D. Fritsch, M. Englich & M. Sester, eds, 'IAPRS', Vol. 32/4, ISPRS Commission IV Symposium on GIS - Between Visions and Applications, Stuttgart, Germany.

Klein et al. 299

# SEGMENTATION OF REMOTELY SENSED IMAGES BASED ON THE UNCERTAINTY OF MULTISPECTRAL CLASSIFICATION

**Ulrike Klein, Monika Sester**
Institute for Photogrammetry (ifp)
University of Stuttgart
Geschwister-Scholl-Strasse 24
D-70174 Stuttgart
Email: Ulrike.Klein@ifp.uni-stuttgart.de, monika.sester@ifp.uni-stuttgart.de

**Günter Strunz**
Deutsches Zentrum für Luft- und Raumfahrt e. V.
Deutsches Fernerkundungsdatenzentrum (DFD)
Postfach 1116
D-82230 Oberpfaffenhofen
Email: strunz@dfd.dlr.de

## ABSTRACT

Since the launch of high-resolution sensors, the use of satellite images as a major source of spatial information has been the subject of extensive research in a broad range of applications. In particular, the extraction of land cover information from remotely sensed data and the use of this information as input into geographical information systems (GIS) has received considerable attention over the last ten years. The successful use of GIS as a decision support tool can only be achieved, if it becomes possible to attach a quality label to the output of each spatial analysis operation. Thus the accuracy of multispectral classification gained more attention. In a GIS, the data is usually stored in terms of objects instead of individual pixels. To this end, the classification result has to be segmented. An important aspect of this research is the propagation of the uncertainty of a pixel belonging to a class to the uncertainty of the pixel belonging to a region. Different approaches for image segmentation will be presented, that take the thematic uncertainty of the pixels into account. They will be applied and verified to a small test area.

## 1 INTRODUCTION

With the increasing popularity of GIS, geographic data in GIS are often being used to support policy decisions. Since no information about quality of the data is normally available, it is assumed that the data are free of errors. However, this assumption is often not warranted due to a variety of reasons (Burrough, 1986, Goodchild and Gopal, 1989). Quality of geographic data has a profound impact on the reliability of the resulting policy decision based on spatial analysis because the quality of data affects the quality of decisions and the evaluation of decision alternatives.

Thus the issue of spatial data uncertainty is given high priority on the GIS research agenda, and is one of the most frequently covered topics in recent scientific literature on GIS. With the increasing use of remotely sensed data as input into geographical information systems, the accuracy of multispectral classification also gained more attention. Accuracy assessment includes positional accuracy and thematic accuracy (Janssen and van der Wel, 1994).

The assessment of positional accuracy mostly yields one single measure, the root-mean-square (RMS) error, and refers to the accuracy of the geometrically rectified image. Rectification includes georeferencing and geocoding.

Thematic accuracy refers to the correspondence between the class label assigned to a pixel and the true class. From this comparison the proportion of correctly classified pixels and class-dependent measures are derived. However, these global measures do not give sufficient information since a quality assessment for individual areas is not possible. Alternatively one might consider the class membership probabilities that are generated by classification as indicators of the uncertainty of pixel assignment. Therefore, in the following we will distinguish between the terms accuracy and uncertainty.

Accuracy in GIS currently is a research topic of high interest. The approaches mainly concentrate on vector GIS, modelling geometric (positional) uncertainty with appropriate measures (e.g. error band (Caspary and Scheuring, 1992, Blakemore, 1984), fuzzy techniques (Glemser, 1994)). Shi et al. (1994) present an approach to visually overlay thematic and geometric uncertainty. Integrating the quality of raster objects in a hybrid GIS requires the definition of special data structures and the design and implementation of analysis procedures that work on the data. Basically, either a single probability value (mean value of the probabilities and the standard deviation) can be assigned to the object, or individual per-pixel-probabilities can be modelled (Glemser and Fritsch, 1998).

Since in a GIS the data is usually stored in terms of objects instead of individual pixels, the classification result has to be segmented. An important aspect in this context is the propagation of the uncertainty of a pixel belonging to a class to the uncertainty of the pixel belonging to a region.

## 2 DATA SETS

A test area with an extension of 2.2 km by 2.8 km was defined to compare the proposed approaches. It is located approximately 80 km east of Stuttgart.

D. Fritsch, M. Englich & M. Sester, eds, 'IAPRS', Vol. 32/4, ISPRS Commission IV Symposium on GIS - Between Visions and Applications, Stuttgart, Germany.

300    IAPRS, Vol. 32, Part 4 "GIS-Between Visions and Applications", Stuttgart, 1998

As input data for the classification DPA high resolution remote sensing data were used. The Digital Photogrammetric Assembly (DPA) is an optical airborne imaging system for real time data collection (Fritsch, 1997). The ground pixel size is dependent on the flying height and is for example 0.60 m for multispectral data when flying 2300 m above ground. Beside the multispectral sensor, the DPA camera system offers also three panchromatic CCD line arrays for inflight stereo imaging. The data were resampled to a pixel size of 4m because this resolution is sufficient for the approaches of segmentation. In addition to the multispectral channels of the DPA sensor textural patterns which are computed from the multispectral data are used. Figure 1 shows the DPA data of the test area in which the land cover classes agricultural area, settlement and forest shall be classified.



Figure 1: DPA data

The training areas for the land cover classes agricultural area, settlement and forest are generated from ATKIS data. ATKIS is the German topographic cartographic spatial database (ATKIS, 1988) and presently contains more than 60 different feature types for the whole area of Germany in the scale 1:25.000. Beside this scale there are further levels of data aggregation in the scales 1:200.000 and 1:1.000.000.

## 3    TRADITIONAL APPROACH

### 3.1    Classification

Supervised classification is the procedure most often used for quantitative analysis of remote sensing image data (Richards, 1993). It rests upon using suitable algorithms to label the pixels in an image as representing particular ground cover types. There are a lot of different methods among those maximum likelihood classification is the most common supervised classification method. The essential practical steps are as follows.

- The first step is to define the set of land cover types into which the image is to be segmented. In this context most classification methods assume that an image scene can be decomposed into a small number of spectrally separated classes, each of which can be allocated uniquely to one of the defined types of land cover. This corresponds to a model of the Earth's surface that consists of a collection of homogeneous patches of land with precise boundaries. In reality, however, changes in land cover are less abrupt and the definition of different land cover classes is more ambiguous.

- For each of the desired set of classes representative pixels called training data have to be chosen.

- With these training data the statistical parameters of the classifier algorithm can be estimated.

- In a last step every pixel in the image is classified into one of the chosen land cover types using the decision rule for the trained classifier. In the case of the maximum likelihood classifier the probabilities that a pixel belongs to each of the defined set of possible classes are estimated. The class to which the pixel is finally assigned is that having the highest probability. Class membership probabilities on which the assignment is based are usually disregarded, so that after classification no information on the probabilities is available. So it is not possible to decide if a strong membership (e.g. 0.90 for forest and 0.10 for agriculture) or a weak membership (e.g. 0.51 for forest and 0.49 for agriculture) exits.

The outcome of the classification is a pixel oriented representation of different land cover classes and can be represented in form of a thematic map. Figure 2 shows the result of the classification procedure for the chosen test area. Errors in the definition of land cover type and errors in the assignment of pixels to a particular class result in the classification uncertainty, i. e. the thematic uncertainty.



☐ agricultural area
☐ settlement
■ forest

Figure 2: Classification result

In a GIS the data is usually stored in terms of objects instead of individual pixels. To this end, the classification result has to be segmented.

D. Fritsch, M. Englich & M. Sester, eds, 'IAPRS', Vol. 32/4, ISPRS Commission IV Symposium on GIS - Between Visions and Applications, Stuttgart, Germany.

Klein et al.                                                                                                                                  301

## 3.2 Indicators of Classification Uncertainty

Map accuracy is usually assessed by comparing the classified land cover to the actual land cover obtained from ground surveys, aerial photographs or already existing GIS data. The results of this comparison are then recorded in the confusion matrix. From the confusion matrix global and class-dependent measures of accuracy are derived (Congalton, 1991, Stehman, 1997). The most fundamental disadvantage is that no information about the spatial distribution of the uncertainty within the classes is available.

Alternatively one might consider the class membership probabilities that are produced by statistical classification as indicators of the reliability of pixel assignment. The advantage of working with these class membership probabilities is, that they provide information at the level of each individual pixel. However it should be pointed out that they cannot be considered as pure indicators of classification accuracy because they do not take into account all problems related to the definition of the class signatures on which the classification is based.

Therefore it is obvious to denote the parameters that are derived from the confusion matrix as direct measures of *classification accuracy* or as *external measures*. In contrast, the class membership probabilities can be named as indicators of *classification uncertainty* or as *internal measures*. In the following, there will be a concentration on the internal measures.

## 3.3 Segmentation of Classification Results

Image segmentation provides a logical transition from the units of pixels to spatially cohesive units, or regions. A reason for segmenting an image into regions is that subsequent processing steps like spatial data analysis require per-region, rather than per-pixel, input.

The result of the classification is normally segmented using region growing algorithms (Haralick and Shapiro, 1992). Adjacent pixels are grouped together if they meet a pre-specified similarity criterion. Here, the similarity criterion requires that adjacent pixels have the same land use label. With this segmentation technique land cover classes are modelled as non-overlapping areas that are used as input data into GIS usually without any accuracy assessment.

In the following three alternative approaches of image segmentation will be presented that take for each pixel the class membership values or the probability vector, respectively, into account.

## 4 SEGMENTATION BASED ON UNCERTAINTIES

The probability vector contains the probabilities with which the pixel can be assigned to the defined land cover classes. In the case of the test area, these are the classes agricultural area, settlement and forest. The probability vector contains as much elements as land cover classes are defined, so in this case it is a vector with three elements. Therefore the value range of the first most likely probability lies in the interval [0.33,1.00], that of the second most likely probability in the interval [0.00,0.50], that of the third most likely probability in the interval [0.00,0.33] and all probabilities per pixel add up to 1.00.

In Figure 3 the probability of the first most likely class for all three object classes is displayed. The dark regions indicate high probability, while the bright regions have a high degree of uncertainty. Uncertainty occurs along the edges of the parcels and along roads. The outlines of the individual parcels in the object class agricultural area can be recognized clearly in the representation of the probabilities. Additionally, there are regions with a relatively high degree of uncertainty. In these regions the confusion between different land cover types becomes apparent. A segmentation based only on the highest probabilities will yield the same results like in the conventional maximum likelihood approach, since the same data is used. Consequently, the whole probability vector has to be included in the segmentation. Investigations with more classes have revealed, that in general only at most three probabilities have values greater than zero. So it is sufficient to consider the first, the second and the third most likely probabilities in the segmentation process. That means the following: If the probabilities for a pixel have e.g. the values 0.60 for agricultural area and 0.40 for settlement, this pixel will be included both in the segmentation of the class agricultural area and in the segmentation of the class settlement.
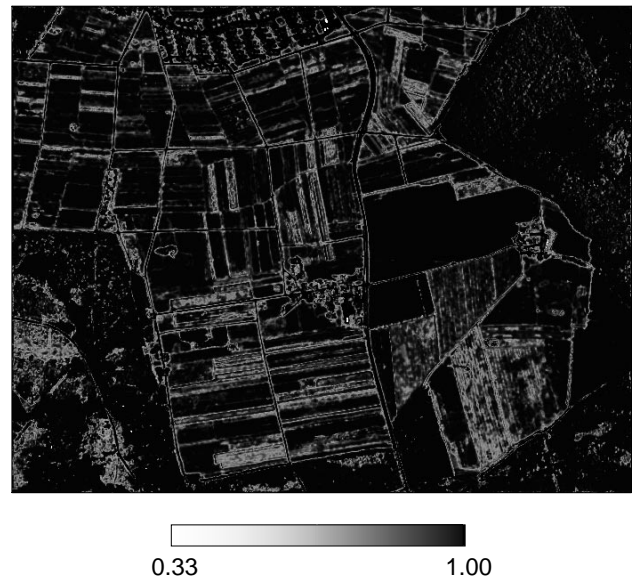


| 0.33 | 1.00 |

Figure 3: Probability of the first most likely class for all three object classes

With this procedure the land cover classes are modelled as overlapping areas. This is to be seen as an advantage since as a result mixed pixels that occur along the boundaries between different land cover classes can be modelled, without having to define additional classes. Having in mind the modelling of the geometrical uncertainty of vector data e.g. minimum-maximum-method (Blakemore, 1984), the error band describes the minimal and maximal possible extension of the object or the variation of the boundary between two adjacent objects, respectively. Consequently, the region within the error band can be considered as a mixed region. This means that overlapping objects are also allowed in the case of modelling the geometrical accuracy of vector data.

D. Fritsch, M. Englich & M. Sester, eds, 'IAPRS', Vol. 32/4, ISPRS Commission IV Symposium on GIS - Between Visions and Applications, Stuttgart, Germany.

302                                                    IAPRS, Vol. 32, Part 4 "GIS-Between Visions and Applications", Stuttgart, 1998

a) agricultural area



b) settlement



c) forest



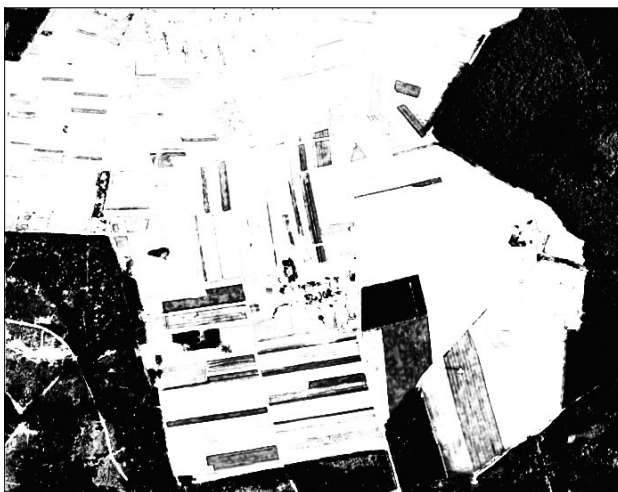0.00                              1.00
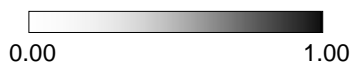
Figure 4: Representation of the probabilities

The basic data for the segmentation are the overlapping object classes and the corresponding probabilities per pixel. The task consists in finding closed regions within the individual object classes. In the segmentation process performed for the test area pixels with probabilities less than 0.20 are not included.

Figure 4 shows the probabilities for the land cover classes agricultural area, settlement and forest. The probabilities for class membership are represented for every individual land cover class since the object classes are overlapping. The dark regions indicate high probability, while the bright regions have a high degree of uncertainty. If no object class is assigned, the pixels are represented in white, e.g. in the visualisation of the probabilities of the object class settlement in the upper right part of the image. The pixel in this part are assigned with a probability of 1.00 to the object class forest and with a probability of 0.00 to the object class settlement.

The confusion between land cover types becomes apparent by comparing the different representations. This is shown in Figure 5 for a part of the image. Objects that appear in only one object class e.g. the object A in the land cover class forest can unambiguously be assigned to that class. Objects that appear in two object classes e.g. the object B in the land cover classes agricultural area and forest indicate problematic regions.
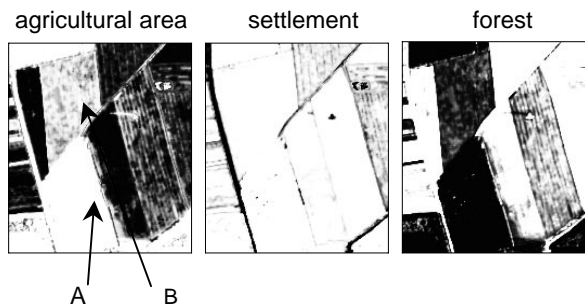
agricultural area          settlement              forest



A          B

Figure 5: Detail of the representation of the probabilities

### 4.1 Segmentation of objects of heterogeneous quality

A very simple procedure to the segmentation based on the uncertainties consists in including neighbouring pixels into a region independent of the order of magnitude of the probability. This procedure has to be carried out for every given object class. As already mentioned above, pixels with probabilities less than 0.20 are not included.

Figure 6 shows the segmented objects for agricultural area. The chosen 4-connectivity results in 1344 objects. The objects formed in such a way differ from those of traditional segmentation in the additional quality information, and of course in the overlapping regions with other object classes. Since the aggregated objects consist of regions of different thematic uncertainty, they can be described as objects of heterogeneous quality. Consequently, the modelling of quality of these objects in a GIS requires that the probability per pixel is available. The number of objects depends on how many neighbouring pixels are considered to be contiguous i. e. whether adjacency is defined in terms of 4-connectivity or of 8-connectivity.

D. Fritsch, M. Englich & M. Sester, eds, 'IAPRS', Vol. 32/4, ISPRS Commission IV Symposium on GIS - Between Visions and Applications, Stuttgart, Germany.

Klein et al. 303



Figure 6: Segmentation result for agricultural area

## 4.2 Segmentation of objects of homogeneous quality

Assuming that thematic uncertainty in image classification is field-based rather than pixel-based, the image is segmented in fields according to similarities in the probability vectors of adjacent pixels by use of a region growing algorithm. In the algorithm the probability of the current pixel is compared with the probability of a neighbouring pixel. If the difference is less than some predefined threshold, then the pixel is included into the region, otherwise it is not. Again, adjacency can be defined in terms of 4-connectivity or in terms of 8-connectivity.



Figure 7: Segmentation result for agricultural area

Based on the chosen similarity criterion for the segmentation, regions of similar thematic uncertainty are created. They can be denoted as objects of homogeneous quality. As a quality information of the objects, we can choose the mean value of the probabilities and the standard deviation as an alternative to the probability per pixel. The number of objects depends on the chosen threshold and on the chosen neighbourhood type.

Figure 7 shows the segmented objects for agricultural area. Using 4-connectivity and a threshold value of 0.15 results in 13395 objects.

## 4.3 Segmentation of objects with alternatives

In the case of the procedures described in sections 4.1 and 4.2 segmentation is carried out separately for the individual object classes. Only the superposition of the results reveals overlapping regions, but no statement can still be made, which one of the object classes is the most likely one. Therefore, in this section an approach which provides the objects and their alternatives is presented.

In this third approach the segmentation is carried out based on same class memberships of neighbouring pixels but independent on the order of magnitude of the probabilities. Two neighbouring pixels will be assigned to the same object, if they both show either class membership to the same object class or several class memberships to the same object classes. Two examples shall explain this: If the probabilities of two adjacent pixels have both the value 1.00 for forest, they are both assigned to the same object of the class forest. If the probabilities of a pixel have the values 0.60 for agricultural area and 0.40 for forest and the probabilities of an adjacent pixel have the values 0.70 for forest and 0.30 for agricultural area, they are assigned to the same object of the mixed class agricultural area with forest. This requires the definition of all available mixed object classes in addition to the object classes defined already. In the case of the test area, these are the three mixed classes "agricultural area with settlement", "agricultural area with forest" and "settlement with forest". A fourth mixed class can be characterized by the existence of all object classes. Consequently, seven object classes are defined in total. With regard to the object classes, it is to be distinguished between pure object classes and mixed object classes. The pure object classes are characterized by the assignment of the land use type with a probability of 1.00. For the description of the quality of the mixed object classes, we can again choose for every object the mean value of the probabilities and the standard deviation as an alternative to the probability per pixel.
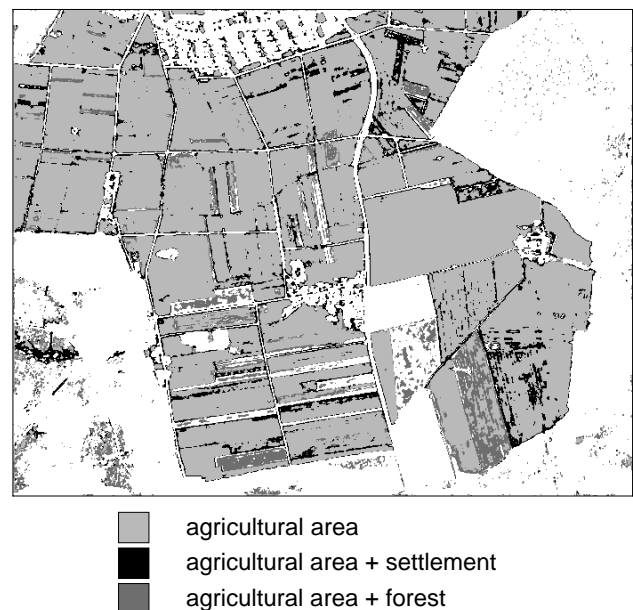


■ agricultural area
■ agricultural area + settlement
■ agricultural area + forest

Figure 8: Segmentation of alternative object classes of agricultural area

D. Fritsch, M. Englich & M. Sester, eds, 'IAPRS', Vol. 32/4, ISPRS Commission IV Symposium on GIS - Between Visions and Applications, Stuttgart, Germany.

304                                    IAPRS, Vol. 32, Part 4 "GIS-Between Visions and Applications", Stuttgart, 1998

The segmentation of the data shown in Figure 8 results in 746 objects for agricultural area, 2899 objects for agricultural area with settlement and 2132 objects for agricultural area with forest, again using 4-connectivity. In the figure only the classes related to agricultural area are visualized.

### 4.4    Comparison

The presented approaches shall be compared using a part of the image (Figure 9). The object under investigation is in the lower, middle part of the image (Figure 2). It is an object of the class agricultural area with a relatively inhomogeneous stripe in it. Figure 9a) visualizes the high probabilities for the main object (dark grey values) and the low probabilities (bright grey values) for the stripe.

The approach 'Segmentation of objects of heterogeneous quality' (Section 4.1) is well suitable to describe form and spatial extension of the objects. Since the individual objects are formed independent from the order of magnitude of the probabilities, they form a homogeneous region (Figure 9b) – observe that also the strip with low probabilities still is assigned to the region. However, the region does not have a uniform accuracy. Therefore, for further processing in a GIS, the per-pixel-probabilities given in Figure 9a) have to be transferred to the GIS.

In the approach 'Segmentation of objects of homogeneous quality' (Section 4.2) the object of Figure 9c) is partitioned into one larger object and approximately 200 smaller objects. All pixels within these individual objects have a similar thematic uncertainty. The representations of the probabilities (cf. Figures 3 and 4) show the following: Regions in which all pixels have the same probability are shown in one homogeneous grey value, e.g. the black regions have probability values of almost 1.00. Regions in which the pixels have different probabilities are shown in different grey values. That means that individual large objects indicate regions with high probability, and many smaller contiguous objects indicate inhomogeneous regions in respect of the uncertainty.

The approach 'Segmentation of objects with alternatives' (Section 4.3) offers the possibility to indicate an alternative class for those regions that are assigned only with a low probability to an object class. In such a way, Figure 9d) shows that most of the pixels of the uncertain stripe are alternatively assigned to the object class forest. The boundary of the object are alternatively assigned to the object class settlement. This can e.g. point at a path along the parcel.

The different segmentation results (Figure 9b, 9c, 9d) should now be compared with the classification result (Figure 2) and the satellite image (Figure 1) describing the reality. The comparison is carried out for the stripe mentioned repeatedly. This stripe is assigned both to the object class forest and to the object class agricultural area. Since the probabilities for the membership to the class forest are larger, most parts of the stripe are assigned to the object class forest in the classification. However, by visual inspection of the satellite image an agricultural area is identified.
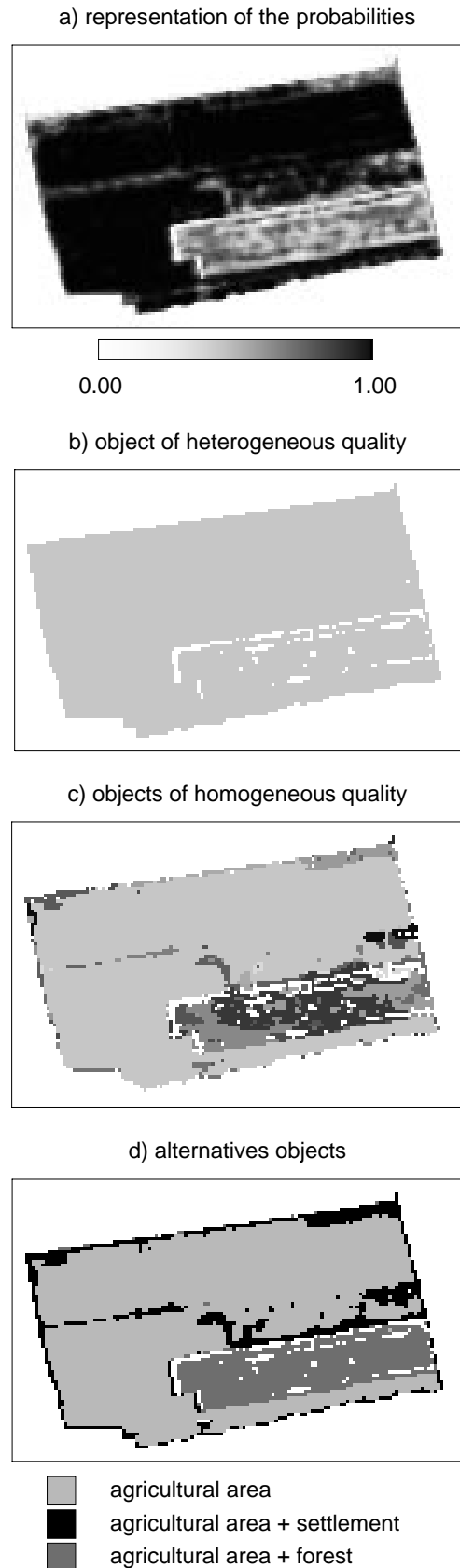
a) representation of the probabilities

0.00                              1.00

b) object of heterogeneous quality

c) objects of homogeneous quality

d) alternatives objects

agricultural area
agricultural area + settlement
agricultural area + forest

Figure 9: Detail of the segmentation results for agricultural area

D. Fritsch, M. Englich & M. Sester, eds, 'IAPRS', Vol. 32/4, ISPRS Commission IV Symposium on GIS - Between Visions and Applications, Stuttgart, Germany.

Klein et al. 305

The occurrence of mixed object classes indicates problematic regions. They can form lines or areas, as Figure 9d) shows. The problematic regions forming lines describe the thematic uncertainty on the boundary between two objects. The problematic regions forming areas indicate problems in the classification. Most of the mixed objects "agricultural area with forest" are wrongly assigned to forest in the classification. For this test area this is an indication that another object class has to be defined to improve the classification result. Obviously, the wrongly classified areas are agricultural areas whose coverage have similar spectral properties like forest.

## 5 SUMMARY

The successful use of GIS as a decision support tool can only be achieved if it becomes possible to attach a quality label to the output of each spatial analysis operation. With the increasing use of remotely sensed data as input into GIS, the accuracy of multispectral classification also gained more attention.

The quality of the classification can globally be described by accuracy measures that are derived from the confusion matrix. Alternatively the class membership probabilities can be used to describe the classification uncertainty of each pixel. Since in a GIS the data is usually stored in terms of objects instead of individual pixels, the classifications result has to be segmented. In this procedure the uncertainty of a pixel belonging to a class has to be propagated to the uncertainty of the pixel belonging to an object.

Three approaches of image segmentation are presented that take the class membership probability for each pixel into account. The approaches mainly differ in quality levels. An important property of the approaches is the possibility to detect problematic regions and to improve the classification.

## 6 REFERENCES

ATKIS (1988): *Amtlich Topographisches-Kartographisches Informationssystem (ATKIS)*. Arbeitsgemeinschaft der Vermessungsverwaltungen der Länder der Bundesrepublik Deutschland (AdV), Bonn.

Blakemore, M. (1984): *Generalization and Error in Spatial Databases*. Cartographica, Vol. 21.

Burrough, P. A. (1986): *Principles of Geographical Information Systems for Land Resources Assessment*. Oxford Science Publications, Clarendon Press, Oxford.

Caspary W., Scheuring R. (1992*): Error-Bands as Measures of Geometrical Accuracy*. In: Proceedings of the European Conference on Geographical Information Systems (EGIS '92), Vol. 1, 226-233.

Congalton, R. G. (1991): *A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data*. Remote Sensing of the Environment, Vol. 37, 35-46.

Fritsch, D. (1997): *Experiences with the airborne three-line camera system DPA*. In: Photogrammetric Week '97, Eds. D. Fritsch/D. Hobbie, Wichmann, Heidelberg, 63-74.

Glemser, M. and Fritsch, D. (1998*): Data Uncertainty in a Hybrid GIS*. In: Proceedings of the ISPRS-Symposium "GIS-Between Visions and Applications", Stuttgart, September 1998.

Glemser, M. (1994): *Behandlung der Genauigkeit räumlicher Daten in Geo-Informationssystemen*. In: Die benutzte Erde, Alfred-Wegener-Stiftung (Ed.), Ernst&Sohn, Berlin.

Goodchild, M. F., Gopal, S. (1989*): The Accuracy of Spatial Databases*. Taylor and Francis, New York.

Haralick, R. M., Shapiro, L. G. (1992*): Computer and Robot Vision*. Vol. 1, Addison-Wesley, New York.

Janssen, L. L. F., van der Wel, F. J. M. (1994*): Accuracy Assessment of Satellite Derived Land-Cover Data: A Review*. Photogrammetric Engineering & Remote Sensing, Vol. 60, No. 4, 419-426.

Richards, J. A. (1993*): Remote Sensing Digital Image Analysis*. Springer-Verlag.

Stehman, S. V. (1997): *Selecting and Interpreting Measures of Thematic Classification Accuracy*. Remote Sensing of the Environment, Vol. 62, 77-89.

Shi, W., Ehlers, M. and Tempfli, K. (1994*): Modelling and Visualizing Uncertainties in Multi-Data-Based Spatial Analysis*. In: Proceedings of the European Conference on Geographical Information Systems (EGIS '94), Paris, 454-464.