OBJECT-BASED CHANGE DETECTION AND CLASSIFICATION IMPROVEMENT OF TIME SERIES ANALYSIS

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ABSTRACT:

The paper presents a new approach for post-classification change detection. Classification results are integrated in an object-based hierarchical knowledge framework, compared and aggregated on a change detection layer. The approach is - dependent on the complexity of the input classifications - semi-automated and transferable. The change detection framework is illustrated by two different applications. The first application is a change detection analysis of land use / land cover classifications which aims at identifying changes in land use since the land reform in Zimbabwe. The second application analyses changes in built-up area to reflect the urban development of the city of Harare, Zimbabwe.

1. INTRODUCTION

Many change detection approaches are documented in the literature (see for example Coppin et al., 2004), also in the area of post-classification methods. Usually pixel-by-pixel or object-by-object comparison is used in post-classification change detection, resulting in a complete (and complex) matrix of change. In this paper we introduce a new approach using a topologically enabled object-by-object comparison, where changes are aggregated to a change detection layer. The resulting layer is an easy to use quantification and visualization of relevant changes.

The approach is based on object-based image analysis (OBIA), a well-established methodological framework for integrated image analysis (Blaschke, 2010). The research was conducted within the frame of the FP7 GMES project G-MOSAIC (GMES Services for Management of Operations, Situation Awareness and Intelligence for Regional Crises) and is illustrated by means of two application examples.

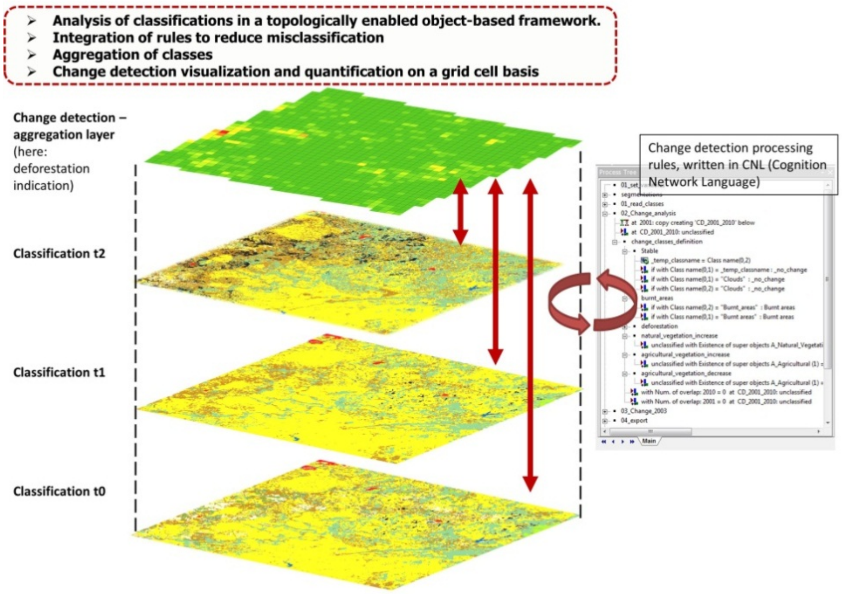

Figure 1. Object-based post-classification change detection framework

2. METHODOLOGY

Existing multi-temporal (e.g. land cover) classification results (vector or raster data) are integrated in a hierarchical knowledge framework, which is flexible in terms of (1) number of classes, (2) aggregation of classes and (3) number of time slots to be analysed. The different classification results are embedded in a topological enabled hierarchy (topological relationships between the objects in vertical and horizontal direction), in which they are compared and aggregated to a change detection layer (e.g. a user defined regular gridded layer). The knowledge

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framework is programmed in CNL (Cognition Network Language) in the eCognition (Trimble GeoSpatial) software environment. It is able to integrate rules to improve the classification and change detection results according to given constraints, for example to correct change detection results which are not possible / not likely in certain timeframes or not possible in general (not interchangeable classes). These constraints are automatically noticed and indicated in the change detection layer. While these constraints depend on the classification input and have to be adapted accordingly, the knowledge framework itself is developed with a focus on transferability to other data sets. The import of class names from the existing classification layers and the change detection analysis itself is – as far as possible – automated.
The change detection layer can be adjusted according to several needs (size and form). Due to the horizontal and vertical topology of the framework (see figure 1) the change of single classes and aggregated classes can be calculated on the change detection layer regarding relative and absolute changes (area), but also in terms of fragmentation of classes through time or similar measures.

3. APPLICATION EXAMPLES

The object-based post-classification change detection framework is demonstrated in two different applications. The first application is a change detection analysis of land use / land cover (LU/LC) classifications which aims at identifying changes in land use since the land reform in Zimbabwe. The second application analyses changes in built-up area to reflect the urban development of the city of Harare, Zimbabwe, between two time slices.

3.1 Land use / land cover analysis

LU/LC classifications of different Landsat scenes (2001, 2003, 2008, Landsat 5 and 7) were analysed. The aim here is to identify land use changes since 2000 when the Fast Track Land Reform Programme was launched by the Zimbabwean government. The programme led to restructuration in the agricultural sector and its success or failure is still controversial (see Scoones et al., 2010). Our application investigates the effects of this land reform with respect to land degradation and deforestation in an area south-east of the city of Harare. Several change detection constraints (possible class transformations) are worked out together with the Forestry Commission in Zimbabwe who has the necessary local experience in land cover mapping. In our analysis we were facing two main challenges.

(1) The introduction of constraints to reduce errors in the underlying classifications based on logical rules (cf. Figure 2). Since not all three images underlying the initial classification were acquired in the same season, some classes were not assigned correctly. Some of those errors could be corrected by comparison of the three different results in the hierarchical framework. For example, if classifications in 2001 and 2008, which were based on imagery from the same season, are showing forested area in the same location, the same area could most likely not be grassland or bush land in the 2003 classification. Also problems due to cloud coverage in the images can be corrected as well as sliver polygons etc.

(2) The definition of land degradation and deforestation. It is crucial to first define those changes that are considered as land degradation or deforestation in the context of Zimbabwe for which we used local expert knowledge. In such a process it is important, that the composition of change classes is flexible since analysis and validation was conducted in several feedback loops. As shown in Figure 2 (part 5), the classes can be easily grouped and rearranged (applying a simple drag & drop) according to changing priorities during the analysis. We also introduced super-classes which are groups of land uses, e.g. agricultural use and natural vegetation. Figure 3 shows the finally used aggregation of classes and derived change patterns.

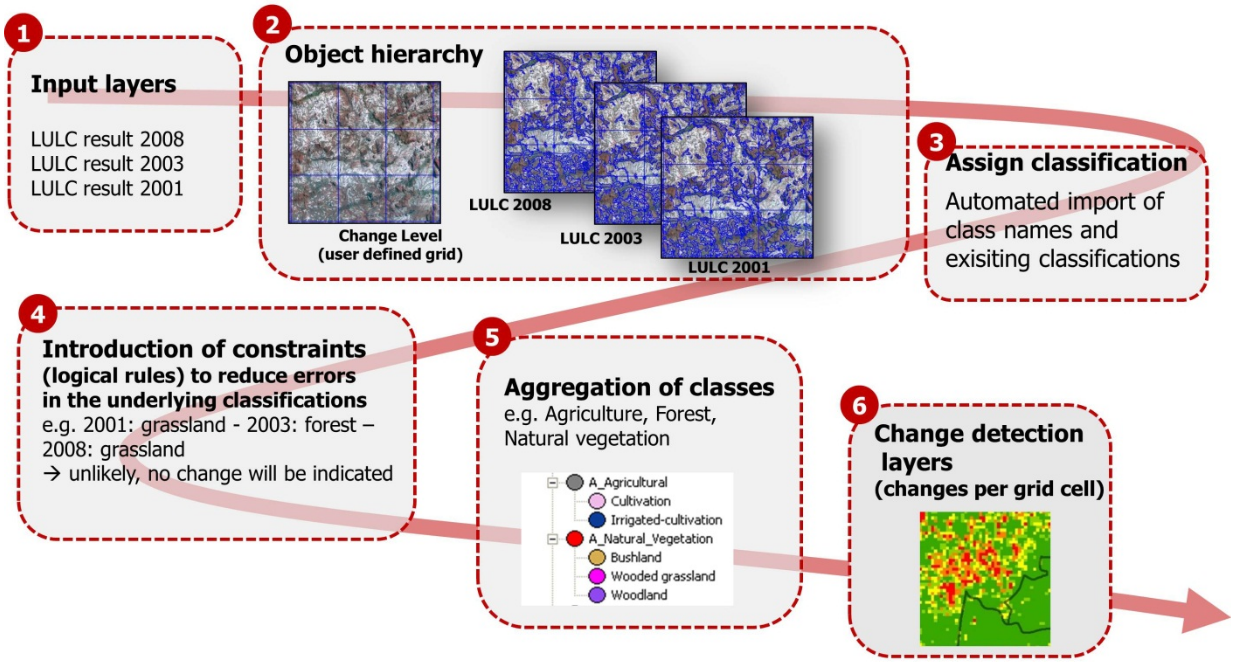

Figure 2. Workflow of the post-classification change detection approach of three different LU/LC classifications for the Zimbabwean study area. The workflow is semi-automated (Steps 1-3 and 6 are fully automated, Steps 4 and 5 require formalized expert knowledge)

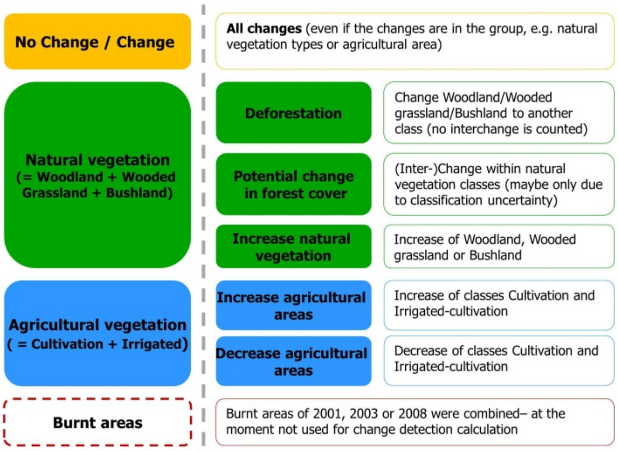

Figure 3. Aggregation of LULC classes (left) and derived change patterns (right) based on local expert knowledge. The framework is flexible, i.e. re-aggregation of different combinations of classes is easily feasible

The results are aggregated to a change detection layer showing the different LU/LC development phases in the area. In this case a regular gridded layer was chosen. The change detection layer can be adjusted both regarding size of the units but also the shape (arbitrary shapes - regular or not, administrative areas etc.). All the different change detection results per class or aggregated classes are written to the attribute table of the layer and can be exported for example as a Shapefile to a GIS-software for further processing (map production, GIS analysis etc.).

Figure (4B) shows an example for deforestation, aggregated on 4.98 km x 4.98 km grid (a multiple of the spatial resolution of the initial data sets of 30 m). Figure 5 shows the results for changes regarding the decrease of agricultural areas; in this case the results are exemplarily aggregated to a 900 m x 900 m grid.

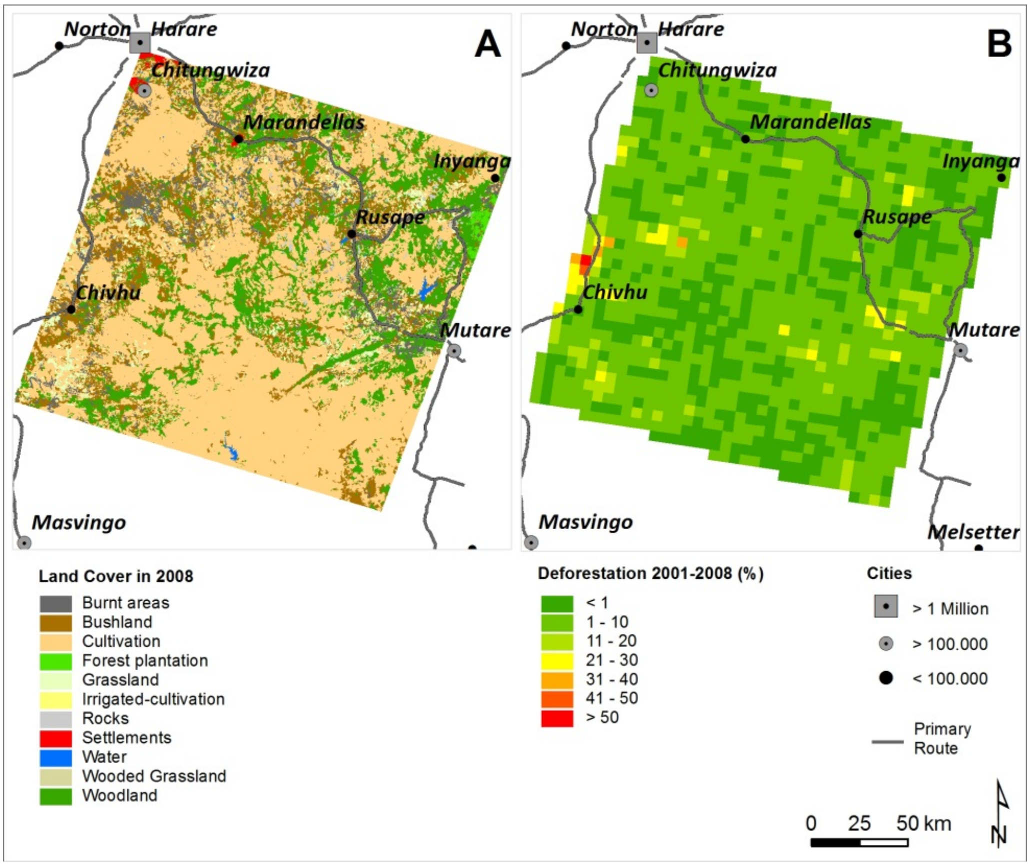

Figure 4. Land use/cover change analysis in eastern Zimbabwe: A) Input: land cover in 2008 (vector data) and B) Output: change detection aggregation layer showing the percentage decrease in forest areas in a regular vector grid

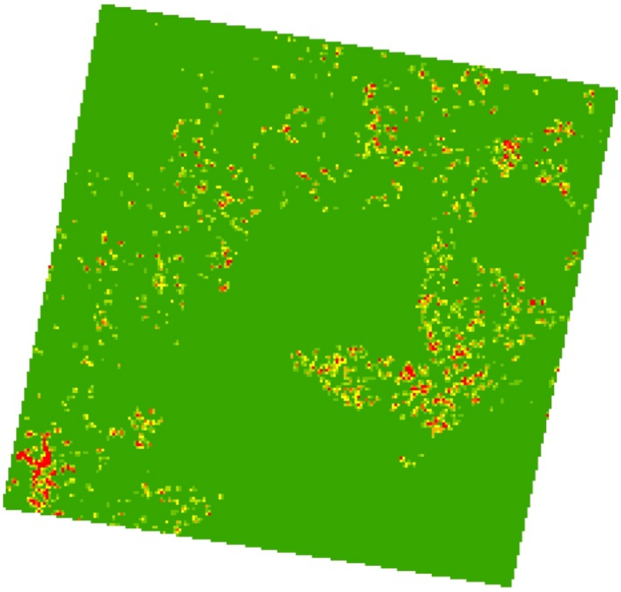

Figure 5. Decrease of agricultural area (% per vector grid cell (900 m x 900 m), for colour coding see Figure 4)

3.2 Built-up change detection

The second application focuses on the urban development of the city of Harare, Zimbabwe between 2004 and 2009. The inputs for the post-classification change detection analysis are built-up layers that were automatically extracted from SPOT and RapidEye satellite imagery using the method of Pesaresi (2000). The result of the change detection analysis provides information about the intensity of urban development in the given area and highlights important changes. In this case there is only one class (built-up) to be analysed. This makes the approach almost fully automated, repeatable and transferable to other data sets (other areas or different time slots) once the framework is established. Figure 6 shows the built-up layer extracted from the RapidEye 2009 data set.

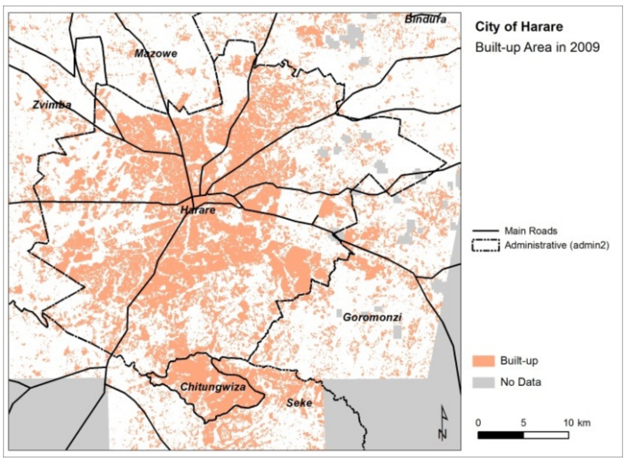

Figure 6. Built-up layer for 2009 (based on RapidEye data) covering the city of Harare

The result of the change detection analysis (Figure 7) highlights hot-spots of increasing built-up areas for the entire city. The method also labels the direction of change, here in- or decrease of built-up which can be used for further interpretation.

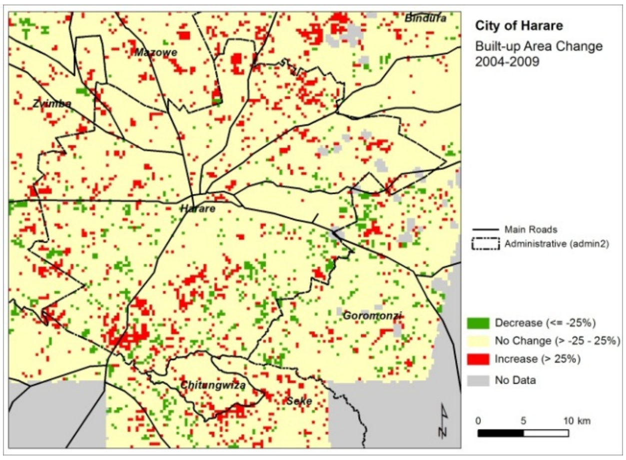

Figure 7. Built-up change detection analysis for the city of Harare, showing increase (red) and decrease (green) in a regular grid of 300m x 300m (a multiple of the initial data resolution)

4. CONCLUSIONS

Both examples are showing a high degree of automation for the post-classification change detection analysis. Depending on the application, different degrees of complexity of the change detection constraints were implemented. The transfer of the knowledge framework between the different data sets (classification results) and resolution was also successfully tested.

The method is able to correct to some degree errors in the underlying classifications by comparing the development of classes within different periods. This requires however that the constraints are well formulated. Depending on the complexity of the input data (compare example 1 vs. example 2), the approach is almost automatically reproducible if for example the input classifications are changing. However, the results are still highly dependent on the quality of the input data (input classifications; cf. Coppin et al., 2004).

Compared to conventional change detection analysis methods, we think the ease of use especially for a fast modification of the analysis parameters (e.g. aggregation of different classes, aggregation of results on different scales etc.), the transferability and the visualisation component of this new method is an important contribution in the field of post-classification change detection analysis.

5. ACKNOWLEDGMENTS

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