

## **Automated GIS data collection and update**

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### **ABSTRACT**

This paper examines data from different sensors regarding their potential for an automatic change detection approach. After a brief discussion of the used approach, results are shown on examples of data from several sensors: scanned analogue aerial photos, an airborne digital line scanner (DPA camera system), the Indian satellite IRS-1C, the MOMS-2P camera and from a laser scanning system as an additional information source. The GIS data which have to be updated are from the German national topographic cartographic database (ATKIS) and were captured in the scale of 1 : 25,000.

### **1. INTRODUCTION**

Geographic information systems (GIS) are dependent on accurate and up-to-date data sets. The manual revision of GIS data is very cost and time consuming. On the other hand more and more high resolution satellite systems are under development and will be operational soon - thus high resolution remote sensing data will also be available soon. With these new satellite systems it will be possible to capture large areas of the landscape in short time periods. However, a shortening of the updating cycles of GIS databases is only possible if the manual part of the updating process can be at least partly automated. A software package was developed to verify ATKIS data in an automatic way. ATKIS is the German topographic cartographic spatial database (AdV 1988) and presently contains more than 60 different feature types for the whole area of Germany in the scale of 1:25,000 (beside this scale there are further levels of data aggregation in the scales 1:200,000 and 1:1,000,000 which were not used in this work). The software package was developed in such a way that data from different sensors can be used as a source and therefore it is possible to examine the potential of data from different sensors for the automatic change detection approach. Since not only satellite data but also data from airborne sensors were examined, the potential of future high resolution satellite systems can also be estimated.

### **2. PROJECT**

This research is carried out by order of the Surveying Institute of the State of Northrhine-Westphalia, Germany. The project is supported by the German Aerospace Center (DLR – formerly DARA).

### **3. AUTOMATIC CHANGE DETECTION OF REMOTE SENSING DATA**

The approach for the change detection is fully automatic and can be subdivided mainly into two steps (see figure 1). In a first step the remote sensing data have to be classified pixel wise into different land use classes. This is done by a supervised maximum likelihood classification. The problem for an automatic approach here is the supervised part of the classification algorithm. Normally this part involves the work of a human operator and requires a lot of experience because the quality of the training areas is a crucial factor for the quality of the classification result. As the digitizing of the training areas is time intensive and new training areas have to be digitized for every new data set (because of atmospheric effects, different spectral diffusion depending on the sunlight, different spectral characteristics of vegetation depending on season or soil, etc.), a method is needed to derive the training areas in an automatic way. Having assumed that the number of wrongly

captured GIS objects and the number of changes in the real world are substantially less than the number of all GIS objects of the data set, the training areas can be derived automatically from the already existing GIS data. The higher the quality of the training areas the better will be the result of the classification. Therefore, the object geometry is not used as stored in the GIS database - a preprocessing has to be performed first. A detailed description of the computing of training areas can be found in (Walter 1998; Walter and Fritsch 1998).

After the classification it must be decided which of the GIS objects do not match the remote sensing data. This can be objects where a change in the landscape has occurred or objects, that were not collected correctly. All GIS objects are subdivided into three classes. The first class contains all objects which could be detected with a high certainty in the remote sensing data, the second class contains all objects which are detected only partly and the third class contains all objects which could not be detected at all. The decision to which class an object belongs is made by measuring the percentage of pixels which are classified to the same object class as the object in the GIS database belongs to. Besides the percentage of correctly classified pixels, also the homogeneity of the classification result and the form are used for verification. A detailed description of the verification of the classification results can be found in (Walter 1998; Walter and Fritsch 1998).

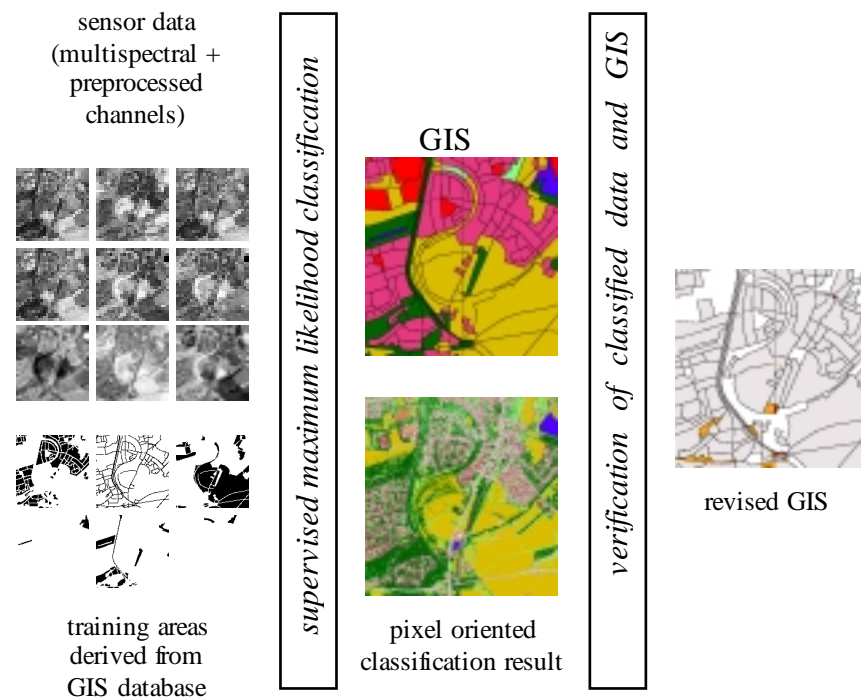


Figure 1: Overview of the automatic approach for GIS change detection.

#### 4. IMPLEMENTATION

The approach is implemented in a software package based on UNIX and X-Windows. Figure 2 shows a selection of different windows of the program. The software was implemented in such a way that all parameters of the approach can be changed interactively by the user and stored as a project. Additionally a visualization component is available to explore the results interactively on the screen. The software is designed in such a way that there exists no limitation regarding the resolution, the size or the channels of the images. This enables the examination of data from very different sources. In the following, results of the classification of images from different sensors are

presented and examined for their potential for an automatic update of ATKIS data. Presently ATKIS contains more than 60 different object classes. It is clear that not all object classes can be distinguished alone by their spectral and textural characteristics without addition of further information sources. Therefore we divided all ATKIS objects into the five land use classes: *forest*, *settlements*, *agricultural areas*, *streets* and *water*.

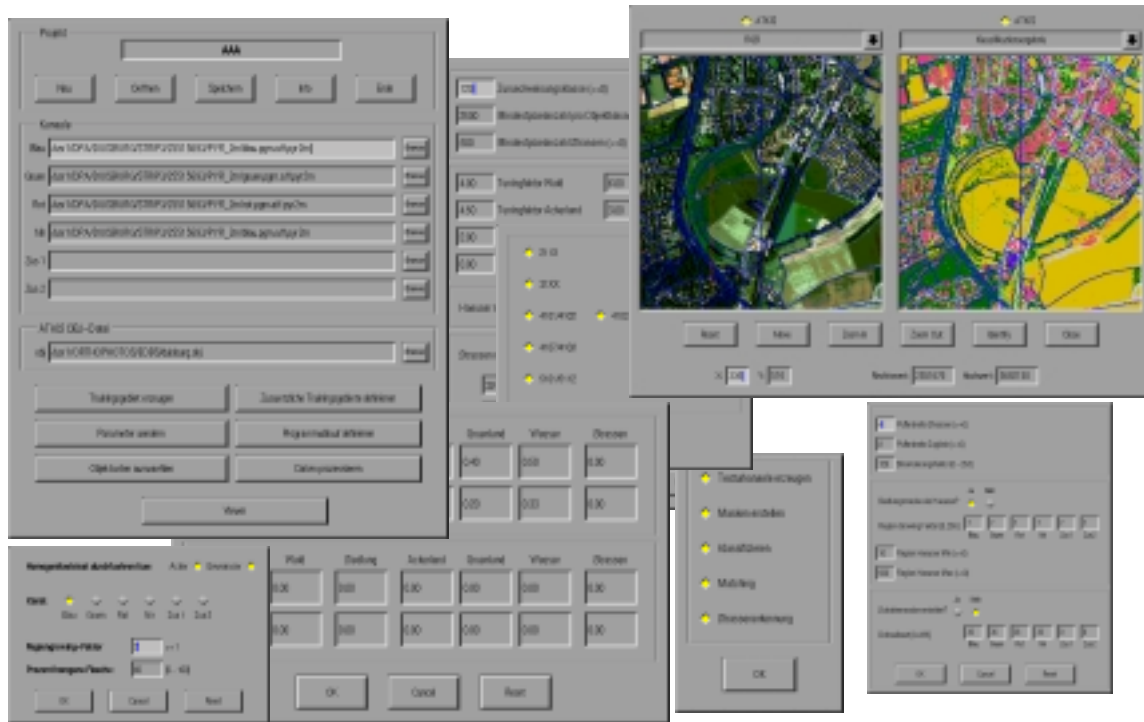


Figure 2: Software package.

## 5. CLASSIFICATION RESULTS DPA

The Digital Photogrammetric Assembly (DPA) is an optical airborne imaging system for real time data collection. 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. Besides the multispectral sensor, the DPA camera system offers also three panchromatic CCD line arrays for in-flight stereo imaging. For more details of the DPA camera see: (Hahn, Stallmann and Stätter 1996).

The data of the test area have a ground pixel size of 0.75 m. This corresponds at an area of 2 km \* 2 km to a pixel number of more than seven million pixels. Because the classification is a complex process, this leads to a high computing time as well as high memory requirements. However, experiences show that high resolution must not necessarily improve the results of the classification. In order to find a compromise between quality of change detection and computer requirements the data were resampled to a pixel size of 2 m. Figure 3 shows the result of the classification of DPA data at an example. Forests are recognized being homogeneous and well detectable. Agricultural areas show sometimes inhomogeneities because of planting structures, but nevertheless they can be detected also very well. The land cover class which could be detected best is *water*. Larger streets are recognized without problems but sometimes street pixels are overlaid with pixels which represent house roofs because of their similar spectral characteristics. This applies in particular to flat roofs.

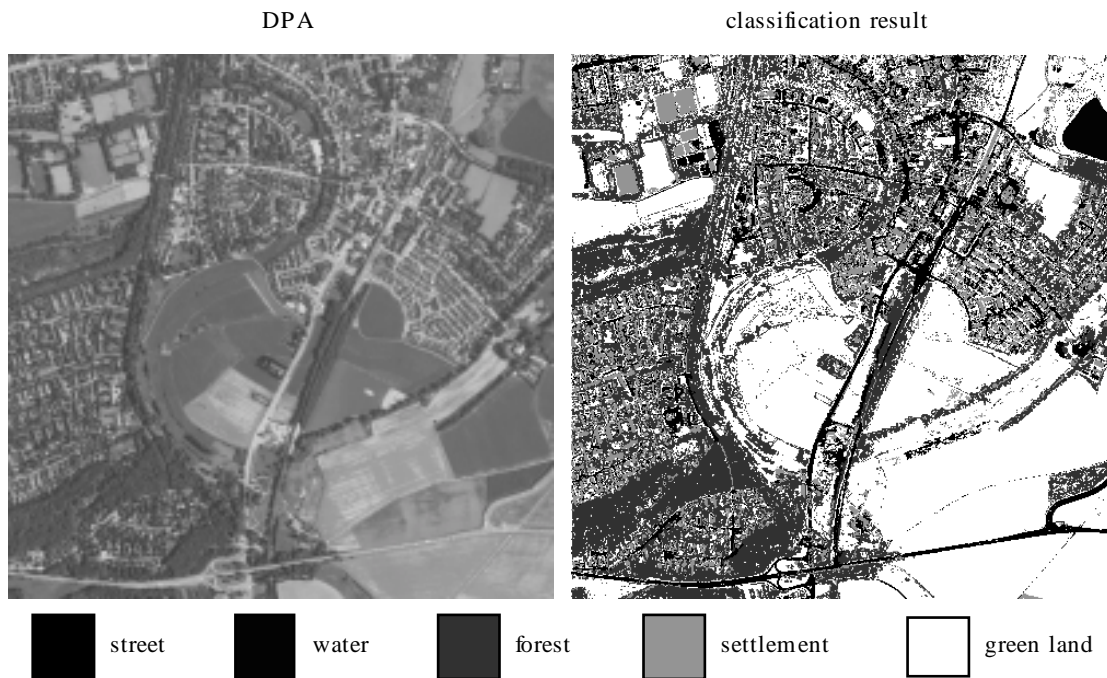


Figure 3: Classification of DPA data.

The land use class *settlement* can not be recognized as homogeneous uniform areas, but it is subdivided into several classes. It can be seen that pixels are only recognized as settlement areas if they represent house roofs. The other pixels are classified as streets, forest and agricultural area depending on the "ground truth". The reason for this result is the high resolution of 2 m. More detailed results of the classification of DPA images can be found in section 10.

## 6. CLASSIFICATION RESULTS IRS-1C

The Indian Remote Sensing Satellite IRS-1C carries a multispectral camera (LISS) with 25 m ground pixel size, a high resolution panchromatic sensor with 5.8 m ground pixel size and a wide field sensor for the optimized determination of vegetation indices with 188 m ground pixel size. The data used in this work are from the LISS camera. For more details of the IRS-1C satellite system see for example (Srivastava et al. 1996).

Figure 4 shows a classification result of IRS-1C data. The image is shown as a CIR image because IRS-1C does not capture data in the blue range. In order to improve the interpretation of the IRS-1C image, a DPA image of the same area is represented. Because of the low resolution, an interpretation of the data is very difficult for an operator. However, it can be seen in the classification result that at least some structures which have a size of only one pixel are classified correctly. But the further processing of the data is problematic because if an object is marked as uncertain it is very difficult for an operator to decide if there has been a change or not if he has only IRS-1C data as a decision base.

This problem can be seen even more clearly in figure 5. The test area consists completely of farmland with a small farm in the center of the figure. Although the IRS-1C-image shows a high spectral variance in the farmland, this is classified as a homogeneous area. The structure of the farm is also recognized very clearly. However, if the settlement object is marked as not found (since it contains only a small number of pixels classified as settlement) there is not enough information content in the IRS-1C to be able to interpret the situation correspondingly.

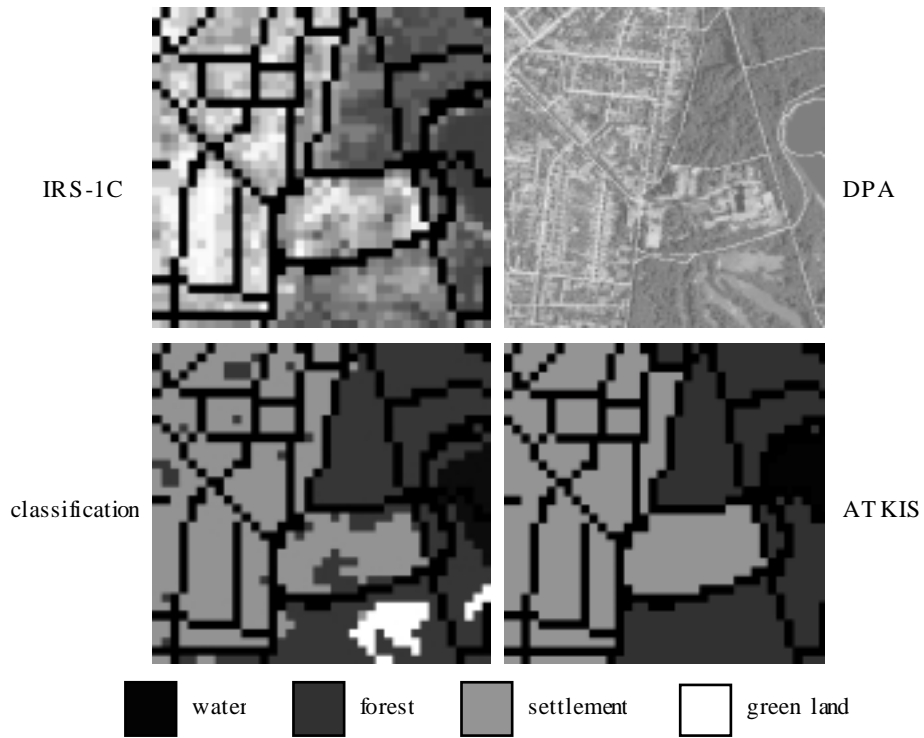


Figure 4: Classification of IRS-1C data (example 1).

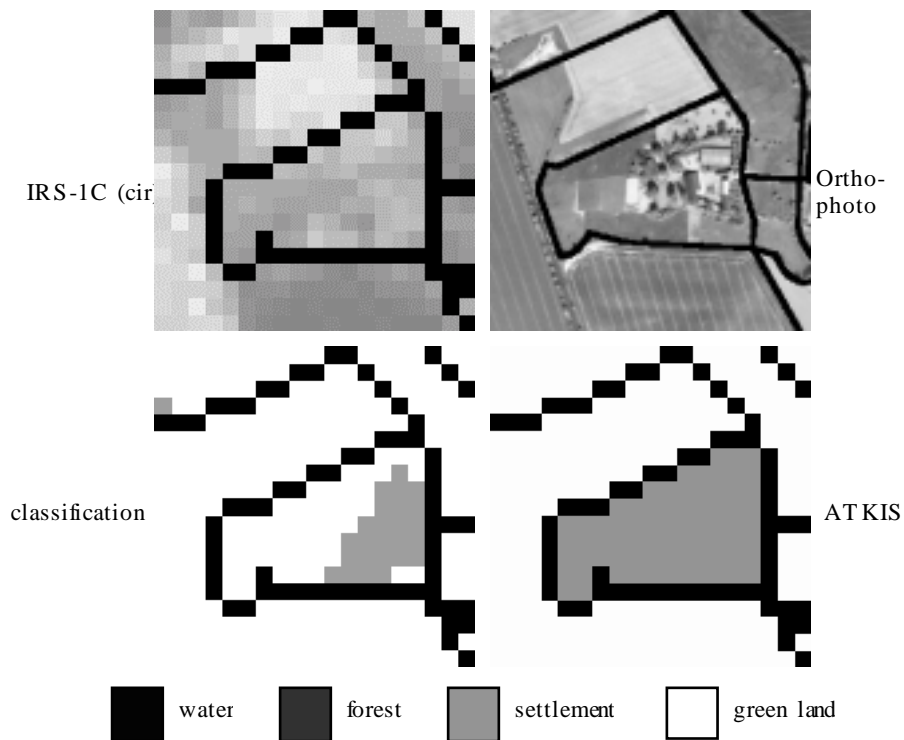


Figure 5: Classification of IRS-1C data (example 2).

In summary it can be said, that IRS-1C data are only in a reduced manner suitable for the update of ATKIS data. An object must have a minimum size from 2 \* 2 pixel so that it is classified certainly in the image. This corresponds to an extension of 50 m \* 50 m. If objects have a high contrast to

their neighboring objects and if the object border is close to the pixel boarder (no mixed pixels) smaller objects can still be recognized correctly. Because of the low geometric and radiometric resolution an interpretation of the classification result by a human operator is very difficult.

**7. CLASSIFICATION RESULTS MOMS-2P**

The Modular Optoelectronic Multispectral Scanner 2 (MOMS-2P) is docked to the Russian Space Station MIR. MOMS-2P combines a high resolution three-channel stereo module and a four-channel multispectral unit. The ground pixel size of the multispectral channels is 18 m. For more details of the MOMS-2P camera system see for example: (Schiewe 1995). Figure 6 shows an overview of the scene (mode C) that was used for the study. A pixel precise classification is also partially possible here.

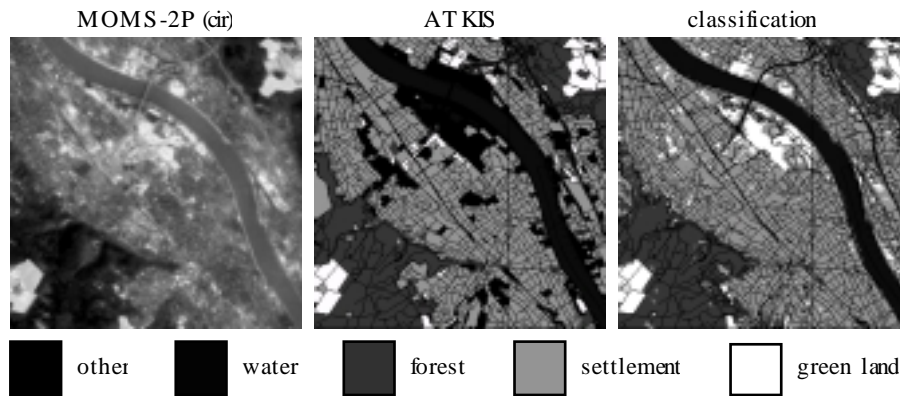


Figure 6: Classification of MOMS-2P data (overview).

However, it can be seen in figure 7 that problems can occur during classification. For comparison, an orthophoto of the same area is represented. Especially the distinction between the land use classes *forest* and *settlement* shows errors in the classification result.

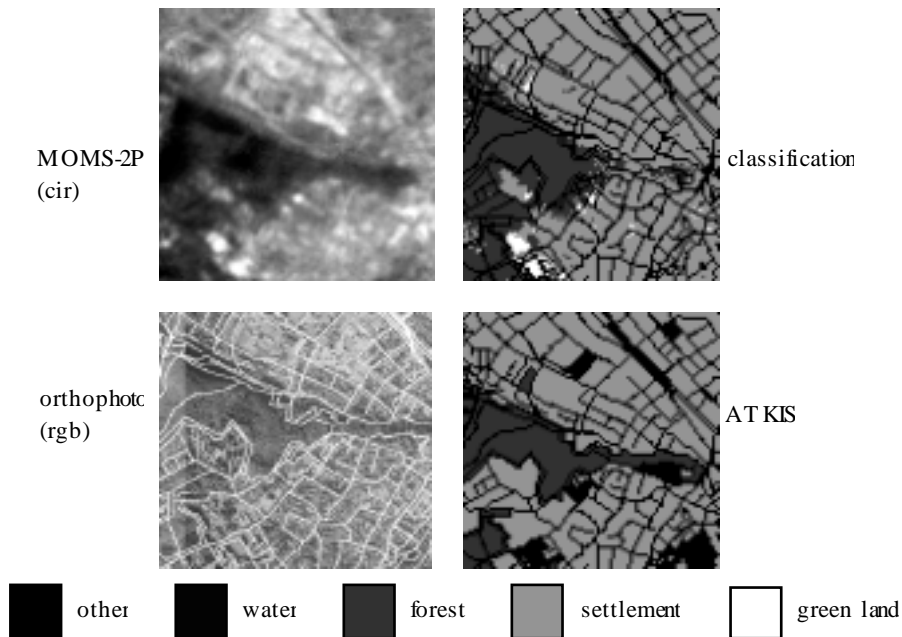


Figure 7: Classification of MOMS-2P data.

The bad classification result can be explained with the small contrast of the MOMS-2P image. Figure 8 shows a histogram comparison of the different channels of IRS-1C data (which was already represented further up) and the MOMS-2P data. It can be seen that all channels of the MOMS-2P image have gray value dynamics of far less than 100 different values. This is why the classification of the IRS-1C data lead to better results since images which are considerably more rich in contrast (in spite of lower technical specification of the camera concerning radiometric and geometrical solution) were available. The reason for the low contrast of the MOMS-2P image is presumably due to the weather conditions.

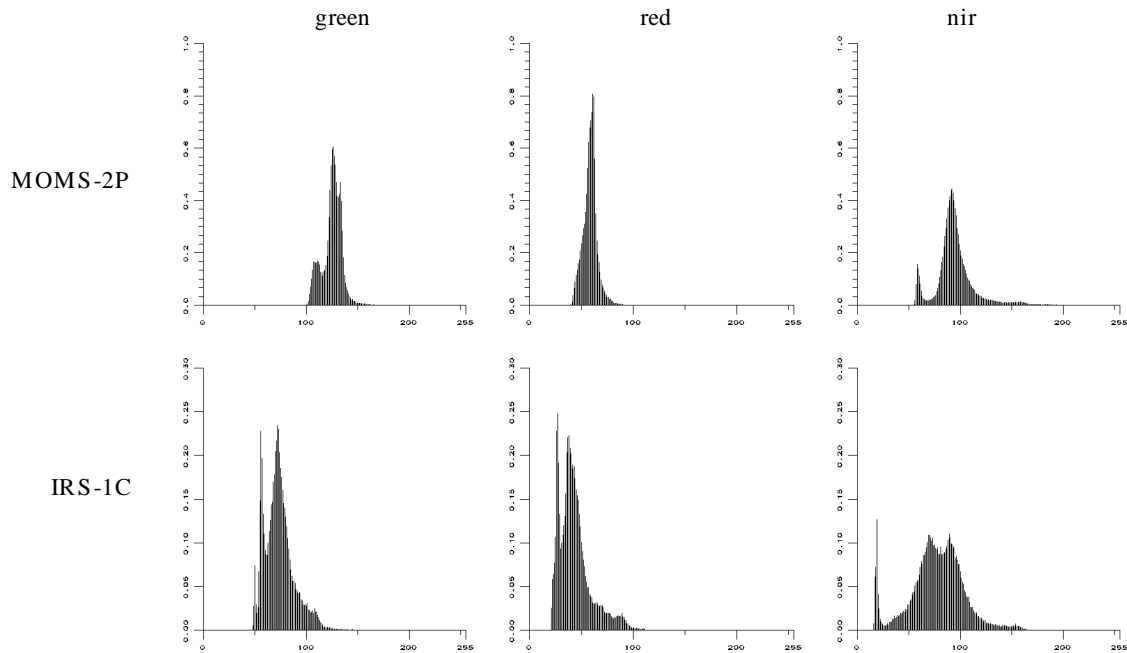


Figure 8: Comparison of MOMS-2P and IRS-1C histogramms.

## 8. CLASSIFICATION RESULTS RGB ORTHOPHOTOS AND LASER DATA

Because the software was developed in such a way that there exist no restrictions regarding the input data for the classification it is also possible to use laser data as an additional information channel. Figure 9 shows a classification result of a rgb orthophoto (resampled to 2 m) without and with laser data as an additional channel. Especially streets and building can be separated more precisely when using laser data.

The bad differentiation of streets and houses in the rgb classification results from the very similar spectral characteristics of these two classes. If, however, laser data are used as an additional channel, pixel that represent house roofs can be distinguished very well from pixel that represent streets because of their height above the ground.

The used part of the image represents an area where very good classification results can be achieved. However, problems arise in areas which are hidden by shadow. Figure 10 shows an example for this situation. Although laser data were used as an additional channel, the classification result is not very good. Especially pixel that represent streets have a completely different spectral characteristic in this example (streets are represented typically by very bright pixels) as in areas without shadow. In situations like this, street pixel are very often classified as forest because forests are represented typically by dark pixels.

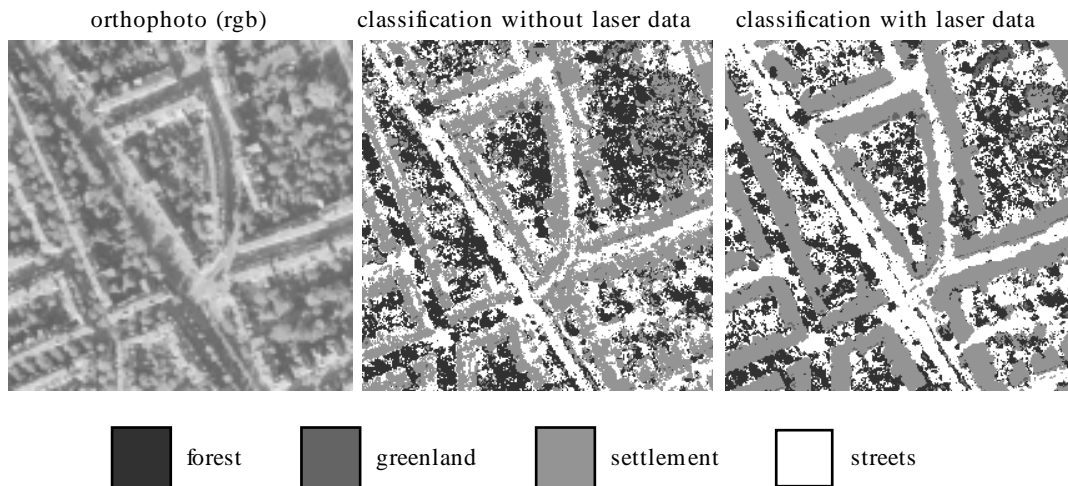


Figure 9: Classification of rgb orthophoto with and without laser data.

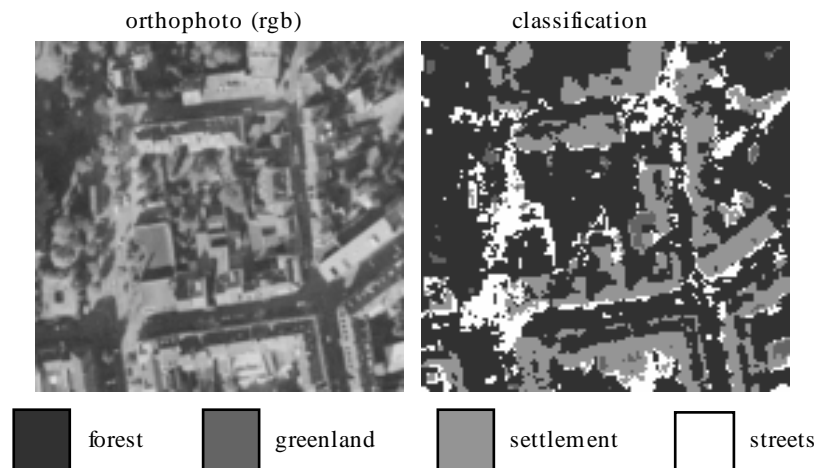


Figure 10: Classification in shadow areas.

In summary it can be stated that rgb data are not suitable to achieve homogenous good classification results. Even by adding of laser data no satisfying results can be achieved. A near infrared channel is necessary to classify pixels in shadow areas correctly.

## 9. CLASSIFICATION RESULTS CIR ORTHOPHOTOS AND LASER DATA

A further test was the classification of cir images and laser data. The following examples were computed with a pixel size of 0.5 m to show the high potential of this combination of data. Figure 11 shows a classification result of a scanned cir orthophoto. The results of the classification of the cir orthophoto can be compared with the results of the DPA data. The additional blue channel of the DPA sensor has barely new information in comparison with the cir channels of the orthophoto because it is strongly correlated with the green channel. It can be seen in the example that vegetated and non vegetated areas can be separated very well by the classification. More problems arise when differentiating streets and houses. These two classes have very similar spectral characteristics and therefore can be separated only very hard.



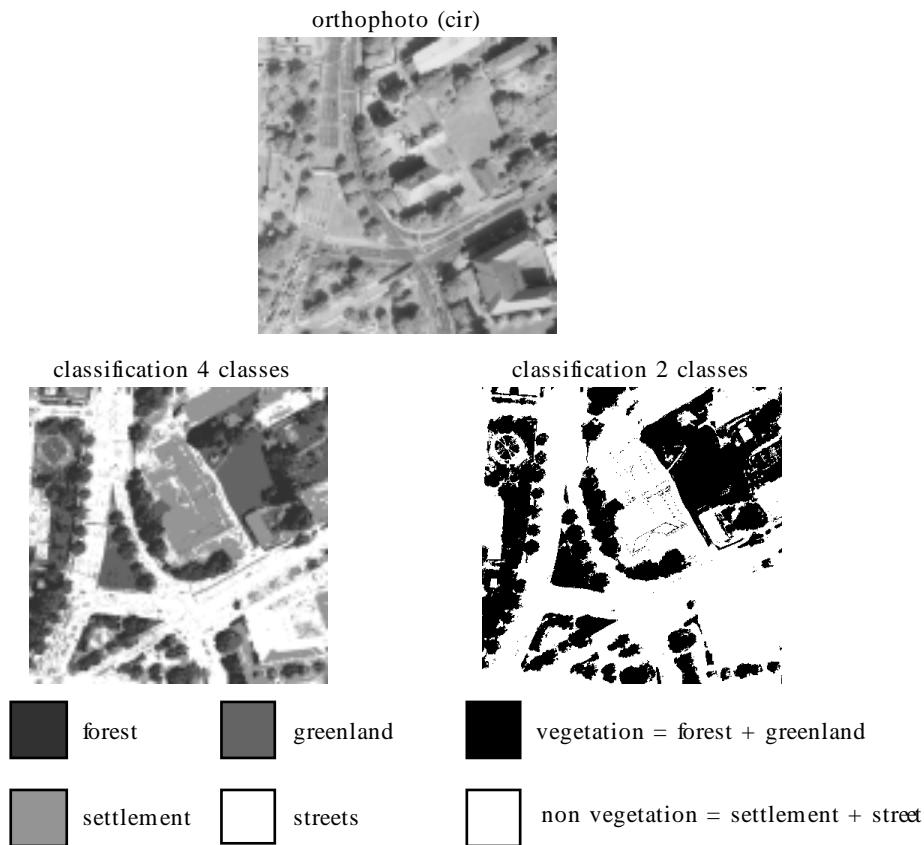


Figure 11: Classification of a cir orthophoto.

Figure 12 shows the classification result of the same part of the image with and without the use of laser data as an additional information channel. The laser data improve the classification result significantly because they have a complementary “behavior” as multispectral data. With laser data the classes *farmland* and *street* can be separated very good from the classes *forest* and *settlement* because of the different heights of the pixels above the ground whereas in multispectral data the classes *farmland* and *forest* can be separated very good from the classes *streets* and *settlement* because of the strongly different percentage of chlorophyll.

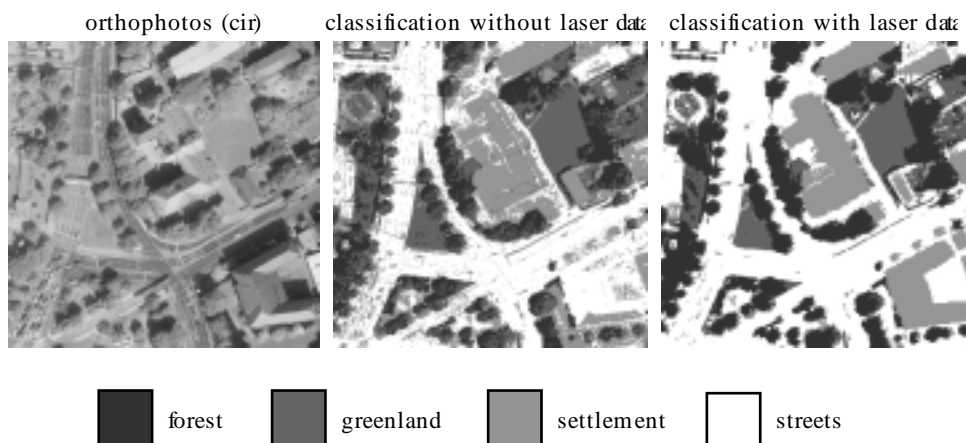


Figure 12: Classification of cir orthophoto without and with laser data.

Shadow areas can be classified considerably better in cir images than in rgb images. In areas with very strong shadow it comes also to wrong classifications in cir images, however considerably less than in rgb images. Figure 13 shows an example for this situation. The shadow of the church is so strong that no spectral and textural information is available. As a result, some pixels are classified wrongly and some pixels are assigned to the zero class. If however shadow is introduced as an additional land use class, the pixels are assigned to this class and can then be processed separately in a post processing step.

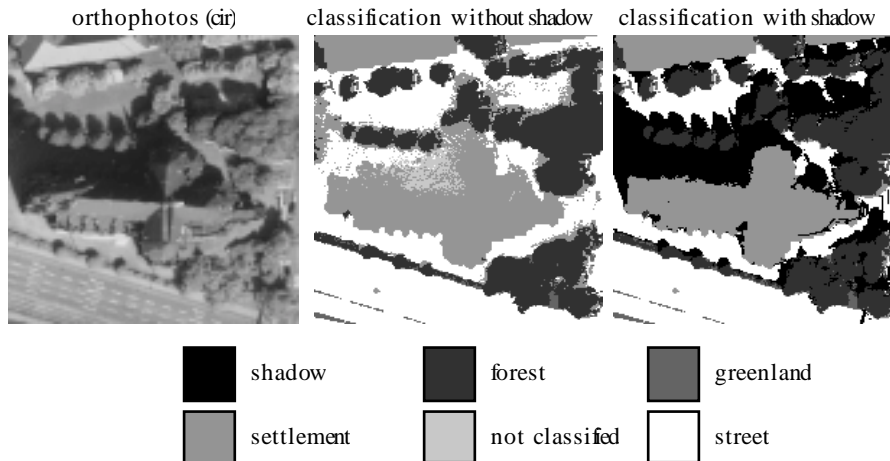


Figure 13: Classification with and without shadow as an additional class.

Because there is no information in the GIS database about shadow areas, they have to be derived from the laser data (Haala and Walter 1999; Haala, Walter and Stätter 1999). For the automatic generation of training areas for shadow the local height which is provided by the laser data as well as the elevation and azimuth of the sun at the time of image acquisition is required. The elevation and azimuth of the sun can either be determined manually by an interactive measurement of the edge of a shadowed area in the image and the corresponding object height in the normalized laser data or derived automatically from the geographical latitude and longitude of the captured area and the time of image acquisition. Figure 14 shows the automatic processed training areas for the additional land use class shadow.

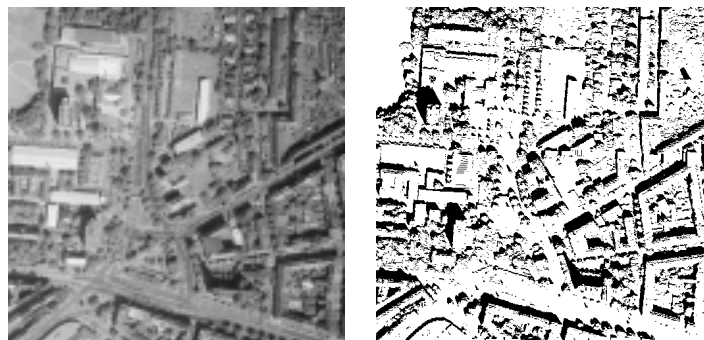


Figure 14: Automatic detection of training areas for the additional land use class shadow.

In order to avoid the *shadow* class in the final result the approach can be further refined by splitting each of this land use classes into one land use class for shadow areas and one land use class for non shadow areas. After the classification the shadow and non shadow pixels for each land use class are combined again to obtain one unique class for each type of land use. The final result of the classification algorithm for the whole test area is given in figure 15.



Figure 15: Classification using 10 classes (5 for shadow areas and 5 for non shadow areas).

## 10. VERIFICATION OF THE CLASSIFICATION RESULTS

All ATKIS area objects are subdivided into three different classes. The first class contains all objects which could be detected certainly in the DPA data, the second class contains all objects which are detected only partly and the third class contains all objects which could not be detected at all. The decision to which class an object belongs is made by measuring the percentage of pixels which are classified to the same object class as the object itself belongs to. Optionally the form and the homogeneity of the correctly classified pixels in the object are used. Very small or narrow objects are evaluated less strict than normal objects.

Figure 16 shows some results of the verification of ATKIS objects in DPA images. The DPA images are represented in the original resolution in the left column. The ATKIS geometry is superimposed in black. The classification result in a resolution of 2 m is represented in the middle column and the result of the verification in the right column.

Figure 16 a) shows two objects which were captured in ATKIS as greenland. In the DPA image it can be seen that meanwhile a settlement area was built up. The result of the verification is that these two objects cannot be found in the image because of the low number of pixels that were classified as greenland

Figure 16 b) shows a construction site where formerly a forest area and greenland was found. The changes in the landscape are so strong that nearly no pixel is classified as forest or farmland and therefore the objects are marked as not found.

Figure 16 c) shows an settlement objects which contains a big greenland area. The object is marked as partly found because at least the left part of the object was classified as settlement or streets.

Figure 16 d) shows two objects. It can be seen in the DPA image that a parking area is located in the greenland object. The pixels in the parking area are classified as streets or settlement. The majority of the pixels are classified as greenland but they are not distributed homogenous in the object. Therefore the object is marked as partly found. The neighboring smaller settlement objects consists almost completely of forest. This object cannot be found in the image and therefore it is marked as not found.

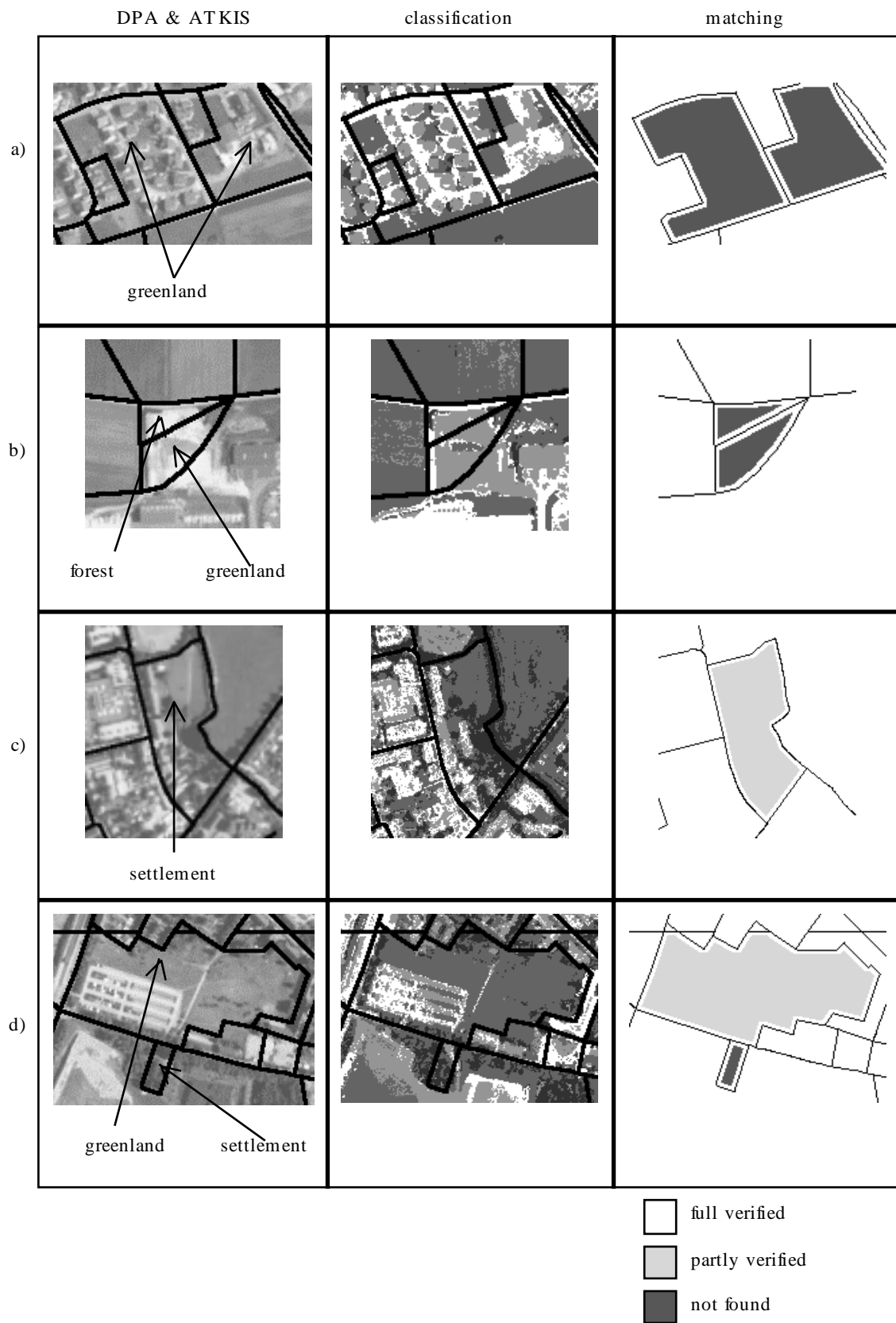


Figure 16: Examples of the verification of ATKIS objects in DPA images.

## 11. SUMMARY

In this paper the potential of data from different sensors for the verification of ATKIS is examined. Data from the sensors IRS-1C and MOMS-2P are only to a limited extent suitable for this approach because of their low resolution. Objects must have a size of 2 \* 2 pixel so that they can be recognized certainly in the figure. A recognition of line objects, like streets, is not possible. A big problem is the verification of the classification results. Even if objects can be recognized pixel precisely, it is not possible for an operator to verify the results without further information sources. With data from the DPA camera system, good results can be achieved. Area objects can be recognized in a sufficient accuracy for ATKIS. However, in inner city areas street pixels may be classified as houses and vice versa. This is a problem for the road detection. A reliable detection of roads with DPA data is only in sparsely populated areas possible. The DPA data were resampled to a resolution of 2 m. This falls into the range which will be covered by future high resolution satellite systems (see for example (Jacobsen 1998; Kilston 1998)). With the availability of such systems an automated verification of data in the scale 1:25,000 based on up-to-date data will be possible.

The tests showed that it is not possible to achieve homogenous good classification results based on rgb data. Even the addition of laser data does not lead to sufficient results. A channel in the nir range is necessary to handle shadowed areas.

The best results were achieved by the combination of cir images and laser data. With this combination it is also possible to verify objects in larger scales down to 1:2,500 (for example ground plans of buildings) if the images and the laser data are captured in a high resolution. This is also the topic which we want to focus our future work on.

A problem is the definition of quality measures to compare the performance of the different sensors. The classification result can be described with statistical measures such as the Kappa value or other measures described in the literature (Congalton 1991; Rosenfield and Fitzpatrick-Lins 1986; Stehmann 1997) but it is difficult to define a quality measure for the object verification. Problems especially appear with objects that are captured according to ownership structures and not to detectable structures in the image. Objects of this kind often have inhomogeneous spectral and textural characteristics and even a human operator is not able to decide if there is a change in the landscape or not if he has no additional information source. Also different operator will come to different decisions. Another problem is that some object classes are defined ambiguously and therefore are not clearly delimitable from each other. In order to get a more practical oriented idea of the quality of the results we will install the software package at the Surveying Institute of the State of Northrhine-Westfalia. Extensive data sets will be processed there and the results will be evaluated by 'ATKIS professionals'.

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