A WORK-FLOW DESIGN FOR LARGE-AREA MULTILEVEL GEOBIA: INTEGRATING STATISTICAL MEASURES AND EXPERT KNOWLEDGE

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ABSTRACT:

In GEOBIA some researchers concentrate on statistical optimization procedures such as the optimization of segmentation parameters or the selection of features suitable for class descriptions while others emphasize on the integration of so-called expert knowledge. By combining both approaches a classification can benefit from the advantages of either of them: Through statistical analysis subjectivity is reduced whereas through the inclusion of expert knowledge the advantages of GEOBIA over 'traditional' pixel-based approaches can be utilized to a greater extent. This paper discusses for twelve common GEOBIA tasks grouped into four stages (pre-classification, segmentation, classification, and post-classification) whether the application of statistical measures or decisions based on expert knowledge seems most suitable and if trial-and-error runs remain necessary. The presented approach is exemplified using a real-world application of classifying large-area QuickBird imagery of an agricultural area in western Kenya.

1. INTRODUCTION

In recent years much research in the field of GEOBIA has been carried out on topics such as e.g. the use of ancillary data (Blaschke and Lang, 2006), segmentation quality assessment (e.g. Neubert et al., 2008), the optimization of segmentation parameters (e.g. Radoux and Defourny, 2008; Möller et al., 2007), and the selection of features suitable for class descriptions (e.g. Marpu et al., 2008; de Stefano et al., 2008). Many of these studies present valuable advancements to the remote sensing science. By using statistical optimization measures subjectivity is reduced which is often caused by fraught trial-and-error runs or sole visual judgement. Without the integration of such objective quality measures classification results can become random and strongly depend on the experience of the image analyst. Others emphasize on expert knowledge (e.g. Hay and Castilla, 2008; Lang, 2008). This integration of a priori knowledge is commonly stated to be one of the key advantages of GEOBIA over 'traditional' pixel-based approaches (cf. Platt and Rapoza, 2008). Without its incorporation a rule-based classification approach is not very different to a simple sample-based nearest neighbour (NN) classification approach.

In order to benefit from the advantages of both approaches they should be combined within an integrative work-flow. I.e. statistical optimization approaches should be applied and expert knowledge should be incorporated wherever appropriate. In this context crucial questions to decide upon are: At which step of the classification is which approach to be applied? For which particular tasks do trial-and-error runs remain the only or the most suitable option? Studies conducted so far often concentrate on only one particular aspect in a rather isolated manner, i.e. little research has focused on the bringing together of the two approaches. This paper addresses this gap by discussing the applicability of the approaches for common GEOBIA tasks resulting in a systematic, structured classification scheme. The theoretical considerations have been applied to a real world classification task, i.e. to the classification of land use / land cover (LULC) for a large heterogeneous area (473 km²) covered by very high spatial resolution satellite imagery. The scheme presented here is in particular suited to large heterogeneous landscapes where NN-like approaches are not sufficient but which require the development of sophisticated rule sets.

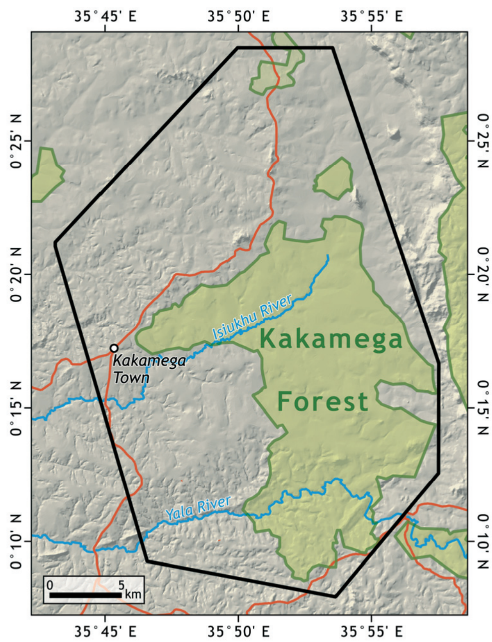

Fig. 1: Coverage of 717 km² QuickBird imagery (polygon) for Kakamega Forest and surrounding farmland in western Kenya.

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2. RESEARCH CONTEXT AND PREPARING STEPS

2.1 Study site and background

Research is conducted based on QuickBird imagery of the farmland surrounding Kakamega Forest in western Kenya (Fig. 1). The forest is known for its botanical uniqueness (Althof, 2005) and considered the easternmost remnant of the Guineo-Congolian rain forest belt (Wagner et al., 2008). Today, only 50% of the officially gazetted forest area is covered by natural forest (Mitchell et al., 2009). Large parts of the forest are affected by disturbance; commercial exploitation began with gold exploration in the 1930s and continued with logging activities until the late 1980s (Mitchell, 2004).

The farmland surrounding Kakamega Forest is characterized by small-scale subsistence agriculture. In literature typical farm sizes are stated to range between 1 and 7 ha (Jätzold and Schmidt, 1982), and 0.4 and 1.6 ha along the western and southern forest edge (Gibbon, 1991). Main cash crop cultivations are sugar cane in the northern and tea in the southern part of the area under investigation; besides the cultivation of maize and beans plays a key role for household consumption (Gibbon, 1991). The area exhibits one of Kenya's highest rural population densities with an average of 643 people / km² (determined in a 2 km buffer around the forest; Lung and Schaab, 2009) amplifying the pressure on the forest e.g. caused by the collection of firewood (Mitchell and Schaab, 2008).

The BIOTA East Africa research project (see www.biota-africa.de) funded by the German Federal Ministry of Education and Research (BMBF) aims at recommendations towards a sustainable use and conservation of forest biodiversity. Through results obtained by the object-based analysis of the QuickBird imagery a spatial typology of the agricultural matrix will be derived. Scenarios of rural livelihood based on this typology can contribute to landscape planning taking into account socio-economic impacts on land use and the influence of landscape elements on biodiversity (Schaab et al., 2009).

2.2 Image and ancillary data, software used

The QuickBird satellite provides very high spatial resolution imagery with a ground sampling distance of 0.61 m for pan-chromatic and 2.44 m for multi-spectral images (DigitalGlobe, 2004). Due to the large extent of the area under investigation in east-west direction (Fig. 1) two overflights were necessary which took place in late February and early March 2005. A total of 717 km² were acquired of which 473 km² covers farmland. Thorough pre-processing was conducted including corrections of atmospheric and orographic influences, a special mosaicing procedure, and a testing of different pan-sharpening algorithms (Lübker and Schaab, 2008b).

During a field trip in 2007 ground truth information was collected for twelve study sites sized approx. 2 km². A total of 636 samples were recorded of which about 2/3 refer to land use information and 1/3 to structural elements (Lübker and Schaab, 2008a). For five selected study sites a subsequent detailed visual interpretation was carried out at a scale of approx. 1 : 1,000. For each site between 2,500 and 4,000 objects could be identified. As image derivates the Soil Adjusted Vegetation Index (SAVI) was calculated based on the pan-sharpened imagery, and an edge image was generated based on the Canny Algorithm using the panchromatic image band. Further, ancillary data is available from a topographic map with a scale of 1 : 50,000 (from 1970): a digital elevation model (DEM) generated from counter lines (Herz, 2004), and a river dataset. In addition a boundary between the farmland and the actual forest was visually interpreted based on the QuickBird imagery. These data sets are used as ancillary data in the classification stage.

All segmentation and classification steps were conducted within the eCognition Developer 8 software. Pre-processing and the derivation of the SAVI were carried out with Erdas Imagine 9, whereas ArcGIS 9 was used for the preparation of the ancillary and reference data, during tiling and stitching, and for evaluating different segmentation results.

Tab. 1: Choice of appropriate approach (statistical analysis, trial-and-error, expert knowledge) for common tasks of GEOBIA, grouped by processing stages.

stage	task	statistical analysis	trial-and-error	expert knowledge
pre-classification	general classification strategy			**X**
	grouping of classes			**X**
	choice of image derivates		(x)	**X**
segmentation	optimization of segmentation parameters	**X**		
classification	selection of relevant features	**X**	(x)	(x)
	definition of thresholds	(x)	**X**	
	use of ancillary data	(x)	(x)	
	definition of a priori constraints			**X**
	refinement of class descriptions		**X**	(x)
	order of classification		(x)	**X**
post-classification	cartographic generalization		(x)	**X**
	checking for logical errors		(x)	**X**

X: most appropriate approach; (x): optional application

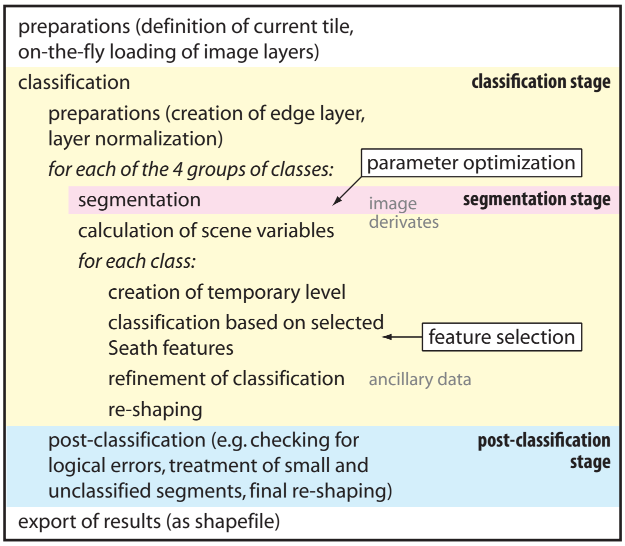

Fig. 2: Outline of the rule set used for the LULC classification, incl. stage of the classification, input from statistical optimization procedures, use of image derivates and ancillary data.

3. CLASSIFICATION WORK-FLOW DESIGN

3.1 Grouping GEOBIA tasks into stages

A LULC classification by means of GEOBIA usually consists of different tasks. We suggest grouping these tasks into four stages (Tab. 1): a) pre-classification, b) segmentation, c) classification, and d) post-classification. Tasks commonly carried out in the pre-classification stage include considerations on the general classification strategy, on a grouping of LULC classes, and on the choice and use of image derivates. The segmentation stage deals with segmenting the imagery into meaningful objects. In the actual classification stage tasks carried out include the selection of features relevant to class descriptions, the definition of feature thresholds, the refinement of class descriptions, the definition of a priori constraints, the use of ancillary data, and in case of a consecutive classification also the order in which classes are classified. During the post-classification stage the preliminary classification result is further improved by applying cartographic generalization techniques and checking the results for logical errors.

The boundaries of these stages can be ambiguous. Tasks of the post-classification stage like cartographic generalization and checking for logical errors can also be integrated into the actual classification stage when appropriate. In the case of classification-based segmentation (see Benz et al., 2004) the segmentation task directly interacts with the classification stage.

3.2 Rule set development

The rule set for classifying LULC in the farmland surrounding Kakamega Forest as used in the process tree of eCognition is summarized in Fig. 2. It comprises the three stages segmentation, classification and post-classification; since in the pre-classification stage only general decisions are made it is not apparent here. In the sequence of rules the segmentation stage is interweaved with the classification stage since it has to be carried out for each group of LULC classes separately. After the segmentation, scene variables are defined based on quantiles which account to the spatially varying conditions.

For large amounts of data (here more than 30 GB of imagery), tiling and stitching is necessary due to memory limitations. When a server license is not available this process is rather laborious in eCognition. Certain workarounds exist within eCognition but are little suitable for large projects such as the one presented here. For this study the processing of 300 tiles was necessary. Additional rules in the beginning and at the end of the rule set facilitate the work-flow by automating the loading of image layers and the export of the classification results as a shapefile.

The rule set is a result of structured considerations for each classification task whether it should be based on statistics, expert knowledge or trial-and-error. It demonstrates how the actual classification was carried out practically.

3.3 Classification work-flow

3.3.1 Pre-classification stage

By deciding on a **general classification strategy** we understand here the choice between a) classifying all desired LULC classes or groups of classes at once or b) making use of a consecutive classification of classes or groups of classes where the order of classification matters. While the first strategy better allows for defining fuzzy class membership values, the latter comes closer to the procedure applied during a visual interpretation. In any case the decision for one or the other is solely based on expert knowledge since statistical analysis as well as trial-and-error runs would by far be too complex and seem little promising. In the classification carried out it was decided for a consecutive classification strategy in order to include experiences gained from the visual interpretation. Objects not assigned to any class had to be treated separately.

For a broad classification of LULC classes a **grouping of classes** representing the segmentation levels is useful. Like this the characteristics of the individual classes regarding object size and shape are accounted for while at the same time the number of segmentation levels is kept at a feasible number. Again, this task depends on the experience of the analyst but can be revised during the statistical parameter setting optimization (see below). For the farmland classification the classes were combined into four meaningful groups (Tab. 2) that were reviewed during parameter optimization. For the grouping experiences gained through the visual interpretation based on ground truthing were once more valuable.

Image derivates such as vegetation indices and edge layers can help to improve segmentation and classification quality. The **choice of image derivates** is mainly based on expert knowledge, e.g. obtained from literature, and trial-and-error runs. Literature sources and trial-and-error runs let to the assumption that the SAVI and a Canny edge layer would be suitable for the here discussed classification. Their suitability for the segmentation of the four class groups as well as their use in class descriptions was also verified in statistical analyses (see below).

Tab. 2: Grouping of LULC classes derived in the classification of the farmland surrounding Kakamega Forest.

increase in object size →

group A	group B	group C	group D
river	tree / shrub vegetation	homestead	maize
dirt road	shadows	bare soil	tea
tarmac road			sugar cane
house			napier, sweet potato
			fallow land, grass land, grazing area
			minor shrub vegetation
			burnt land
			fish pond

3.3.2 Segmentation stage

In the segmentation stage the **optimization of segmentation parameters** is crucial since all subsequent classification steps depend on the segmentation quality. Since eCognition's region-based multiresolution segmentation comprises five degrees of freedom (Lübker and Schaab, 2009) trial-and-error runs seem inappropriate for solving such a multi-dimensional problem. Expert knowledge might be incorporated to some extent as a priori constrains for an optimization procedure. However, optimal segmentation settings can differ greatly for different imagery and LULC classes. This lets statistical analysis to be the best suited option. The optimization of segmentation parameters carried out in the farmland classification is based on a two-step procedure using empirical discrepancy and goodness methods. As a discrepancy method the 'area fitness rate' was introduced comparing candidate segmentations with the reference data obtained through visual interpretation while an 'objective function' was used as goodness method. Parameter settings were optimized per individual group of classes; the optimization accounts for all five degrees of freedom. For a detailed description of the methodology and its implementation see Lübker and Schaab (2009).

3.3.3 Classification stage

The **selection of features** to be used in class descriptions and the settings of their thresholds can be seen as the core task of any rule set development since the quality of a class description determines how correctly this class can be distinguished from others. Selecting the most relevant features for a class description can either be accomplished through excessive trial-and-error comparisons or through statistical analysis. Such analyses are based on reference data and calculate class separability expressed through e.g. Bhattacharyya distances. Expert knowledge can be of advantage when selecting input features for analysis or in order to limit trial-and-error runs. Feature selection tools assist the user also in the **definition of thresholds** to be used in class membership definitions. For large and heterogeneous areas under investigation, however, extensive trial-and-error runs in spatially well distributed image subsets remain a necessity. Instead of using fixed threshold values quantiles can be defined as scene variables that to some extent account for spatially varying conditions in large area coverage. In the classification carried out the Seath tool (Marpu et al., 2008) was used that calculates class separability based on Bhattacharyya distance. From the twelve study sites (see Chapter 2.2) 980 sample objects were selected and used as input data for the statistical analysis. 69 different object characteristics including layer values, shape, texture, and customized features such as image ratios were tested for. The features as suggested by the tool were not directly adapted to the rule set; instead the ten best scoring features were further investigated visually. Thresholds had to be determined in the way suggested above for large areas, i.e. by making use of quantiles.

The **use of ancillary data** for GEOBIA is an often discussed topic in literature (Blaschke and Lang, 2006), supported by the fact that with software like eCognition the integration of data from multiple sources and of both raster and vector representation into remote sensing applications has become straight forward. What ancillary data is to be used in a classification scheme is after all determined by its availability. The use of ancillary data strongly depends on expert knowledge; however, trial-and-error runs as well as statistical approaches can be used in order to further improve their employment. For the presented classification only limited ancillary data were available (see Chapter 2.2). In the rule set the farmland boundary was used to exclude non-farmland areas such as Kakamega Forest for further investigations, buffered river data was used for the classification of riverine grass and shrub vegetation, and slope derived from the DEM was used as limiting factor for the classification of certain crop types. The latter example shows that the usage of ancillary data overlaps with the task referred to as description refinement. Approaches applied rely on expert knowledge though to some extent trial-and-error was applied, e.g. when testing for different buffer sizes and slope angles.

Similarly to the refinement of class descriptions the definition of **a priori constraints** can help to enhance the classification result by further restricting the class description. These limiting definitions are based on expert knowledge and may involve ancillary data, minimum area sizes, and relations to already classified objects. Constraints used in class definitions of the discussed study include minimum sizes for parcels and houses, the assumption that certain crop types are not cultivated on slopes, and the relation between homesteads and houses.

For most LULC classes a single class description based on statistically determined features alone might not be sufficient. An additional **refinement of class descriptions** using further rules and/or sub- or temporary classes becomes necessary. Here, rules using context-based features such as distance or neighbourhood relations to already classified objects can be defined. In order to set-up these rules trial-and-error runs present the most realistic option. However, at this stage the rule set can become very complex and a testing of what elementary effect a single used features and defined rule has on the end result can become challenging. The LULC classification presented is thus based on numerous trial-and-error runs, although building these complex rules could as well be considered the result of expert knowledge.

The **order of** a **classification**, i.e. in which sequence classes are classified, plays only a role in consecutive classifications. When following the approach of a visual interpretation, classes that contain rather small objects and that are relatively easy to delineate are classified first. The decision on a particular classification order is based on expert knowledge; trial-and-error runs may be used in order to confirm the assumptions made. In Tab. 2 the order in which the LULC classes were classified can be seen: the four groups were consecutively classified from A to D, within each group from top to bottom. For some otherwise difficult to classify LULC classes a preliminary classification of a class from a higher segmentation level was necessary. In the case of tea, sugar cane, and fallow land / grass land / grazing area also some trial-and-error tests had to be conducted.

3.3.4 Post-classification stage

In the context of GEOBIA different kinds of **cartographic generalization** can be applied: a) shape generalization enhancing objects by smoothing their outline or making them follow geometric shapes like e.g. a rectangle or circle; b) merging of over-segmented objects, and c) omission of very small objects by defining minimum sizes. These generalization techniques can also be referred to at an earlier stage of classification for the refinement of class descriptions, i.e. the two tasks overlap. The application of such generalization techniques requires expert knowledge, their degree of utilization must, however, be tested by trial-and-error. In the study presented generalization techniques were e.g. applied to over-segmented parcels (merging) and tree / shrub vegetation (smoothing of outline). Further improvements regarding the shape of houses would have been desirable but suitable processes are rarely available.

While a **checking for logical errors** should already be conducted as part of the refinement of class descriptions during the classification stage, it can again become necessary towards the end of the classification chain to change objects based on classes from a higher level. Such a checking for logical errors is based on expert knowledge; similar to other tasks fine-tuning might also require some trial-and-error. In the classification carried out, some parts of maize parcels appear similar to bare soil and with a linear structure lead to a false classification as dirt road. This was for example addressed in the post-classification stage.

4. CONCLUSIONS

Common GEOBIA tasks could be identified and grouped into four stages of classification. For each task it was discussed whether a statistical optimization procedure, the integration of expert knowledge, or trial-and-error runs are most applicable. These theoretical statements were underlined by a real-world example of classifying the agricultural matrix surrounding Kakamega Forest in western Kenya. This structured approach allows defining where in the classification chain the different approaches should be integrated. Like this classifications can benefit from the advantages of both approaches: Subjectivity is minimized where it is desirable while the inclusion of expert knowledge leads to more sophisticated rule sets.

For the classification carried out statistical optimization analyses were used in only two out of twelve tasks identified, namely parameter optimization and feature selection. However, these two tasks are of essential importance for any classification. They require making numerous decisions which could easily exhaust the user when trying to find the best solution based on trial-and-error. Unfortunately, only very few ready-to-use and adjustable tools exist for these statistical optimization procedures. For the definition of thresholds and the refinement of class descriptions the application of trial-and-error runs is indispensable while for six further tasks trial-and-error is an option. The dependency on trial-and-error leads to a major drawback of object-based image analysis: In order to build solid and sophisticated rule sets for large-area applications of heterogeneous landscapes long developing times have to be accepted. In addition, expert knowledge plays an important role in the development of any work-flow. Out of twelve tasks seven rely on expert knowledge while for two further tasks its integration is optional. With this integration of context and human perception into rule set development the advantage of GEOBIA over pixel-based approaches is apparent. But at the same time it makes GEOBIA a complex matter requiring for expert users.

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