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AUTOMATIC QUALTIY CONTROL OF CROPLAND AND GRASLAND GIS OBJECTS USING IKONOS SATELLITE IMAGERY

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ABSTRACT:

As a consequence of the wide-spread application of digital geo-data in Geoinformation Systems (GIS), quality control has become increasingly important. A high degree of automation is required in order to make quality control efficient enough for practical application. In order to achieve this goal we have designed and implemented a semi-automatic technique for the verification of cropland and grassland GIS objects using 1 m pan-sharpened multispectral IKONOS imagery. The approach compares the GIS objects and compares them with data derived from high resolution remote sensing imagery using image analysis techniques. Textural, structural, and spectral features are assessed in a classification based on Support Vector Machines (SVM) in order to check whether a cropland or grassland object in the GIS is correct or not. The approach is explained in detail, and an evaluation is presented using reference data. Both the potential and the limitations of the system are discussed.

1. INTRODUCTION

Today, many public and private decisions rely on geospatial information. Geospatial data are stored and managed in Geoinformation Systems (GIS) such as the Authoritative Topographic Cartographic Information System (ATKIS) or the Digital Landscape Model (DLM-DE) in Germany (Arnold, 2009). In order for a GIS to be generally accepted, the underlying data need to be consistent and up-to-date. As a consequence, quality control has become increasingly important. In the European Norm DIN EN ISO 8402 (1995), *quality* is defined as the "Totality of characteristics of an entity that bear on its ability to satisfy stated and implied needs". In the context of GIS this means that the data model must represent the real world with sufficient detail and without any contradictions (*quality of the model*). Secondly, the data must conform to their specification (*quality of the data*). There are four important measures for quality control of geodata: *consistency*, *completeness*, *correctness*, and *accuracy* (Joos, 2000). Only the consistency can be checked without any comparison of the data to the real world. All the other quality measures can be derived by comparing the GIS data to the real world, as it is represented in aerial or satellite images. In order to reduce the amount of manual work required for quality control, a high degree of automation is required. In this paper, we describe a method for the verification of agricultural objects for quality control that is based on 1 m pan-sharpened multispectral IKONOS images. The focus will be on the separation of grassland and cropland objects for the quality management of ATKIS, because it has been found that these classes are not easily separated, e.g. (Regners & Prinz, 2009). After giving an overview on related work in Section 2, our new approach is described in Section 3. First results are presented in Section 4. The paper concludes with a discussion about the potential and the limitations of this approach.

2. RELATED WORK

Lu and Wenig (2007) gave an overview about the state of the art classification techniques. They emphasise that besides textural and spectral approaches, approaches using context information (such as structures) become more important with increasing resolution of the images. In this section we briefly review approaches for extracting different agricultural object types based on textural, structural and spectral features using high resolution images.

Textural features are related to local spatial patterns of grey levels inside an object. There have been quite a few attempts to use the textural characteristics for the classification of different agricultural object classes. For instance, autocorrelation is used by Warner and Steinmaus (2005) to identify orchards and vineyards in IKONOS panchromatic imagery. After defining a square kernel and after radiometric normalization, the autocorrelation is determined for the cardinal directions and both diagonals, which results in one autocorrelogram per direction. An orchard pixel is detected if an orchard pattern is identified in more than one autocorrelogram centred on that pixel. This method assumes the rows of plants to be equally spaced. Rengers and Prinz (2009) use the neighbourhood grey-tone difference matrix (NGTDM) to classify cropland, forest, water, grassland and urban areas in aerial and IKONOS images. This method is based on the differences of the grey values of two pixels and the differences of the grey values of the local neighbours, from which textural features such as coarseness, complexity and textural strength are derived. The results presented in (Rengers & Prinz, 2009) show that with the exception of grassland and cropland the classes mentioned above can be distinguished well. A similar conclusion is drawn by Busch et al. (2004), who apply a texture-based classification method based on Markov random fields (Gimel'farb, 1996) to aerial and IKONOS satellite images. Their method is well-suited to classify settlement areas, industrial areas, forests, and

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the combined class cropland/grassland. The results reported in (Rengers & Prinz, 2009) and (Busch et al., 2004) show that a purely textural analysis is not sufficient for separating cropland and grassland. Spectral and / or structural information is required for that purpose.

Haralick et al. (1973) used textural features derived from the grey level co-occurence matrix such as energy, contrast, correlation and entropy are used along with the mean and standard deviation of the gray values of all four available channels to classify coastline, forest, grassland, urban areas and irrigated and non-irrigated cropland using a linear discriminant function method. By combining a textural analysis with the spectral features the classification accuracy could be improved over a purely radiometric analysis. More recently, Itzerott and Kaden (2007) tried to distinguish various types of farmland using solely the Normalised Difference Vegetation Index (NDVI) that is computed from the near infrared and the red bands of a multispectral image. Analysing typical crops and grassland in Germany, they could show that grassland possesses an NDVI that is significantly larger than zero in all seasons, whereas untilled cropland has a very low NDVI except for a short period. However, they observed strong regional and temporal variations of the NDVI, so that statistical parameters describing the NDVI of the different agricultural classes in one region are hard to transfer to other regions. Training with a multitemporal dataset within a large area would be necessary. Hall et al. (2003) use the NDVI to separate vines and bare soil in aerial images with a spatial resolution of 0.25 m. Afterwards, the orientation of the rows is calculated using a priori knowledge about the distances between the rows and between the individual plants within a row. However, such a priori knowledge is usually not available for cropland objects.

Structural features have been used frequently to distinguish agricultural object classes such as vineyards, orchards, or plantations. The structural characteristics exploited for the extraction of these objects, namely straight parallel lines, also occur in cropland, where they are caused by tilling. However, some assumptions usually made in the extraction of vineyards or orchards cannot usually be made for cropland. For instance, Chanussot et al. (2005) estimate the orientation of vineyard rows automatically from aerial images by using the Fourier spectrum of an image and its Radon transform. Wassenaar et al. (2002) detect orchards and different kinds of vineyards in aerial images using a Fast Fourier Transformation, using specific knowledge about the distances between vine rows to reduce the search space in the frequency domain. Delenne et al. (2008) use a frequency analysis based on Gabor filters to estimate the row width and orientation and to detect the boundaries of vineyards. All these methods assume the rows of vines to be approximately equally spaced or even utilize knowledge about the actual spacing of these rows. Both assumptions cannot be made for cropland. In cropland the distance between furrows can vary from one field to the next depending on the type of crop planted in the field, on the kind of machine used for tilling, and on the visibility of the structures in the image.

Trias-Sanz (2006) uses only structural features to discriminate objects with similar radiometric and textural properties, namely cropland, forest, orchards, and vineyards. These object classes can be distinguished only by orientation characteristics. A small window is extracted randomly inside an object to be classified, and this window (called texton) is used to compute a variogram of the image. A histogram of direction angles is derived from the Radon transform of the variogram. The maximum of this histogram corresponds to the primary direction of edges in the

image, and it is used in the classification process. The approach can be used to discriminate a large number of object classes by properly choosing the texton, but can give wrong results if the texton size is selected inappropriately. Another disadvantage of this approach is that the cultivation structures and field crop have to be homogeneous in appearance. Therefore, LeBris and Boldo (2007) use a segmentation to extract homogenous regions before applying the algorithm of Trias-Sanz (2006).

A differentiation between agricultural classes such as grassland and cropland only on the basis of spectral, structural **or** textural features in monotemporal imagery seems to be impossible. An approach which combines these features is introduced by Ruiz et al., (2004, 2007) and Recio et al. (2006). Besides spectral (mean and deviation of the red, infrared and NDVI channel) and textural features determined from the grey level co-occurrence matrix (Ruiz et al., 2004), structural features determined from a semi-variogram, Hough- and Fourier transformation (Ruiz et al., 2007) are used to detect olive trees, citrus orchards, forests and shrubs using images of 0.50 m spatial resolution. The final decision is based on a decision tree (Recio et al., 2006). In addition to the features described so far, information about the shape of the object can be use for the classification process. Such information can be derived e.g. from a given GIS. Hermosilla et al. (2010) extend the approach of Ruiz et al. (2007) by using object shape as an additional feature to distinguish the classes building, forest, greenhouse, shrub lands, arable land and vineyard. Whereas this could improve the classification accuracy, it resulted in an increase of the number of undetected errors in a GIS to be verified by that approach.

Our method differs from the cited approaches by the way the textural analysis is carried out and by the definition of the structural, spectral and textural features. Furthermore, we use a different method for classification. The fact that our approach is embedded in a system for the verification of GIS objects has some implications for the strategy used for classification. The parameters of the method have to be tuned according to the quality requirements of the GIS: an undetected false classification in the GIS is penalized higher than a correct classification erroneously highlighted as false.

3. APPROACH

3.1 Overview

The goal of our approach is the separation and verification of cropland and grassland GIS objects using 1 m orthorectified and pan-sharpened multispectral IKONOS images. In this paper we assume that each ATKIS GIS object corresponds to exactly one class. The verification process is carried out separately for each GIS object. The object's boundary polygon given by the GIS is used to limit the analysis to areas inside the object. In a first step we use a supervised classification technique that analyses image texture with the help of Markov Random Fields (Müller, 2007, Busch et al., 2004) to distinguish the combined class 'agriculture', which comprises both cropland and grassland objects, from other classes such as 'settlement', 'industry' or 'forest'. If a cropland or grassland object is classified as belonging to any other class than 'agriculture', it is considered to correspond to an error in the GIS. As the algorithm of Busch et al. (2004) cannot differentiate between grassland and cropland objects, all the other objects (i.e., those passing the first classification stage) are passed on to a second classification process designed to discriminate grassland and cropland. The second classification and the following verification process is the main focus of this paper.

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This second classification process is based on Support Vector Machines, which have been applied successfully in the field of remote sensing and pattern recognition, e.g. (Vapnik, 1998; Fujimura et al., 2008). Whereas we only want to distinguish the classes 'grassland' and 'cropland', it is necessary to split the latter into the two classes 'tilled cropland' and 'untilled cropland', because they appear differently in the data. Hence, we have to apply multi-class SVM (Vapnik, 1998) to our problem. In the subsequent sections we describe the features used in the SVM classification and the actual classification process, including the training required for the SVM classifier.

3.2 Features

3.2.1 Textural Features: Textural features derived from of the co-occurrence matrix can give important hints to separate different agricultural classes. We use the Haralick features *energy, contrast, correlation and homogeneity* in our classification approach (Haralick et al., 1973). Figure 1 shows a scatter plot of texture homogeneity and contrast for the objects of a reference dataset. There are relatively clear clusters corresponding to grassland and untilled cropland. However, the figure also shows that there is a considerable overlap between the cluster for tilled cropland and the others; hence the need for additional features that support a clear separation of these classes.
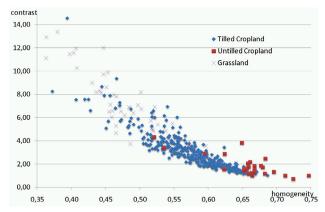

Figure 1. Scatter plot of Haralick features contrast and homogeneity of objects of a reference dataset.

3.2.4 Spectral Features: Information about vegetation is contained in the infrared band of multispectral images and in features derived from it (Ruiz et al., 2004; Hall et al., 2003; Itzerott &Kaden, 2007). Similar to the cited works, we use the *mean and standard deviation of the red, infrared and NDVI as* spectral features. Figure 2 shows a scatter plot of the mean NDVI (scaled from 0 to 255) and the infrared band for the same objects as in Figure 1. The spectral features are well-suited for separating tilled cropland from untilled cropland, but the clusters for grassland and tilled cropland still overlap.

3.2.3 Structural Features: A main difference in the appearance of cropland and grassland objects in satellite images is caused by cultivation, which is conducted more frequently in crop fields than in grassland. The agricultural machines normally cause parallel straight lines which can be observed in the image. The derivation of structural features is limited to the internal area of the object, and starts with the extraction of edge pixels using the Canny operator (Canny, 1986). These edge pixels are transformed into Hough space. In Hough space, parallel lines are mapped into points having the same line orientation ϕ (Figure 3). From the accumulator in Hough space, a histogram

of the line orientations is derived. This histogram is smoothed using a Gaussian kernel. All local minima and maxima in the histogram are detected and sorted (highest maximum/lowest minimum first); if two local maxima are found to be nearly coincident (i.e., if they are separated by an orientation difference smaller than 45°), the stronger maximum is selected, and the smaller one is discarded. The first and second largest surviving maxima (Max_1 and Max_2) and the smallest minimum (Min_1) of the histogram are then used to derive the structural features used in the SVM classification. The first structural features are $s_1 = Min_1$, $s_2 = Max_1$, $s_3 = Max_2$, the *ratio between first minimum and first maximum*: $s_4 = Min_1 / Max_1$, and the *ratio between first minimum and second maximum*: $s_5 = Min_1 / Max_2$. If there is a significant peak in the histogram s_2 will be much higher than s_3, and s_4 will have a smaller value compared to a histogram without a significant peak (cf. Figure 3). Another structural feature s_5, also used by Durrieu et al. (2005) is derived from the ratio between Max_1 and Max_2: $s_5 = 1 - Max_2 / Max_1$. If there is a significant first but no significant second peak, s_5 will be close to 1, whereas in case there are two peaks that are nearly identical, s_5 will be close to 0. The existence of a single significant peak in the histogram indicates tilling, because our model assumes that there is only one significant tilling direction in the GIS object.
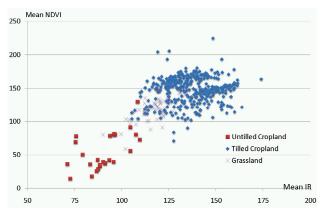

Figure 2. Scatter Plot of mean NDVI and Infrared of the objects of a reference dataset.
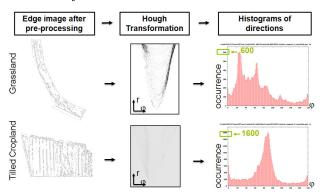

Figure 3. Steps of the structural analysis.

This approach fails if line structures caused by cultivation are not observable (e.g. maize close to harvest, untilled crop fields), if lines in crop fields are not straight respectively parallel to each other (e.g. on hillsides), if grassland possesses parallel lines (e.g. mowed grassland), and at a specific point in time when the crop looks like green grass and structures are not visible. The first three problems may be compensated by spectral features, though the differentiation between cropland and mowed grass may be difficult if the mowed grass (which is

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no longer vivid) covers the ground so densely that its spectral signature is close to bare soil. The time when the crop looks like grass (shortly after gestation) has to be avoided by not using images acquired during this time.

3.3 SVM Classification and Verification of GIS Objects

The SVM classifier is a supervised learning method used for classification and regression. Given a set of training examples, each marked as belonging to one of two classes, SVM training builds a model that predicts whether a new example falls into one class or the other. The two classes are separated by a hyperplane in feature space so that the distance of the nearest training sample from the hyperplane is maximised; hence, SVM belong to the class of *max-margin classifiers* (Vapnik, 1998). Since most classes are not linearly separable in feature space, a feature space mapping is applied: the original feature space is mapped into another space of higher dimension so that in the transformed feature space, the classes become linearly separable. Both training and classification basically require the computation of inner products of the form $\mathbf{\Phi}(\mathbf{f}_i)^T \cdot \mathbf{\Phi}(\mathbf{f}_j)$, where $\mathbf{f}_i$ and $\mathbf{f}_j$ are feature vectors of two samples in the original feature space and $\mathbf{\Phi}(\mathbf{f}_i)$ and $\mathbf{\Phi}(\mathbf{f}_j)$ are the transformed features. These inner products can be replaced by a Kernel function $K(\mathbf{f}_i, \mathbf{f}_j)$, which means that the actual feature space mapping $\mathbf{\Phi}$ is never explicitly applied *(Kernel Trick)*. In our application we use the Gaussian Kernel $K(\mathbf{f}_i, \mathbf{f}_j) = \exp(-\gamma \cdot \| \mathbf{f}_i - \mathbf{f}_j\|^2)$, which implies that the transformed feature space has an infinite dimension. The concept of SVM has been expanded to allow for outliers in the training data to avoid overfitting. This requires a parameter ν that corresponds to the fraction of training points considered to be outliers. Furthermore, classical SVM only can separate two classes, and SVM do not scale well to a multi-class problem. The most common way to tackle this problem is the *one-versus-the rest*-strategy where for each class a two-class SVM separating the training samples of this class from all other training samples is trained, and a test sample is assigned to the class achieving the highest vote from all these two-class classifiers (Vapnik, 1998).

For the classification process in our approach, the SVM algorithm needs to learn the properties of the classes to be classified, namely the classes 'grassland', 'tilled cropland' and 'untilled cropland'. The training is done using a set of objects with known class labels. The class labels are assigned to the training objects interactively by a human operator. In a first step a feature vector consisting of the spectral (6), textural (4) and structural (5) features defined in Section 3.2 is determined from the image data for all the training objects. Hence, the overall dimension of the feature vectors is 12. Each feature is normalised so that its value is between 0 and 1 for all training objects. Then, the feature vectors of all segments are used to train the three SVM classifiers required for the one-versus-the rest strategy.

In the classification itself, the feature vector is determined for each test object, and it is normalised using the normalisation parameters determined in training. The object is classified using the previously trained SVM classifiers into one of the classes 'tilled cropland', 'untilled cropland' or 'grassland'. However, for the process of GIS verification, the separation between tilled and untilled cropland is meaningless. Hence, for the verification process, a cropland GIS object will be accepted (and classified as 'correct') if the object is classified as 'tilled cropland' or 'untilled cropland'. Otherwise it is classified as an error and thus rejected. A grassland object is verified as correct if the

object was classified as 'grassland'. Otherwise it will be rejected and classified as an error in the data base. The classification and the verification of the test objects are carried out independently from each other.

4. EVALUATION

In this section, we present the evaluation of our approach using a pan-sharpened IKONOS scene in the area of Halberstadt, Germany, acquired on June-18, 2005 and having a ground resolution of 1 m. The reference dataset is based on ATKIS. However, according to the ATKIS specifications, any cropland or grassland object may actually contain areas corresponding to another class as long as certain area limitations are met (AdV, 2010). In this work, we assume each GIS object to correspond to exactly one of the classes. Furthermore, both for training and for the evaluation we have to distinguish untilled cropland from tilled cropland, information that is not contained in ATKIS. The original ATKIS database was thus modified for our tests: each ATKIS cropland or grassland object consisting of units corresponding to different classes was split manually into individual objects corresponding to a single class. All the cropland objects in the resulting GIS data set were classified manually into tilled vs. untilled cropland according to a visual inspection of the images. Finally, GIS objects smaller than 5000 m^2 were discarded because we cannot assume the structural approach to work with such small objects. Of the remaining GIS objects, less than 50% were used for training, whereas the other objects were used for the evaluation of our method. As the original data base did not contained any errors, we changed the class label of about 10% of the test objects that were chosen randomly. Figure 4 shows the test scene with super-imposed GIS objects. The numbers of objects used for training and evaluation as well as the number of errors added for testing the verification approach are summarised in Table **1**.

class	training	test / errors
'grassland'	32	89 / 8
'tilled cropland'	165	223 / 23
'untilled cropland'	11	21 / 2
Σ	208	333 / 33

Table 1. Objects used in the training and test datasets.

In the training phase we fixed the maximum training error ν to $\nu = 0.1\%$. The parameter γ of the Gaussian Kernel was fixed at $\gamma = 0.01$. The training results were used to classify the test objects. In order to evaluate the classification process, the results of classification were compared to the reference. Table 2 shows the confusion matrix of the classification results, whereas the completeness and the correctness of these classes are presented in Table **3**.

algorithm ref.	'tilled cropland'	'untilled cropland'	'grassland	Σ
'tilled c.'	176	0	47	223
'untilled c'.	1	12	8	21
'grassland'	3	0	86	89
Σ	180	12	141	333

Table 2. Confusion matrix of the test objects.

The confusion matrix in Table 2 shows that our approach does a good job in separating tilled cropland from untilled cropland, but the separation of both cropland classes from grassland is very uncertain. Since tilled and untilled cropland can be

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separated by the textural and the spectral features, the structural features used in the classification are still not efficiency enough, and additional features need to be investigated in the future. The classification errors shown in the confusion matrix also cause some of the completeness and correctness values in Table 3 to be very low.

class	completeness	correctness
tilled cropland	78,9%	97,8%
untilled cropland	57,1%	100%
cropland (untilled + tilled)	77,1%	97,9%
grassland	96,6%	61,0%

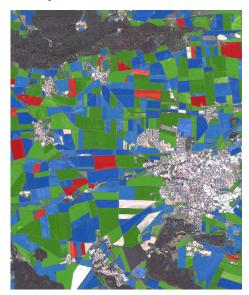Table 3: Completeness and correctness of the classification.

Figure 4.   Training and test objects super-imposed to the Ikonos scene. Blue: training objects; green: correct test objects; red: errors.

Figure 5 shows an example for a grassland object misclassified as 'untilled cropland'. The reason for this is the fact that the bare soil is visible in a large part of the object.

Figure 5.   Classification errors. 'grassland' object classified as 'untilled cropland'

As mentioned before, the main focus of our approach is the verification of the GIS objects. It is embedded in a semi-automatic system that uses the automatic tool to focus the attention of the human operator to possible errors in the GIS. Thus, work is saved largely due to the fact that the operator needs no longer to check any object that was accepted by the automatic module. Under these circumstances, and given the fact that quality control is essentially carried out to remove errors in the data base, classification errors that cause errors in the GIS to remain undetected, i.e. the erroneous acceptance of a wrong object, are to be avoided by all means. As a consequence, the acceptance of objects has to be very reliable.

On the other hand, the erroneous rejection of a correct GIS object may reduce the economical effectiveness of the system, but it will not result in an error remaining in the data base. The confusion matrices for the verification process carried out on the basis of the classification results described above are presented in
Table **4** and 5 for cropland and grassland objects, respectively. Note that these numbers also contain objects that were rejected based on the texture-based classification described in (Busch et al., 2004).

automatic reference	accepted	rejected
correct	162 (66.4%)	57 (23.4%)
false	1 (0.4%)	7 (2.9%)

Table 4. Confusion matrix for the verification of cropland.

automatic reference	accepted	Rejected
correct	20 (22.5%)	61 (56.6%)
false	0 (0.0%)	25 (28.1%)

Table 5: Confusion matrix for the verification of grassland.

The confusion matrix in Table 4 shows that our approach does a reasonably good job in verifying cropland objects. Only one of eight errors in cropland objects (Table 1) remains undetected, and the number of wrong cropland objects in the GIS is thus reduced by 87.5%. The economical efficiency is at 66.4%, i.e. 66.4% of the cropland objects need not to be inspected by the human operator because these objects were accepted automatically. Of the 23.4% of the objects that are erroneously rejected by the system, 3.3% were rejected by the texture-based classification described in (Busch et al., 2004). Unfortunately, the verification of grassland objects is far less successful. On one hand, all errors contained in the GIS could be detected, but on the other hand, the efficiency of the system is only at 22.5%. Of the objects rejected erroneously by the system, 5.6% can be attributed to texture-based classification. Unlike with cropland, the texture-based classification rejected one object correctly. It is clear that the classification of grassland and cropland objects still needs to be improved. In particular, the structural features used for classification seem to require a revision.

5.   CONCLUSION AND OUTLOOK

The method used to separate cropland from grassland objects described in this paper achieved reasonable results when applied to the verification of cropland objects, but the results for grassland objects are still unsatisfactory. In the future we will revise the structural features used for classification, which apparently fail to separate grassland from cropland objects properly in the current version of the approach. For instance, rather than focusing on the orientation of lines alone, we could also consider the distance between lines by designing features that highlight periodical patterns corresponding to parallel lines. Structural features based on other types of analysis, e.g. variograms, could be added to the classification process. In addition, we could try to use training for determining the parameter γ of the Gaussian Kernel in the SVM classification. Finally, we need to analyse which features are the most relevant ones and have the biggest impact on the classification result.

The main goal of our approach is its application for the verification of ATKIS grassland and cropland objects. In ATKIS one agricultural object may consist of different management units. For instance, a cropland object may consist of fields covered by different crops. It has been stated above

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that the generalisation of agricultural objects in ATKIS even allows that within such an object there may be small areas having another land use as long as they do not exceeded a certain size. This is why segmentation is necessary to subdivide the original GIS objects into radiometrically homogeneous regions (Helmholz & Rottensteiner, 2009). These regions can be classified into 'grassland', 'tilled cropland' and 'untilled cropland' in the way described in this paper. Afterwards, the overall classification of the GIS object is carried out by a combination of the classification results of the individual regions, taking into account the specifications for the generalisation of ATKIS objects. The final decision about acceptance or rejection of an ATKIS object will be based on this combined classification according to the ATKIS object catalogue (AdV, 2010).

We also hope to be able to detect other object classes with similar structural features such as vineyards and plantations. However, in this case, the image resolution would have to be adapted for the structural analysis, because the rows of plants only appear as parallel lines at a coarser resolution than 1 m. This future research would also have to determine the optimal scale for each object class.

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