensible in contrast to those generated by the *Diff_norm*-channels only.

	Diff_red	Diff_green	Diff_nir	PC1	PC2	PC3	PC4	PC5	PC6
Diff_red	1,0000	0,9589	-0,1284	-0,0453	0,1755	-0,1647	-0,9539	-0,0602	0,1381
Diff_green	0,9589	1,0000	-0,2652	-0,0455	0,3097	-0,1795	-0,9261	0,0245	-0,0947
Diff_nir	-0,1284	-0,2652	1,0000	-0,0577	-0,9725	0,2066	-0,0740	-0,0060	-0,0047
PC1	-0,0453	-0,0455	-0,0577	1,0000	-0,0011	-0,0042	0,0003	-0,0088	-0,0033
PC2	0,1755	0,3097	-0,9725	-0,0011	1,0000	0,0016	-0,0001	0,0033	0,0012
PC3	-0,1647	-0,1795	0,2066	-0,0042	0,0016	1,0000	-0,0004	0,0123	0,0046
PC4	-0,9539	-0,9261	-0,0740	0,0003	-0,0001	-0,0004	1,0000	-0,0008	-0,0003
PC5	-0,0602	0,0245	-0,0060	-0,0088	0,0033	0,0123	-0,0008	1,0000	0,0097
PC6	0,1381	-0,0947	-0,0047	-0,0033	0,0012	0,0046	-0,0003	0,0097	1,0000

Table 2: Correlation-coefficients between spectral differences and PCs of t0- and t1-channels for the test area Herne.

	t0_green	t0_red	t0_nir	t1_green	t1_red	t1_nir
t0_green	1,0000	0,9638	-0,0176	0,4175	0,4200	0,1534
t0_red	0,9638	1,0000	-0,1744	0,4296	0,4599	0,0354
t0_nir	-0,0176	-0,1744	1,0000	-0,0168	-0,1124	0,4808
t1_green	0,4175	0,4296	-0,0168	1,0000	0,9606	0,0316
t1_red	0,4200	0,4599	-0,1124	0,9606	1,0000	-0,1328
t1_nir	0,1534	0,0354	0,4808	0,0316	-0,1328	1,0000

Table 3: Correlation-coefficients between spectral channels of t0- and t1-channels for the test area Herne.

A further aspect that has to be taken into account for the parameterization of segmentation algorithms is their transferability to image data of different sensors. The main aspects which have to be considered here is the influence of spatial resolution and radiometry to the generated segments. For radiometrically comparable sensors the influence of the spatial resolution can be handled to a certain degree as demonstrated in Hofmann 2005. Although the IKONOS data used in this investigation has been resampled to a resolution of 5m the radiometry of IKONOS- and SPOT-data is different. Considering that for the segmentation of change-objects indicators are used, which are derivatives of the original channels, the influence of different sensor characteristics to the segmentation is hardly predictable. Thus, we decided to parameterize the MRS and Spectral Difference Segmentation individually for each scene and having in mind, that for an operational change layer generation data of the to-be-come Rapid Eye sensor will be used. For both scenes we applied a sequence of MRS and Spectral Difference Segmentation as outlined in chapter 2. The principle algorithm underlying the MRS are well described in Baatz & Schäpe, 2000 whereas the Spectral Difference Segmentation merges neighboring objects if the difference between their mean intensities (here: the channel differences of t0 and t1) is below a given threshold. In the context of temporal spectral differences, in accordance with Definiens, 2004 the formalism for the MRS is given as follows: let the homogeneity of shape for an object be defined by:

$$h_{shape} = w_{cmpct} \cdot h_{cmpct} + \left(1 - w_{cmpct}\right) \cdot h_{smooth}$$

whereas h_{cmpct} (homogeneity in compactness) is defined by:

$$h_{cmpct} = n_{Merge} \cdot \frac{l_{Merge}}{\sqrt{n_{Merge}}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{\sqrt{n_{Obj1}}} + n_{Obj2} \cdot \frac{l_{Obj2}}{\sqrt{n_{Obj2}}} \right)$$

and h_{smooth} (homogeneity in smoothness) is defined by:

$$h_{smooth} = n_{Merge} \cdot \frac{l_{Merge}}{b_{Merge}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{b_{Obj1}} + n_{Obj2} \cdot \frac{l_{Obj2}}{b_{Obj2}} \right)$$

with:

$w \in [0,1]$

n = No. of pixels of a segment

l = borderlength of a segment

b = shortest possible border length given by the bounding box of a segment

The indices *Merge*, *Obj1* and *Obj2* represent the resulting segment (*Merge*) and the segments to be merged (*Obj1* and *Obj2*), whereas single pixels can be regarded as segments as well. The homogeneity of channel differences of t0 and t1 is explained by:

$$h_{cd} = \sum_{i=1}^{cd_n} w_{cd_i} \left(n_{Merge} \cdot \sigma_{cd_i}^{Merge} - \left(n_{Obj1} \cdot \sigma_{cd_i}^{Obj1} + n_{Obj2} \cdot \sigma_{cd_i}^{Obj2} \right) \right)$$

with cd_i as temporal difference of channel i analogous to the homogeneity of color as described in Definiens, 2004.

Then, change-objects are generated, if their fusion value f is below the so-called Scale Parameter (Definiens, 2004) SP:

$$SP \geq f = w \cdot h_{cd} + (1 - w) \cdot h_{shape}$$

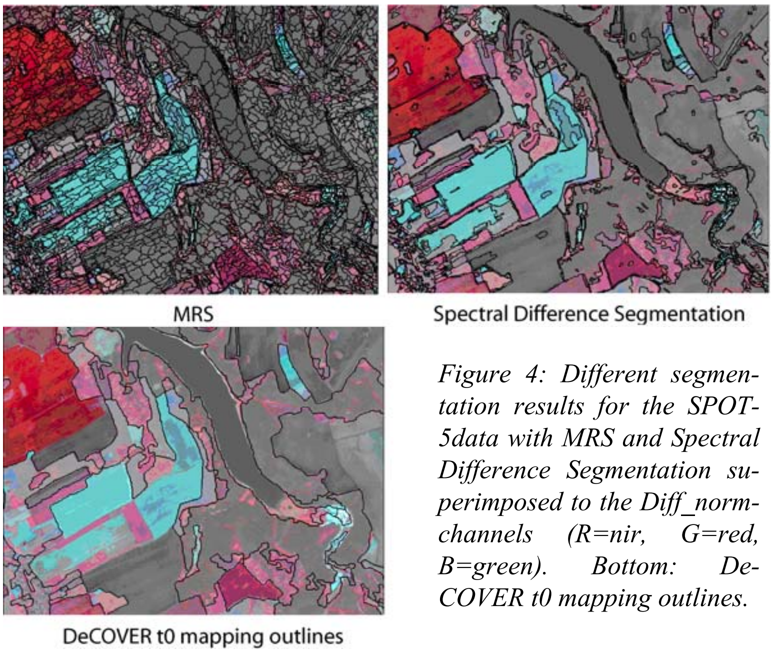

Figure 4: Different segmentation results for the SPOT-5data with MRS and Spectral Difference Segmentation superimposed to the Diff_norm-channels (R=nir, G=red, B=green). Bottom: DeCOVER t0 mapping outlines.

In our research we have weighted each channel difference equally, i.e. by 1.0 and the homogeneity of shape was in both scenes weighted by 0.2 with a weighting of smoothness to compactness of 0.5 each in each scene. However, due to the different radiometric properties of IKONOS and SPOT 5 the Scale Parameters were different (100 for IKONOS and 10 for SPOT 5). In both scenes the DeCOVER-t0-mapping was integrated in the segmentation as limiting factor, i.e.: existent DeCOVER-t0-borders must not be destroyed by any subsequent segmentation. Since for the IKONOS-data these parameters already led to well describable change-objects, at this stage no further merges using a Spectral Difference Segmentation were necessary. The SPOT-5 data however was at this stage already over-segmented (see Fig. 4). Therefore, the segments of the initial MRS were merged by applying a Spectral Difference Segmentation with a maximum spectral difference value of 10. This means neighboring segments with a mean difference of the temporal differences of the channels is below 10 are merged.

In accordance to Definiens, 2007, the spectral difference between two segments is calculated as follows: the normalized weight w_{cd} of channel i (here: a temporal channel difference cd_i) of a segment is defined as:

$$wn_{cd_i} = \frac{w_{cd_i}}{\sum_{i=1}^{n} w_{cd_i}}$$

then, the spectral difference between two segments is defined as the sum of the weighted differences of the segments' mean values in each channel:

$$sd = \sum_{i=1}^{n} wn_{cd_i} \cdot abs\left(cd_{i_{Obj1}} - cd_{i_{Obj2}}\right)$$

In order to be capable to describe the homogeneity of changes on the basis of properties of sub-segments in each scene, a further segmentation level holding clearly smaller segments (over-segmentation) was generated. Therefore, the IKONOS scene was sub-segmented applying the MRS with a scale parameter of 33 followed by a Spectral Difference Segmentation with a threshold of 75. In the SPOT5-scene the segments of the MRS were aggregated by a Spectral Difference Segmentation with a maximum allowed difference of 10 (see Fig. 4).

3.3 DEFINING CLASSES OF CHANGE

After having generated segments on the basis of per-pixel indicators, it has to be determined whether a segment represents a change or not. Therefore, either further per-pixel indicators with their respective statistics within the generated segments (change-objects) can be used or new indicators on a per-object basis can be generated. Whichever indicators are used, either absolute thresholds or clear expressions for a degree of change have to be found. The latter has its advantage in determine changes by expressions of like: *"the more/less [indicator value(s)], the more/less an object is a change/no change"*. This means in conjunction with the Pt-matrix the more/less certain indications are given, the more/less probable the given a-priori change is.

3.3.1 DEFINITION OF CHANGE, NO-CHANGE AND DIFFERENT TYPES OF CHANGE

As Table 2 and Table 3 (see chapter 2) already show, most of the changes indicated by the per-pixel indicators are changes in vegetation, i.e. either an increase or decrease of the vegetations vitality. Therefore, a change in vegetation is given, if a segment, which has been segmented on the basis of the *Diff_norm*-channels, shows discrepancies in the NDVIs calculated for t0 and t1. By calculating the ratio between the mean $NDVI_{t1}$ and mean $NDVI_{t0}$ of an object no change is given if the ratio is at 1.0. In terms of indicating a gradual change the more the ratio between the mean $NDVI_{t1}$ and mean $NDVI_{t0}$ of an object is unequal to 1.0 the more a change in vegetation is given. This expression can be depicted by a fuzzy membership function as displayed in Fig. 5, whereas here each NDVI has been normalized to a range of 0.0 to 1.0 before and as upper and lower bound for absolute membership (i.e. a definite change) 0.9 and 1.1 respectively were set.

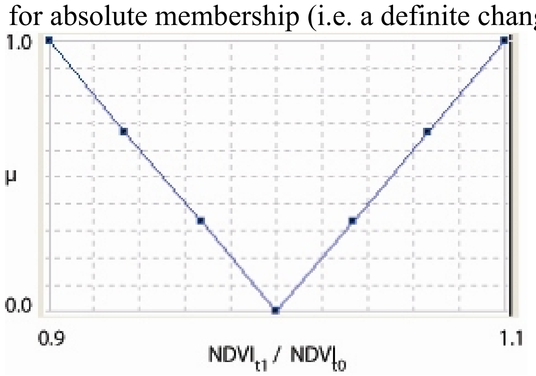

Figure 5: Fuzzy membership function to express changes in the vitality of vegetation by the ratio of the NDVIs of t0 an t1.

In terms of expressing gradual changes, the membership function in Fig. 5 can be interpreted as follows: if the ratio between $NDVI_{t1}$ and $NDVI_{t0}$ of an object is exactly 1.0 no change in vegetation is given. If it is below 0.9 or above 1.1 there is definitely a change in vegetation given. If the ratio is between 1.0 and 1.1 or 0.9 and 1.0 a gradual change of vegetation according to the degree of membership (μ) is given. This way, an increase or decrease in vegetation vitality can be described analogous so that a definite decrease is given with a ratio below 0.9 and vice versa for an increase. However, as demonstrated in Fig. 6, increases or decreases of the NDVI are given in agricultural areas the same way as for example changes from vegetated to non-vegetated areas and vice versa.

As shown in Fig. 6 due to the relatively high dynamic of agricultural areas in the NDVI (or any other measurers sensitive for vegetation vitality), increases or decreases of the NDVI mostly occur in such areas. However, in the most cases these increases or decrease cannot be interpreted as changes of land use. On the other side, changes of vegetation in agricultural areas typically occur steadily and more or less equally distributed within a field[2]. Thus, in many cases such changes can be discriminated from other changes by regarding the homogeneity of change within a change area. To describe the homogeneity of a changes related to its area, e.g. the differences of the standard deviations ($\Delta\sigma$) for each channel at t0 and t1 within the change area can be analyzed. However, a disadvantage of this approach is to find suitable thresholds to determine whether a change is homogeneous or not, since the standard deviation

[2] field in this context are areas with equal cultivation and not of equal land tenure are meant.

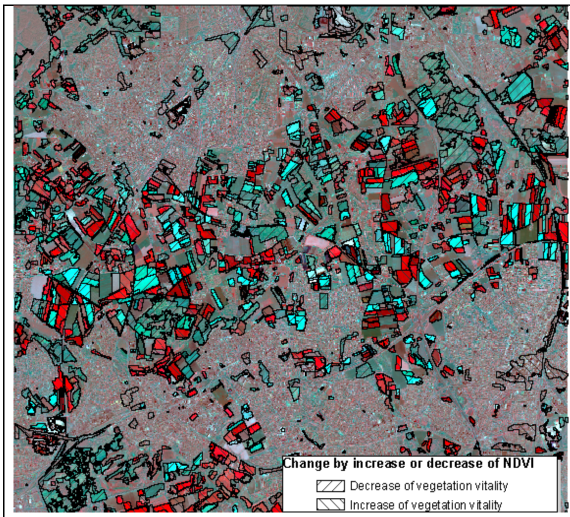

Figure 6: Classified change segments by decrease or increase of the NDVI superimposed to Diff_norm-channels (R=Diff_norm nir, G=Diff_norm red, B=Diff_norm green.)

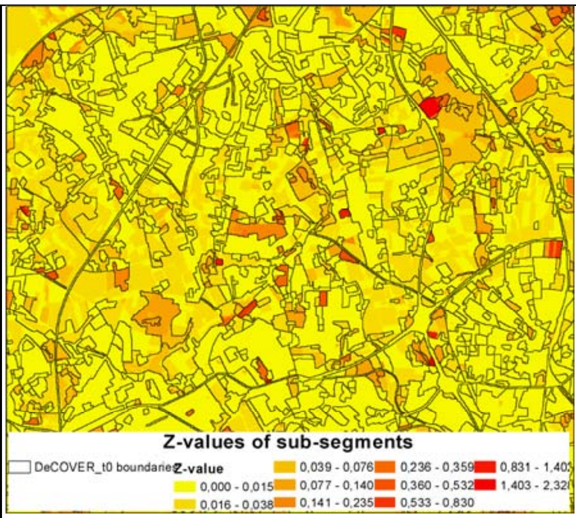

Figure 7: Z-values of sub-objects based upon the segments' channel mean values of t0 and t1.

depends on the size of a segment. Thus, in order to evaluate the usability of Δσ we determined the thresholds of -20 respectively +20 empirically. Besides, these values approximately coincide with the overall σ/2 of the per object Δσ.
When working with object hierarchies, as like with Definiens™ Developer, another approach to define the homogeneity or heterogeneity of change within an area is to analyze the relationship of the size of a change area to the number of sub-segments generated by an over-segmentation as described in chapter 3.2. For this approach an indication can be given by the ratio of sub-segments to the number of pixels within the segment itself: assuming a segment containing k pixels and n sub-segments whereas the segmentation to generate the sub-segments aggregates pixels, so that for the segment itself $k \geq n \geq 1$ is true. Then by dividing n by k a maximum of homogeneity is given if $n = 1$ and $k > 1$. Since n / k converges to 0 if $n \neq k \neq 1$, a minimum of homogeneity is given if $n = k$ and $n > 1$ and $k > 1$. Therefore, a linear membership function can be defined which expresses the degree of homogeneity in change respectively. (see Table. 4).

An approach, that it capable to combine an arbitrary number of properties to determine a degree of change is given by a modification of a procedure which has been used by Earth Satellite Corporation, named Cross-Correlation-Analysis (Koeln et al., 2000). In this method, class boundaries from the older thematic map separate image pixels into distinct class zones. Within these boundaries the pixels as of a new unsupervised classification are validated using a multivariate z-statistic. This idea has been adopted and slightly adjusted within this project using the DeCOVER_t0 mapping as reference (super-objects within the object-hierarchy) and computing the Z-Value for each sub-object within the boundaries of a t0 mapping object:

$$Z_t = \sqrt{\sum_{i=1}^{n} \left(\frac{v_{i_{t1}} - \mu_{i_{t0}}}{\left(\sigma_{i_{t0}}\right)^2} \right)^2}$$

with:
$v_{i_{t1}}$ = mean of property i of the sub-object at point of time t1.

$\mu_{i_{t0}}$ = mean of property i of the super-object at point of time t0.
$\sigma_{i_{t0}}$ = standard deviation of property i of the super-object at point of time t0.

In our research we have calculated the Z-values based upon the spectral channel mean values of sub- and super-segments (see Fig. 7) .

indication class	description						
	fuzzy-operator	properties	membership function	thresholds		referencing classes	refer-encing
				lower bound	upper bound		
change in vegetation	or	= decrease in vegetation	-	-	-	increase in vegetation	=
		= increase in vegetation	-	-	-	decrease in vegetation	=
incease in vegetation	-	$\frac{\overline{NDVI}_{t1}}{\overline{NDVI}_{t0}}$		1,0	1,1	-	-
decrease in vegetation	-	$\frac{\overline{NDVI}_{t1}}{\overline{NDVI}_{t0}}$		0,9	1,0	-	-
decrease of StdDevs	and	$\Delta\sigma(green)$ $\Delta\sigma(red)$ $\Delta\sigma(nir)$		-20,0	0,0	-	-
increase of StdDevs	and	$\Delta\sigma(green)$ $\Delta\sigma(red)$ $\Delta\sigma(nir)$		0,0	20,0	-	-
homogeneous by area and SO	-	n / k		0,0	1,0	-	-
change by norm_Zt	-	$\mu(norm\_Zt)$		0,0	0,1	norm_Zt	μ
norm_Zt	-	Zt		min(Zt)	max(Zt)	-	-

Table 4: Descriptions of change-indication classes.

With the described properties, which can be understood as object based indicators, it is possible to determine for each segment that has been created on the basis of per-pixel indicators (see chapter 3.2) whether it outlines a change at all and if so, its type of change. By defining each type of change as a fuzzy set, each object is a gradual member of one or more type-of-change classes (indication-classes).By defining sensible classes which reflect the type or kind of change comprehensible, it is then possible for each object to couple the degrees of membership μ to these classes with the class assignment of the t0-mapping and the Pt-values of the Pt-matrix to express the most likely (plausible) change. In our research, we defined the indication-classes as described in table 4.

3.3.2 DEFINING PLAUSIBLE CHANGES ACCORDING TO THE DECOVER TERMINOLOGY

For each change-object that is a fuzzy-member of at least one of the before defined change-indication classes, its class-assignment to a DeCOVER class at t0 and its sorted and indexed Pt-vector is given (see chapter 3.1). Hence, it is possible for each object, to determine a graduate plausibility of change by combining the DeCOVER t0 class assignment, the a-priori Pt-values, the indexed Pt-classes and the degree(s) of membership to one or more change-indication classes. Therefore, we have defined classes in accordance to the DeCOVER nomenclature with possible transitions as illustrated in Table 5a and Table 5b.

vegetated classes		non vegetated classes	indication-classes	
from DeCOVER_t0		to DeCOVER_t1	class name	relation
sports and recreation areas (BSa)	n:n	housing areas (BS)	change by norm_Zt	=
urban green (BSf)		industrial areas (BI)	decrease in vegetation	μ > 0.5
agriculture (VL)		areas used for traffic (BV)	increase of StdDevs	=
open land / semi natural (VN)		construction sites, dump sites, mining and excavation (FA)	homogeneous by area and SO	≠
forests (VW)				

Table 5a: Possible transitions from vegetated to non-vegetated classes according to the DeCOVER nomenclature and respective indication-classes which indicate an appropriate change by μ of an object to these classes.

non vegetated classes		vegetated classes	indication-classes	
from DeCOVER_t0		to DeCOVER_t1	class name	relation
housing areas (BS)	n:n	sports and recreation areas (BSa)	change by norm_Zt	=
industrial areas (BI)		urban green (BSf)	change in vegetation	=
areas used for traffic (BV)		agriculture (VL)	increase of vegetation	μ > 0.5
construction sites, dump sites, mining and excavation (FA)		open land / semi natural (VN)		
rocks, beaches, dunes, sandy areas, glaciers, other naturally not vegetated areas (FN)		forests (VW)		

Table 5b: Possible transitions from non-vegetated to vegetated classes according to the DeCOVER nomenclature and respective indication-classes which indicate an appropriate change by μ of an object to these classes.

This way, for each object its change indication and possible transition can be evaluated (see Fig. 8 and 9).

As Fig. 8 shows, an object is only marked as changed if for none of the indication classes a degree of membership of μ = 0.0 is given. Additionally, it demonstrates the reliability of an indicated change by the overall membership degree given through the fuzzy-and operator. In the examples given, the result (left of Fig. 8) indicates a clear change, since μ to almost each of the indicator-classes is 1.0. The other result demonstrates a slight change indication but to be a change from agricultural (VL) to a not vegetated class (BS, BI, BV, FA, FN), the indication *n / k* (*not homogeneous by area and SO*[3] = 1.30) is very low.

A reasonable way to combine the a-priori Pt-values with the degrees of membership in order to obtain one value to indicate the plausibility of an indicated change is to calculate the mean of the product of the Pt-value of an indicated transition and the μ-values to the indicator-classes:

$$Pt' = \frac{1}{n}\sum_{i=1}^{n} Pt \cdot \mu_i$$

with n = number of indication-classes and μ_i = degree of membership to indication class i. Fig. 9 outlines the conjunction of a-priori Pt-values with membership-values to describe the transition of an object from *agriculture* (VL) to *non-vegetated* (BS, BI, BV, FA, FN). The marked object in

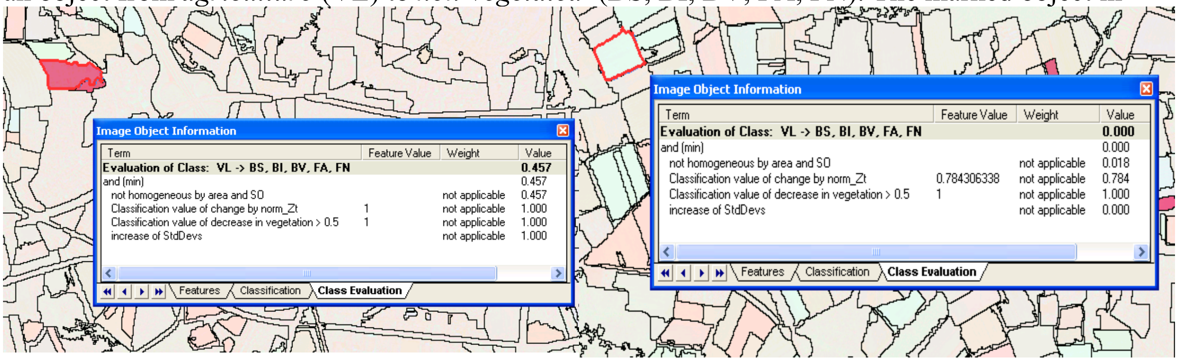

Fig. 8: Evaluation of change-indication for objects to be marked as change (left) (here from agriculture to not vegetated) and no change (right).

Fig. 9 is the same as in Fig. 8 (left). Although the highest a-priori transition probabilities are given to VLg, VLs and VLk (*grassland, other permanent crop* and *complex agricultural*) the indication-classes indicate a transition to non-vegetated. Thus, not the agricultural classes are given as the most probable (most plausible) classes but the most probable class out of the non-vegetation category, in the example BSg (*low density urban area*).

3. CONCLUSIONS AND OUTLOOK

The paper demonstrates the current stage of the development of automated procedures to outline potential changes and to evaluate them automatically as far as possible within the context of the DeCOVER project. Methods were outlined which are capable to detect and outline changes in multi-temporal image data on the basis of per-pixel and per-object change indications. These outlined changes are analyzed by means of methods of object based image analysis and fuzzy class assignments. It has been demonstrated, how the fuzzy-membership of a detected change to defined indication classes in conjunction with a-priori knowledge about transition probabilities can be combined in order to give evidence about a change in terms of the DeCOVER nomenclature.
The current stage of

[3] SO = sub-objects.

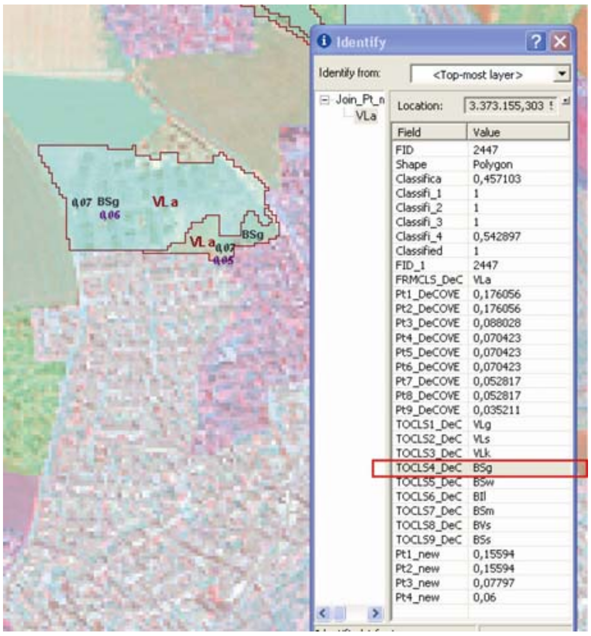

Fig. 9: Change-objects with class-assignments from DeCOVER_t0 (dark red labels) and indicated most probable class-assignments for t1 (black labels) with a-priori Pt values (black lables) and Pt-values adjusted by µ-values of indication classes (purple labels). Right: object table, whereas BSg is marked as the most probable class in t1.

these developments has to be seen as still prototypical. Expected aspects that emerge to become objects of further research in this field are: improving the reliability of a-priori transition probabilities by taking sound analyses of historic information and spatial context into account. Especially within an operative environment it seems to be reasonable to adapt the current probabilities in accordance with changes already detected ("self-learning Pt-matrix"). Spatial context has not been considered yet, although its influence on the probability of a transition cannot be denied. However, in order to focus on potential change-areas and to give indications about what could have happened, the current status seams to be capable to reduce manual effort. Within the context of change segmentation on the basis of indicators, there is still demand about optimizing algorithms and their parameterization.

LITERATURE

Baatz, M.; Schäpe, A., 2000: Multiresolution Segmentation: An Optimization Approach for High Quality Multi-scale Image Segmentation. In: Angewandte Geographische Informations verarbeitung XII, Beiträge zum AGIT-Symposium Salzburg, 2000,Heidelberg, S. 12-23.

Blaschke, T.; Lang, S.; Hay, G., 2008: Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications: Springer. (in print).

Bruzzone, L.; Cossu, R., 2002 : Analysis of Multitemporal Remote-Sensing Images for CD: Bayesian Thresholding Approaches, University of Trento, Technical Report No: DIT-02-0031

Büscher,O.; Buck,O., 2007: DeCover- Geoinformation Services to Update and Supplement Land Cover Data for German Decision Makers, ISPRS Hannover Workshop: High Resolution Earth Imaging for Geospatial Information , IntArchPhRS XXXVI. Band 1/W51. Hannover, CD .

Busch, A.; Gerke, M.; Grünreich, D.; Heipke, C. ; Liedtke, C.; Müller, S., 2005: Automatisierte Verifikation topographischer Geoinformation unter Nutzung optischer Fernerkundungsdaten. In: PFG (2005), Nr. 2, S. 111- 122

DeCOVER, 2008: http://www.decover.info/, information homepage of the DeCOVER-project, last visit Mai 2008.

Definiens, 2004: eCognition User Guide. Definiens Imaging GmbH, 2004.

Definiens, 2007: Definiens Developer 7.0 Reference Book. Definiens AG, 2007.

Fung, T., 1990: An assessment of TM imagery for Land-cover Change detection, IEEE Transactions on Geoscience and remote sensing, 28, 12, 681-684

Gerke, M.; Heipke, C.; Willrich, F., 2004: Automatisierte Qualitätskontrolle von Geobasisdaten auf der Grundlage digitaler Luftbilder : Proceedings Arbeitsgruppe Automation in der Kartographie. In: Mitteilungen des BKG (Hrsg.). Band 31. Frankfurt a. Main, S. 55-58 .

Hofmann, P.; Lohmann, P., 2007: A Strategy for Quality Assurance of Land-Cover/Land-Use Interpretation Results with Faulty or Obsolete Reference Data : IntArchPhRS XXXVI. Band 1/W51. Hannover, 6S., CD .

Hofmann, P. 2005: Übertragbarkeit von Verfahren und Methoden in der objekt-orientierten Bildanalyse – das Beispiel informelle Siedlungen. Doctoral Thesis, University of Salzburg.

Koeln, G.; Bissonnette J., 2000: Cross-Correlation Analysis: Mapping LandCover Changes with a Historic LandCover DataBase and a Recent, Single-date, Multispectral Image, Proc. 2000 ASPRS Annual Convention, Washington, DC http://glc.org/wetlands/flora-fauna.html (last visited February 2008)

Lambin, E. F.; Strahler, A. H., 1994: Change-vector analysis in multitemporal space: a tool to detect and categorize land-cover change processes using high temporal resolution satellite data, Remote Sensing of Environment. 48, 231–244.

Lohmann, P.; Hofmann, P.; Müller, S., 2008: Updating GIS by object-based change detection, Festschrift zum 60. Geburtstag von Prof. Ehlers (in print)

Lu D.; Mausel P.; Brondisio E.; Moran E., 2004: Change detection Techniques, Int. J. Remote Sensing, 2004, Vol. 25, no. 12, 2365-2407

Meinel, G.; Neubert, M.; Reder, J., 2001a: Pixelorientierte versus segmentorientierte Klassifikation von IKONOS-Satellitendaten – ein Methodenvergleich. In: Photogrammetrie - Fernerkundung - Geoinformation, 3: 157-170.

Meinel, G.; Neubert, M.; Reder, J., 2001b: The Potential Use Of Very High Resolution Satellite Data For Urban Areas - First Experiences with IKONOS Data, their Classification and Application in Urban Planning and Environmental Monitoring. Vortrag auf dem 2nd Symposium Remote Sensing of Urban Areas, Regensburg - Regensburger Geographische Schriften 37: 67-68.

Müller, S., 2007 : Extraktion baulich geprägter Flächen aus Fernerkundungsdaten zur Qualitätssicherung flächenhafter Geobasisdaten, Dissertation, Wissensbasierte Bildauswertung-Schriftenreihe des Instituts für Informationsverarbeitung der Leibniz Universität Hannover, Band 9

Neubert, M. & Meinel, G., 2002a: Segmentbasierte Auswertung von IKONOS-Daten – Anwendung der Bildanalyse-Software eCognition auf unterschiedliche Testgebiete. In: Blaschke, T. (Hrsg.): GIS und Fernerkundung: Neue Sensoren – Innovative Methoden. Wichmann Verlag, Heidelberg: 108-117.

Neubert, M. & Meinel, G., 2002b: Fortführung von Geobasisdaten durch die segmentbasierte Auswertung von IKONOS-Daten – erste Ergebnisse. – In: Strobl, J., Blaschke T. & Griesebner, G. (Hrsg.): Angewandte Geographische Informationsverarbeitung XIV. Beiträge zum AGIT-Symposium Salzburg 2002, H. Wichmann Verlag, Heidelberg, S. 403-408.

Schöpfer, E. 2005: Change Detection in Multitemporal Remote sensing Images Utilizing Object-Based Image Analysis, Doctoral Thesis, University of Salzburg

Singh, A., 1989: Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing. 10, 989-1003.