

OPTIMIZATION OF PARAMETER SETTINGS FOR MULTILEVEL IMAGE SEGMENTATION IN GEOBIA

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ABSTRACT:

In geographic object-based image analysis (GEOBIA) segmentation plays a key role since all consequent classification steps depend on its quality. For evaluating the quality empirical discrepancy and goodness methods are available. However, when optimizing parameter settings certain criteria have to be fulfilled, this in order to effectively facilitate the first step in GEOBIA. Besides being objective by making use of statistical methods the approach applied should optimize per class or group of classes, account for all degrees of freedom, use small parameter increments, and be preferably automated. The study presented in this paper combines a newly introduced 'area fitness rate' as a discrepancy method with an 'objective function' as a goodness method. By fulfilling the above criteria it is, amongst others, possible to follow the multilevel approach. Very similar results obtained for five different study sites demonstrate that the parameter settings found are indeed optimized. A visual check strengthens this finding further.

1. INTRODUCTION

Over the last decade geographic object-based image analysis (GEOBIA) has significantly gained importance due to the increasing availability of very high resolution (VHR) earth imagery like Ikonos and QuickBird (Jacobsen, 2004) and of highly sophisticated software such as Definiens eCognition/Developer (Neubert et al., 2008a). The first key step in GEOBIA is the segmentation of imagery into meaningful objects. Since all consequent classification steps depend on the segmentation result achieving a high quality is a prerequisite (Hofmann et al., 2008; Singh et al., 2005). However, the optimal choice of parameters is a difficult task due to the high number of options available. The region-based 'multiresolution' segmentation as implemented in the Definiens Developer software incorporates five degrees of freedom: 1) the choice of input layers (including additionally derived image products) and 2) their weighting, 3) the setting of the scale parameter as well as the homogeneity criteria 4) shape factor and 5) compactness. The choice of additional input layers such as a derived vegetation index or an edge image as well as a weighting among the layers are often neglected in the segmentation step. These should nevertheless be considered during segmentation because ancillary data is often successfully used for classification, too (e.g. Neubert et al., 2008b; Förster and Kleinschmit, 2008).

In order to determine parameter settings that are considered optimal for a specific type of imagery recorded under particular conditions, for a certain landscape and task, trial-and-error methods are commonly applied (Costa et al., 2008; for an example see Im et al., 2008). They are subjective or even misleading and can be very time-consuming. Therefore, there is a demand for more objective and reliable methods determining best-suited parameter settings. Here, empirical statistical approaches are available which can be grouped into 'goodness methods' and 'discrepancy methods' (Zhang, 2001). The discrepancy methods evaluate the matching of a candidate segmentation with a reference data set and can be based on an evaluation of the a) number and b) position of mis-segmented

pixels, c) the number of objects, d) certain objects characteristics, and e) miscellaneous quantities (e.g. the influence of Gaussian and transmission noise). Goodness methods assess segments regarding how well they achieve specific desired properties like a) intra-segment homogeneity, b) inner-segment heterogeneity, and c) shape characteristics.

Studies aiming at an optimization of parameter settings based on these empirical methods should fulfil certain criteria in order to effectively facilitate the first step of GEOBIA. They need to:

1. be objective by using statistical methods,
2. find optimized settings for each class or group of classes separately,
3. cover a representative number of objects per class in preferably more than one test area,
4. account for all degrees of freedom (i.e. five degrees in the case of the multiresolution algorithm),
5. test parameter settings in small increments, and
6. be preferably automated to a large extent.

Given that the first request is fulfilled, requests two and three are the most fundamental: Only with studies that follow the second criterion it is possible to apply the multilevel principal (see Lang, 2008), i.e. consider different scales for different classes or group of classes instead of one single segmentation for the entire classification. Furthermore, an optimization based on only few objects might lead to rather random results. More than one test area should be used in particular for heterogeneous areas under investigation in order to cover the diversity of the landscape and as it is at the same time useful for estimating the reliability of the results. Studies not covering all possible degrees of freedom can be considered incomplete while too large intervals between tested parameter combinations might miss relevant settings. And finally, in order to make an optimization approach of use to others it should be as far as possible automated. In recent publications, various approaches evaluating the quality of segmentation results are presented (e.g. Wang et al., 2004; Weidner, 2008). However, none could be found that fulfils all of the above stated criteria. The development of a methodology as presented in this paper tries to close this gap.

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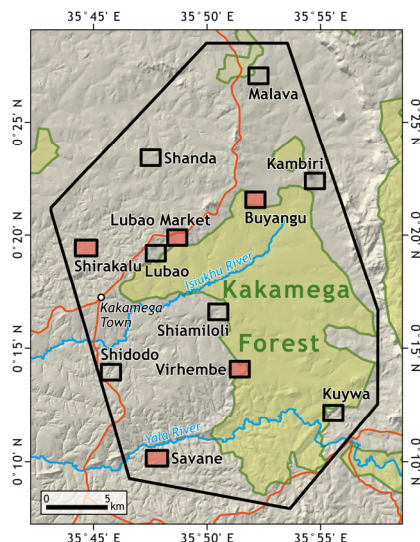


Figure 1. Kakamega Forest and surrounding farmland, western Kenya; coverage of QuickBird imagery (polygon), location of study sites (rectangles) and focus study sites (filled rectangles).

2. MATERIALS AND METHODS

2.1 Study site and image data

An optimization of parameter settings has been performed for QuickBird imagery covering the farmland surrounding Kakamega Forest in western Kenya (Fig. 1). The forest is considered the easternmost remnant of the Guineo-Congolian rain forest belt (Wagner et al., 2008) and known for its botanical uniqueness (Althof, 2005). The adjacent farmland is characterised by small-scale subsistence agriculture and 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). As part of the BIOTA East Africa research activities (see www.biota-africa.de) funded by the German Federal Ministry of Education and Research (BMBF), spatially explicit planning scenarios for the agricultural matrix will be modelled based on the QuickBird image analysis results. Taking population growth rates into account scenarios can help to determine the potential for additional uses and alternative income options thus minimizing the pressure on the forest, e.g. caused by firewood collection.

The VHR QuickBird imagery was recorded on February 21st and March 6th 2005 during two overflights due to the large extent of the area in east-west direction. Imagery for a total of 717 km² was acquired of which the farmland covers 484 km². Thorough pre-processing was carried out including a correction of atmospheric and orographic influences, a special mosaicing procedure, and a testing of different pan-sharpening algorithms (Lübker and Schaab, 2008b). As image derivatives the Soil Adjusted Vegetation Index (SAVI; Huete, 1988) has been calculated based on the pan-sharpened imagery, and an edge image has been generated based on the Canny Algorithm (Canny, 1986) using the panchromatic image band.

2.2 Reference data and classes used

During a field trip in 2007 ground truth information was collected for 12 study sites sized 2 or 2.25 km² (Fig. 1) that have been chosen in a way that they are spatially distributed and reflect the heterogeneity of the area under investigation well. Based on 411 beforehand selected locations that seemed to be

either interesting, unclear or characteristic for the area, 636 samples in total were collected of which about 2/3 refer to land use information and 1/3 to structural elements (Lübker and Schaab, 2008a).

Out of the 12 study sites 5 have been chosen as focus study sites (Fig. 1) for which a visual interpretation covering the complete extent has been performed based on the information obtained during the field verification. The on-screen digitizing was achieved at a resolution of approx. 1 : 1 000 with the pan-sharpened QuickBird imagery and the SAVI image alternately displayed having the cubic convolution resampling method enabled, thus allowing for a delineation accuracy of only a few pixels. In order to keep the work efforts at a still feasible level, objects no larger than approx. 20-25 m² as well as shadows of trees and shrubs have not been separately delineated due to their small size. Like this 16,409 polygons have been created thus presenting a solid base for an evaluation of the segmentation quality using a discrepancy method.

The 28 classes of land use and structural elements assigned during the field verification have been transformed into 27 classes for the visual interpretation (Tab. 1). Classes like 'ground nuts', 'passion fruits', and 'avocados' had to be omitted because only very few examples could be found in the field. Further, these could not be distinguished in the imagery. The class 'burnt area', on the other hand, has been introduced newly while the class 'fallow' could be further subdivided. The class 'bananas' was appended to the class 'vegetables' because they

Table 1. Classes used during ground truthing (left), adjusted for visual interpretation (middle), and finally applied in GEOBIA (right).

Ground truthing	Visual interpretation	Classification	group
forest patch	forest	forest	n.a.*
river	river	river	A
path or track	road	road	A
	road, tarmac	road, tarmac	A
house/hut	house	house	A
tree lot	trees and shadows	tree and shrub veg.	B
bush/shrubs	shrubs		
single tree	single tree		
tree line/group	tree line/group	shadows of tree and shrub veg.	B
homestead	homestead	homestead	C
vegetables	vegetables	vegetables	C
rock	rock	rock	C
bare soil	bare soil	bare soil	C
maize (& beans)	maize (& beans)	maize (& beans)	D
tea (young/old)	tea	tea	D
sugar cane (young/old)	tea zone		
napier	sugar cane	sugar cane	D
sweet potatoes	napier	napier, sweet potatoes	D
fish pond	sweet potatoes		
fallow	fish pond	fish pond	D
grass	fallow, grass/ grazing	fallow, grass/ grazing	D
bananas			
ground nuts	fallow/grass by the river		
passion fruits	fallow/grass next to road		
avocados	burnt area	burnt area	D
coffee			
mangos			
pinapples			
others	other crops	rest / unclassified	
	others unknown		

* not applicable; the forest area is excluded via a mask prior to the classification.

are usually planted in mix. The defined classes have been again slightly modified for the actual classification where e.g. the class ‘shadow of tree and shrub vegetation’ has been introduced and other classes like ‘napier’ and ‘sweet potatoes’ had to be merged since they appear almost identical in the imagery and therefore are likely to be undistinguishable in an automatic classification. Furthermore, the classes have been transferred into four groups (A to D) representing levels in the multilevel image segmentation. The grouping has been arranged theme-wise and in accordance to similarities in expected segment sizes. During the optimization this grouping is to be verified.

2.3 Parameter combinations tested

The selection of parameter combinations has been made in accordance with the fourth (account for all degrees of freedom) and fifth request (small parameter increments) made earlier in this paper and is described in the following. The first and second degree of freedom in multiresolution segmentation have been treated together by defining layer combinations in which the influence of a single layer has been set to 100%, 50% or 0%. Out of 27 ($3 * 3^2$) possible combinations the 12 most meaningful (e.g. not doing without the multi-spectral bands) have been selected:

Layers and their weightings: {100; 150; 110; 105; 101; 510; 501; 155; 115; 151; 111; 511}
 1st digit: weighting of the four QuickBird bands,
 2nd digit: weighting of SAVI layer,
 3rd digit: weighting of edge layer;
 1: 100%, 5: 50%, 0: 0%

As scale parameter (third degree of freedom) ten values ranging between 20 and 250 have been chosen thus covering commonly used values (Hofmann et al., 2008). In the upper region increments have been enlarged in order to decrease the total number of combinations:

Scale parameters: {20; 40; 60; 80; 100; 120; 140; 170; 200; 250}

For the influence of the shape factor four values between 0.1 and 0.7 have been applied at an interval of 0.2. The value of 0.9 has been excluded since no feasible results are expected:

Shape factors: {0.1; 0.3; 0.5; 0.7}

For the degree of compactness, the same settings have been chosen, this time including the value 0.9:

Compactness values: {0.1; 0.3; 0.5; 0.7; 0.9}

2.4 Combined approach in two steps

The study is split into two parts because if evaluated in one single step 2,400 parameter combinations would have been needed to be evaluated at once resulting in 48,000 segmentation runs carried out for the five focus study sites and four groups of classes. Further, with the subdivision, both discrepancy and goodness methods can be applied each at a time. However, when optimizing the choice of input layers and their weighting goodness methods evaluating multi-spectral characteristics (see chapter 1) must not be used in order to avoid dependencies.

In the first step, the first three degrees of freedom are determined keeping the values for shape and compactness constant at 0.3 and 0.5 respectively leading to 120 parameter combinations and resulting in 600 candidate segmentations. In the second step, the three determined values are adopted and tests are carried out for shape and compactness. Since they have influence on the ‘size’ of the resulting segments two additional scale parameter are considered, one being 5 or 10 lower and one being 5 or 10 higher than the earlier determined scale parameter. Here, 60 parameter combinations are tested resulting

in 1,200 segmentations since the optimization is carried out for four different classes (having different optimized scale parameters and layer weightings) in the five focus study sites. The candidate segmentations are generated in Definiens Developer within the Process Tree by making use of variables and then exported as shape files in which parameter settings are included in the file names.

2.5 First step of optimization using an empirical discrepancy method

For the evaluation in the first step of optimization we introduce here a discrepancy method based on the ‘area fitness rate’ (AFR) calculating the degree of overlap between each reference polygon and the associated candidate segments. For each pair of reference polygon and overlapping segment the area of overlap in relation to the area of the polygon or the segment are calculated and multiplied (Fig. 2) as defined by equation (1):

$$AFR = \frac{R \cap S}{R} * \frac{R \cap S}{S}, \in \{0, \dots, 1\} \quad (1)$$

where R = area of reference polygon
 S = area of associated segment

Like this the ‘error of omission’ and ‘error of commission’ are combined within one formula representing a robust statistical measure. An ideally fitting segment leads to a value of 1 while a none-overlapping segment results in a value of 0.

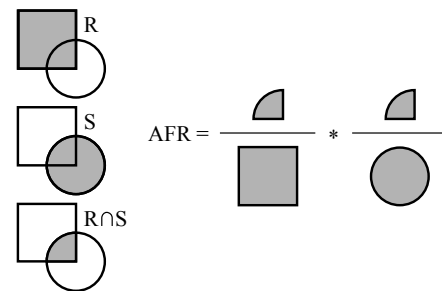


Figure 2. Illustration of the ‘area fitness rate’ (AFR).

Due to of the high number of comparisons to be carried out a largely automated procedure is elaborated in the ArcGIS software making use of the Model Builder in combination with Visual Basic (VB) script language. In the model, after repairing possible topological errors, assigning unique IDs, and calculating area sizes, reference data set and candidate segmentation are combined using the ‘union’ operation keeping all attributes. A tolerance of 0.6 m (i.e. 1 pixel) is applied in order to account for small geometrical inaccuracies in the visual interpretation. After computing the sizes of the areas of overlap the AFR is calculated in each occurrence of an overlap. In most cases more than one segment is overlapping with the reference polygon. The statistical ‘summary’ function using ‘group by reference polygons’ determines the value of the highest fitness rate. The AFR for each reference polygon is then exported as a table which is finally joined to the reference data set. The model was exported as a VB script in order to allow for batch processing. For creating the batch file, file names of the created segmentations are read from the file system via the Windows command line and transferred to Excel. Here, parameter settings used during the segmentation are extracted from the file names serving as input parameters for the model variables needed. Executing the batch file, the calculation can be carried out for a complete study site in one single run which is at an average accomplished in 4.5 hours using a PC with modern hardware

configuration. The results are summarised per class as well as per group of classes for each of the focus study sites by making use of the median value (i.e. the 50% quantile).

2.6 Second step of optimization using empirical goodness methods

For the second step of optimization two indices with opposing gradients are combined in an ‘objective function’ (Espindola et al., 2006). The first index expresses inner-segment homogeneity based on the mean weighted variance (MWV) that is defined as the sum of all products of variance and area divided by the sum of all areas, as defined by equation (2) (Espindola et al., 2006, p. 3037):

$$MWV = \frac{\sum_{i=1}^n a_i * v_i}{\sum_{i=1}^n a_i} \quad (2)$$

where a_i = area of a segment
 v_i = variance within a segment

The second index expresses inter-segment heterogeneity based on Moran’s I test for spatial autocorrelation (for definition see Moran, 1950; Espindola et al., 2006). In general, values for MWV are lower for larger segments while values for Moran’s I test are higher. An optimal segmentation is found when balance is established between inner-segment homogeneity and inter-segment heterogeneity. In the ‘objective function’ the two measures are added after normalising them to a range of 0 to 1 thus holding possible values between 0 and 2. As Goa et al. (2007) showed the classification accuracy can be significantly enhanced by using this ‘objective function’.

The values for MWV are calculated when creating the candidate segmentations in Definiens Developer. Only the NIR-band is used since it has the highest contrast. For the calculation of the

MWV a ‘customised scene feature’ is created that is defined by the two ‘scene variables’ ‘sum of all products of variance and area’ and ‘sum of all areas’ which are being updated in each segmentation process. Since ‘variance’ is not a default object feature it has to be customized via an ‘object feature’. The Moran’s I index is calculated with ArcGIS because the function is already implemented there. However, the Python script has to be adjusted so that the result is not only displayed visually but written to a text file together with the file name. The adjusted script is then loaded into the Model Builder and exported as a VB script. Analogue to the proceeding in the case of the AFR Excel is used to create the batch files. While the calculation of variance requires only fractions of a second per segmentation the calculation of Moran’s I indices requires an average of 8 hours for the class groups B to D but is not feasible for group A. Here, due to the high number of polygons per focus study site (up to 163,000) the calculation of one single segmentation takes approx. 14 hours. Therefore, the discrepancy method is again applied for optimizing scale parameter, shape factor and compactness for class group A, too.

3. RESULTS

Per-class results obtained with the discrepancy method based on AFR applied in the first step typically lie between 0.5 and 0.7 for the best rating segmentation. Looking at the results for the classes ‘road’ and ‘house’ (both in class group A) for the focus study site of Lubao Market and Shirakalu, respectively (Fig. 3a and b) it can be concluded that scale parameters of 20 and 40 reveal the best results. Results for the different layer combinations are less distinct but generally those with a greater weighting of the edge layer score highest. When summarizing the results per group of classes the differences become less strong (Fig. 3c and d). In order to make a decision for a certain layer combination easier and to compare the results for the different focus study sites a ranking has been introduced where the four best results per focus study site are given scores from 1 to 4. In the case of class group A nearly half of the scores are achieved with the overall best layer combination.

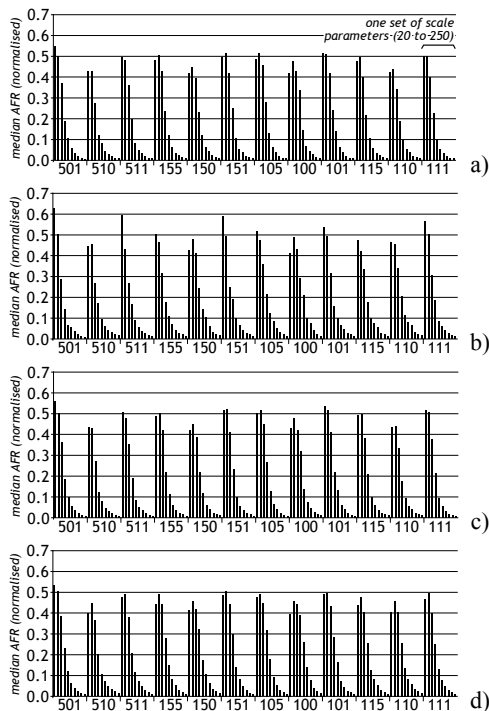


Figure 3. Results of the discrepancy evaluation based on the ‘area fitness rate’ (AFR) for the classes ‘road’ in Shirakalu (a) and ‘house’ in Lubao Market (b); evaluation summarised for class group A in the two sites (c: Shirakalu; d: Lubao Market).

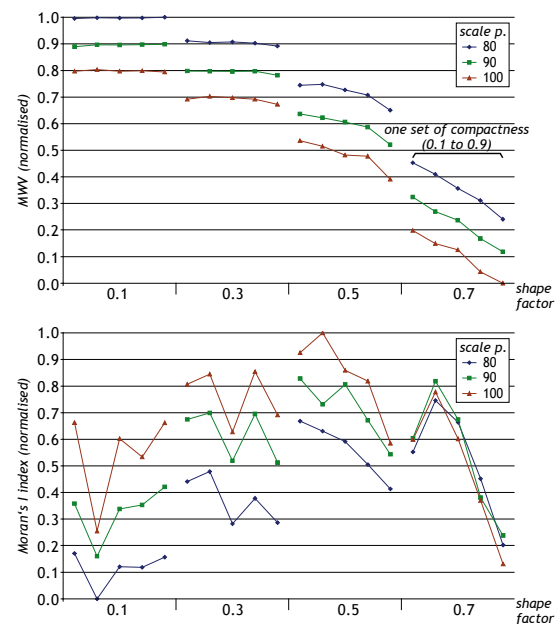


Figure 4. Results of the goodness evaluation for class group D in the focus study site Virhembe: normalised ‘mean weighted variance’ (MWV, top) and Moran’s I index (bottom).

Results obtained with the goodness methods in the second step range between 4,300 (scale parameter 20, group A) and 66,000 (scale parameter 100, group D) in the case of MWV, and between 0.098 (scale parameter 100) and 0.371 (scale parameter 20) in the case of Moran's I index. For the focus study site of Virhembe the normalised results of class group D are displayed in Fig. 4. It can be seen that variances are lower for higher scale parameters as well as for higher shape factors while an increasing compactness value leads to almost equal or slightly better results for low shape factors (0.1 and 0.3) but considerable lower results for higher shape factors (0.5 and 0.7). Values for Moran's I index are also generally lower for lower scale parameters. Even though further trends are not as clear as in the case of variance it can be seen that mid shape factors mostly lead to better results and segmentations with a high influence of compactness and a higher shape factor generally score lower.

The results combined by the 'objective function' have been visualised in, again, set of diagrams (not shown here). Based on them one optimal parameter combination has been visually determined for each of the five focus study sites and four class groups. In ambiguous cases marginally less good results have been noted in addition. In case of class group D the determined values for scale parameter and shape factor are very similar among the focus study sites while for compactness contradictory results are obtained. For class group B the determined values for all three parameters are very similar among the focus study sites, for group C they coincide slightly less well. For class group A that had to be evaluated by the discrepancy method alone (see chapter 2.6), again a ranking has been carried out showing that 44% of the scores have been assigned to 7 out of 60 combinations, the 7 being very similar.

4. CONCLUSIONS

The relatively low mean results for the AFR can be explained by the fact that e.g. neighbouring parcels of same cultivations are often separated by very thin, non-contrastive lines only and adjoining houses can only be identified as such by the shape of their roofs and hence are very hard to detect by the region-growing algorithm. From the combined results of the second step of optimization it can be concluded that the determinability of optimal parameter settings depends on the classes or groups of classes under examination, i.e. for some classes the optimal settings are clearer than for others. Although the procedure applied in the case of class group A in the second step presents a break in procedure it does not mean a drawback since meaningful results could be obtained with just applying the discrepancy method again.

In order to examine the usefulness for an actual classification the segmentations with the determined optimal settings have been visually checked for each of the classes with exemplary chosen objects. Fig. 5 shows that for class group A (top-left) some very small segments are created but generally the delineation of the visual interpretation is matched well in case of the houses; except for a strongly illuminated tinned roof that is segmented on its own. Other objects that are not part of class group A and hence not of relevance here are highly over-segmented. Due to the high weighting of the edge layer in the

segmentation thin polygons reminding of buffers are generated along house margins. Since this could not be avoided it must be accounted for in the subsequent classification. In class group B (top-right) shrubs on a parcel are matched very well. The delineation in some parts seems to be even slightly more accurate than in the reference data set due to the limitations set earlier (for explanation see chapter 2.2). Here, a shrub that is neglected in the visual interpretation because of its small size of less than 25 m² gets correctly segmented. In this example shadows are small enough that they can be jointly segmented together with the shrubs. In the example for class group C (bottom-left) a homestead is over-segmented into two main segments but otherwise the delineation follows the visual interpretation well. Again, two small shrubs are additionally delineated as well as an area east-south-east of the house that exhibits very little vegetation cover. Also for the class group D (bottom-right) the result is promising. A number of parcels are segmented in one segment following the visual interpretation very well; only few parcels are over-segmented, e.g. the large heterogeneous sugar cane parcel in the image centre. Objects like houses and roads that are not relevant for this group are, as expected, not matching well.

By evaluating five test areas with distinct characteristics it is possible on the one hand to account for the heterogeneity of the area under investigation and on the other hand to cross-check if the results are reliable. The fact that in most cases very similar results are obtained for the five focus study sites demonstrates that the results are indeed reliable. Since the sites have been chosen to meet the area's heterogeneity it can be expected that the determined parameter settings are also suitable for the complete imagery. The initially formulated requests for a study of parameter optimization are all met by the presented method. While it has been assured from the very beginning that the focus study sites represent the heterogeneity of the area under investigation well, it has been shown that groups of classes (A to D) have been optimized individually, all degrees of freedom of the multiresolution segmentation have been covered, and parameter settings have been selected in adequately small increments. Further, the procedure could be automated to a large extent. However, the automation should be further refined so that the method can be easily applied also by others.

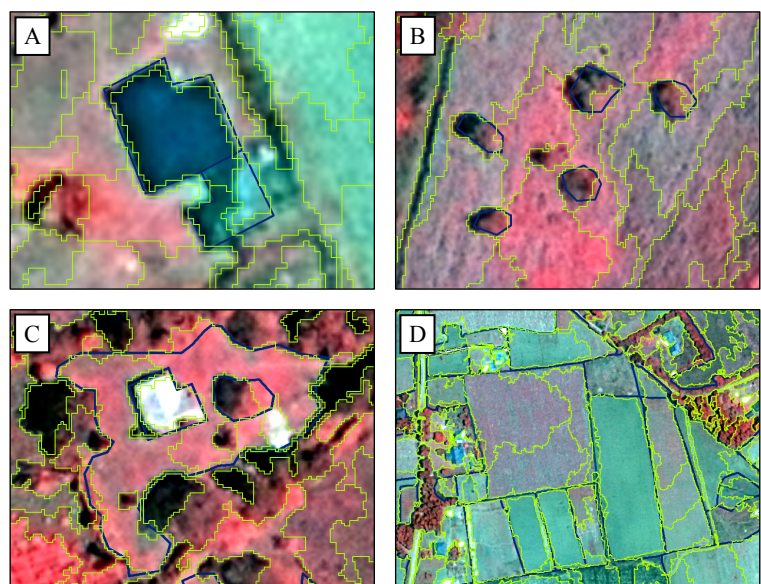


Figure 5. Exemplarily chosen objects for visual checking of class groups A, B, C, and D; visual interpretation (dark coloured lines, objects relevant to the class only), and optimised segmentation (light-coloured lines).

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