

# DLM-UPDATE: INTEGRATION OF EARTH OBSERVATION TECHNOLOGIES IN IT-STRUCTURES OF THE NATIONAL MAPPING AUTHORITIES IN AN USE CASE: UPDATE OF THE ATKIS®-DLM OF THE STATE BUREAU OF SURVEYING AND GEOINFORMATION SCHLESWIG-HOLSTEIN

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## ABSTRACT:

The State Bureau of Surveying and Geoinformation Schleswig-Holstein (LVerGeo SH) is responsible for core tasks such as providing the real estate cadastre and administration of the Authoritative Topographic Cartographic Information System ATKIS®. A part of this task is to update the ATKIS® digital landscape model (ATKIS®-DLM) for the area of Schleswig Holstein. In course of increasing the productivity of the State Bureau of Surveying and Geoinformation the research project "DLM-Update" develops and evaluates a prototype system for an semi-automatic update of the ATKIS® digital landscape model. Based on satellite imagery (SENTINEL-2, LANDSAT) and digital orthophotos, a layer with several land cover classes is generated after an automatic training of a supervised classification via a support vector machine. The land cover classification result is afterwards compared with the respective spatial ATKIS® land use class objects via a rule-based land use to land cover translation and an object-based change detection approach. The final processing results are sub-object-specific evidences for real world changes which are simple to handle and GIS-ready, in order to evaluate the detected changes with an additionally developed toolbar for an ArcGIS environment. This toolbar allows the employees of the State Bureau of Surveying and Geoinformation to review the results and transfer changes interactively into the real estate cadastre. The derived information can be integrated into the established update workflow of national mapping authorities. The project demonstrates time-saving and quality-assuring aspects of earth observation technologies and the usability of remote sensing data, provided by the Copernicus satellite mission, for a semi-automatic update of the ATKIS®-DLM.

## 1. INTRODUCTION

The State Bureau of Surveying and Geoinformation Schleswig-Holstein (LVerGeo SH) is the responsible state authority for the management and renewal of topographic and cadastral cartography in the German federal state of Schleswig-Holstein. One of its core tasks is the regular update of the 'ATKIS® Basis-DLM', the basic digital landscape model (DLM) for Schleswig Holstein. The periodical update of the DLM is based on manual ortho photo interpretation and terrestrial captured geo data (repeated in a period of five years, shorter for important object types, such as roads.). The 'ATKIS® Basis-DLM' has a positional accuracy of at least three meters.

Due to economical restrictions and growing demands towards official geo data, the State Bureau is in need for optimizations of the update process. Automating main parts of the workflow can support the ongoing survey. The presented pilot project 'DLM-Update' supports the manual update of tracking of the 'ATKIS® Basis-DLM' with a supervised classification of remote sensing data and an automatic, object-based change detection process. The here presented workflow is an object-based post-classification approach which uses a translation of land cover information (which is visible in the remote sensing images) to the land use information represented by the 'ATKIS® Basis DLM'.

A review of different remote sensing based change detection methods can be found in Singh (1989), an overview of specific application in environmental monitoring is given by Coppin et al. (2004) and Mas (1999). Change detection methods are often divided into two groups: image-to-image comparison (pre-classification), which derives its change information from a difference in the spectral values of two images, and post-classification methods, comparing the thematic interpretation of an area for time steps  $t_0$  and  $t_1$  (Lang & Blaschke, 2007). Both approaches can be combined by detecting changes to an existing classification via spectral or geometrical change indicators within an up to date remote sensing image (Büscher et al., 2008; Langanke & Lang, 2004).

The focus of the project 'DLM-Update' is the development of a prototype software system that enables the LVerGeo SH to manage the change detection analysis for the federal state of Schleswig-Holstein in an easy to use software interface. Another important objective of the project is the integration of data from the European Earth observation program COPERNICUS into administrative services, in particular a preparation of the use of SENTINEL-2 satellite image data. Because of this, the supervised land cover classification is based on a combination of digital orthophotos and free satellite images (LANDSAT 8 during the development phase and since available, SENTINEL-2 in the final implementation phase).

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The implemented change detection process will focus on the following two levels of detail:

- a) Which Land use objects have changed?
- b) Where on these land use objects did the change occur?  
(= change indicator)

## 2. INPUT DATA

For the update of the digital landscape model ('ATKIS® Basis-DLM') three different datasets are required: digital orthophotos, multi-temporal satellite data and the outdated DLM data.

The digital orthophotos are produced by the LVerMGeo SH in a three-years regular cycle. The 3-bands CIR-product with 40 cm pixel resolution provides a high geometric resolution.

The system is designed to work with SENTINEL-2 images as multi-temporal satellite data which provides a high spectral and temporal resolution. During the development phase LANDSAT data was used for multi-temporal classification. The SENTINEL-2 sensor works with 12 spectral bands from visible spectrum to short wave infrared with a spatial resolution between 10 m and 60 m (ESA, 2012). The repetition rate will be five days when SENTINEL-2A and SENTINEL-2B are in orbit, which is planned for the second half of 2016 (ESA, 2016).

The multi-temporal image data is important for a successful land cover classification. To separate grassland, cropland and non-vegetated land cover classes, the image data has to cover the whole vegetation period of the observed year. That means that out of the available orthophoto and satellite images at least one image has to be acquired within each of the following timeframes: "March-May", "June-July" and "August-October" (Fig. 1).

The 'ATKIS® Basis-DLM' data contains 34 land use object types (AdV, 2008). The 27 object types modelled as polygons are completely evaluated with the presented workflow. From the 7 polyline object types only the streets and paths are checked in a separate analysis module that is not covered by this paper. The data is originally stored in NAS-format, for the analysis the objects are converted class wise to ESRI-Shape-format.



Figure 1. Image data for a test area in Schleswig-Holstein. a) Sentinel-2A image in CIR-representation (8-4-3) from 05.05.2016; b) Digital Orthophoto with 40cm pixel resolution in CIR representation from 22.07.2014; c) Sentinel-2A image in CIR-representation (8-4-3) from 22.08.2015

## 3. SYSTEM OVERVIEW

The system is designed to guarantee an easy handling and useful change detection results without deeper remote sensing knowledge by users in administrative context. It is structured into three modules:

The first module is a stand-alone user interface (Fig. 2) to handle input data and control the analysis process. It is structured into import, analysis and preferences controls on the left sidebar and an interactive map on the right side.

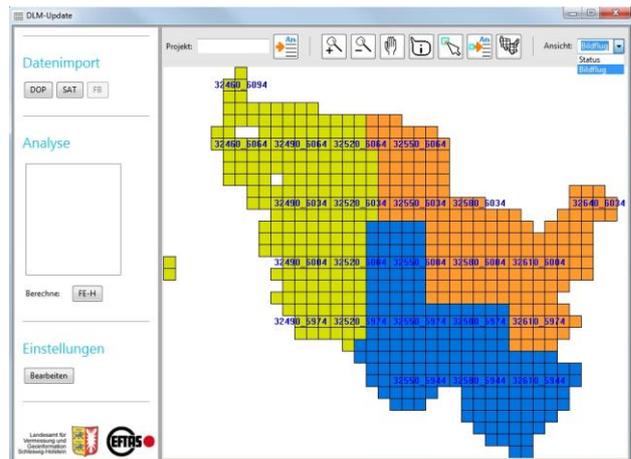


Figure 2. User Interface 1 for controlling input data and analysis process

The second module is the 'remote sensing module' that includes the image analysis and change detection to generate change indicators (see above) without any further user interaction. The analysis workflow consists of the automated generation of training data which are then used to classify the image data into basic land cover classes. Then within the final change detection analysis the classification result is evaluated together with the ATKIS®-DLM objects to derive change indicators.

The third module is another user interface implemented as an ESRI-ArcMap 10.0 Add-In. It provides tools for the visual interpretation of the final change indicators and integrates into the common software environment used for the manual update process of the 'ATKIS® Basis-DLM'.

## 4. LAND COVER CLASSIFICATION

### 4.1 Automatic Training data extraction

Because especially large scale processing tasks are in need for an automated workflow for the acquisition of training data, a key feature of the presented approach is the automatic generation of training data from the existing land cover information within the land use data set (ATKIS®).

Though some changes have occurred in detail, it can be assumed, that the given land use information is still valid for the majority of the objects. By using the land use data as a source for land cover training data, it is important to select such land use objects that can be linked directly (1:1) with a land cover class (e.g. land use = forest and land cover = forest).

By setting up land cover class-specific rules and analysing the spectral characteristics of all pixels included in the potential training data objects, outliers and non-plausible values will be removed from the training data.

For example agricultural grassland is a homogenous class with high green and near infrared values and low red value. Regarding multi-temporal aspects there are only low or medium changes during spring and summer (mainly caused by mowing or dryness). By contrast, cropland objects have a high spectral variability during spring and summer. In these cases the normalized difference vegetation index (NDVI) and the minimum value of the green band are used to identify the changes over time and to detect outliers (e.g. crop areas within grassland). In the end an additional selection process guarantees an equal spatial distribution of training pixels for all land cover classes associated with a similar amount of training data per class (Fig. 3).

This automatic workflow for training data acquisition is the default process in the presented software. As an additional function, the import of manually acquired training samples is still possible.

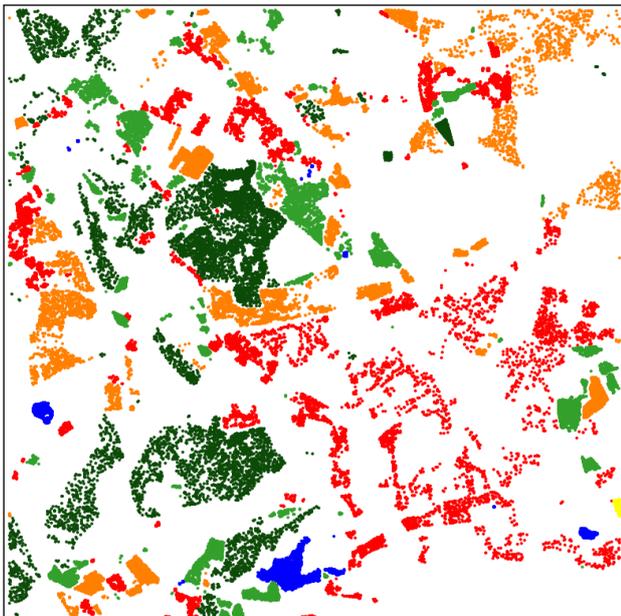


Figure 3: Final distribution of the automatically generated training data

### 4.2 Supervised SVM classification

In order to obtain an exact land cover map of a scene that may be used to find irregularities inside GIS objects, the robust machine learning algorithm called Support Vector Machines (SVM) (Burges, 1998) is applied. The SVM is a large margin classifier that allows classification of non-linearly separable data by using kernel functions (Hofmann et al., 2008). The application of the SVM comprises the steps scaling and resampling, training and finally the classification itself.

During scaling and resampling the remote sensing images of different sources (satellite and aerial) are resampled first to a unity spatial resolution associated with a stacking of the layers of all data sources to build the input features of the SVM. Besides resampling a normalization of the sensor values recorded by complete different sensor hardware is done analogue to (Graf, 2001) to optimize the SVM functionality. It is obvious that a mixed used of 8 bit pixel values with 16 bit pixel values may lead to problems separating the feature space.

The preprocessed features together with a respective class allocation are used to train the SVM with an automatic procedure (Ben-Hur, 2010). This step is a mathematical approach using multidimensional planes - so called hyperplanes - in the feature space with the goal to separate land cover classes. The samples of each class closest to a hyperplane are called support vectors. During training the algorithm iteratively tries to find a set of support vectors resulting in an optimal margin of the closest vector to the hyperplane. Since one hyperplane is only able to distinguish between linearly separable classes, a so called kernel trick is applied using a non linear function on the linear features to increase synthetically the number of dimensions. The resulting set of support vectors, weights and decision functions is called SVM classifier and stored into a file for the classification.

After successful training of the SVM it can be applied to classify data outside the training regions. Each feature is assigned to one land cover class, whereas all classified features build the land cover map (Fig. 4) that is used to evaluate GIS objects. A once trained SVM classifier may only be applied on images with the similar characteristics as the images used for training, e.g. a set of images from the same flight date.

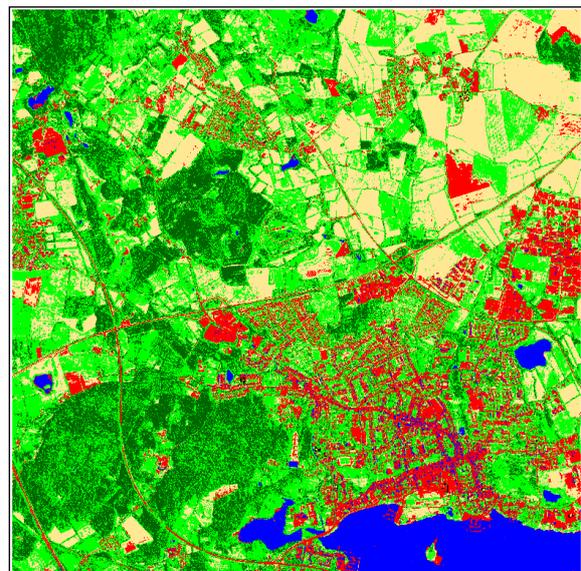


Figure 4: Final result of the SVM classification

## 5. CHANGE DETECTION

An object-based evaluation step builds the core of the proposed GIS update approach. Each object of the GIS will be subject to an assessment of compliance to a given specific object type catalogue, in this case the ATKIS® digital landscape model. If any irregularity with respect to the object type catalogue is found, a GIS object is marked for a subsequent manual inspection with a change indicator. The decision, if a GIS object is compliant to the object type catalogue is based only on the pixel wise results of the land cover classification.

### 5.1 Definition of objects

The object geometries that are used as basis for the change detection are directly taken from the GIS, therefore no objects have to be built like in other object-based image analysis applications. The sizes of single GIS objects vary in our test sites in a wide range from 425 m<sup>2</sup> to 112 ha and each object is assigned to one of currently 28 different object types under consideration. The object types are oriented towards the land usage resulting in object types with high homogeneity like meadows and forests in contrast to heterogeneous object types like residential and industrial areas, whereas in the object type catalogue each object type has a more or less detailed description of its properties related to uncertainty effects.

### 5.2 Evaluation catalogue design

To enable an automatic system that may find irregular GIS objects any kind of evaluation has to be performed. Due to the existence of a detailed object type catalogue the approach works with manually created evaluation rules accumulated to an evaluation catalogue that represents a specific predefined object type catalogue in each case. Other approaches like (Albert et al., 2015) try to classify land usage classes representing object types directly by supervised classification. Here it is assumed that each object type has a typical land cover class distribution, which may frequently be the case, but a complete evaluation of compliance with the rules of the object type catalogue cannot be fulfilled with such approach.

During setting up the evaluation catalogue two challenges arise, firstly the evaluation catalogue has to be compliant to the object type catalogue, the second challenge is the fact that the GIS objects represent polygons of a specific land usage and not single homogeneous land cover classes. This means that on the one hand the evaluation rules should be as precise as possible to confirm the object type catalogue but on the other hand the rules should allow small classification errors and should balance uncertainties in relation to object type definitions to reduce the amount of irregular objects to a reasonable number.

As mentioned above, the evaluation catalogue is designed manually and consists of a set of rules for each object type. The necessary rule attributes were chosen considering the successful approach of (Helmholz et al., 2012). Any single rule of this set of rules for one object type determines the minimum and maximum proportion of a land cover class and a threshold value for the minimum mapping unit (MMU) of a land cover class. The minimum mapping unit is measured on the basis of a connected region of the same land cover class and indicates from what size upwards a new GIS object has to be built combined with a division of the initial evaluation object.

In Table 1 the currently used rule set is illustrated for the object type meadow. As can be gathered from the table an object is marked as irregular, if for example the proportion of the land cover class cropland lies above 12%. On the other hand, if a coherent region belonging to the land cover class sealed with a size of at least 1,000 m<sup>2</sup> exists, the object is marked as irregular, too. The minimal mapping unit values are directly derived from the object type catalogue. By contrast, the values representing the land cover class proportions are based on the specific aim applying the system and set individually by the user of the system.

From Table 2, it can be seen that the object type residential area is much more heterogeneous expressed by the fact that the maximum proportion values range from 50% to 100% for several land cover classes and thus allow a comparative flexible composition of the land cover classes inside an object.

Land Cover Class	Minimum proportion [%]	Maximum proportion [%]	MMU [m <sup>2</sup> ]
Sealed	0.0	12.0	1,000.0
Meadow	70.0	100.0	-
Cropland	0.0	12.0	10,000.0
Forest	0.0	40.0	1,000.0
Water	0.0	12.0	1,000.0
Wetland	0.0	12.0	10,000.0
Soil	0.0	12.0	10,000.0

Table 1. Evaluation rule set for object type *meadow*

Land Cover Class	Minimum proportion [%]	Maximum proportion [%]	MMU [m <sup>2</sup> ]
Sealed	0.0	100.0	-
Meadow	0.0	80.0	10,000.0
Cropland	0.0	50.0	10,000.0
Forest	0.0	80.0	1,000.0
Water	0.0	12.0	1,000.0
Wetland	0.0	20.0	10,000.0
Soil	0.0	50.0	10,000.0

Table 2. Evaluation rule set for object type *residential area*

### 5.3 Examples for Change Indicators

In Figure 5 two examples for correctly detected irregular GIS objects are illustrated. On the left-hand site inside a meadow object a small forest with an area of about 3,500 m<sup>2</sup> that is significant bigger than the size of the minimal mapping unit for forest has been found. On the right-hand site in Figure 5 a meadow area that covers a proportion of more than 80% of the object's size leads also to the status of an irregular object. To improve and accelerate the manual update of an irregular object, the original change indicator regions are prepared as ESRI Shapefiles to support the operator during the manual update.



Figure 5. Two examples for detected irregular GIS objects: Forest region in meadow GIS object (left), meadow area in residential area GIS object (right). Change indicator regions (red) support the operator to locate the erroneous regions.

## 6. EVALUATION

In order to assess the results of the prototype an evaluation with real data was carried out. Primary two aspects are in the evaluations focus. First aspect is the accuracy of the results. The second aspect is the capability to put the prototype into practice within the infrastructure of the State Bureau of Surveying and Geoinformation Schleswig-Holstein. Both aspects are evaluated below.

### 6.1 Results Accuracy

In order to evaluate the results accuracy as realistic as possible a dataset from real work projects was used. The dataset was coming from six project areas with a total area of approximately 216 square kilometers. Considered for the analyses are about 4000 ATKIS®-objects from 27 different planar object types. It was analyzed whether objects with a positive change indicator, coming from the prototype system, are actually updated (true-positive,  $t_p$ ) or not (false-positive,  $f_p$ ). Furthermore, it was analyzed whether objects with negative change indicators were updated (false-negative,  $f_n$ ) or not (true-negative,  $t_n$ ). Hereby objects with negative change indicators are objects, for which no update reasons are found. The assignment is clearly compared in a confusion matrix (see Table. 3). Type I errors and type II errors are represented by the  $f_p$  (type I) and  $f_n$  (type II). Additional parameters for the evaluation are the sensitivity as a true positive rate and the precision as a positive predictive value. The precision is calculated as the sum of all  $t_p$  in relation to the total sum of all positive change indicators. The sensitivity is the sum of all  $t_p$  in relation to all incorrect ATKIS®-objects. Change indicators are always evaluated as accepted if these hints triggered a change process for the respective object. An object change however considered as an object change in the sense of the evaluation when resizing included more than 900 square meters or the object type changes. Smaller changes are seen in the sense of a geometry adjustment.

objects in % (total number)	ATKIS®-object incorrect	ATKIS®-object correct
change indicator positive	20.09 [ $t_p$ ] (801)	16.36 [ $f_p$ ] (652)
change indicator negative	7.55 [ $f_n$ ] (301)	56.00 [ $t_n$ ] (2232)

Table 3. Confusion matrix for the evaluation

The precision value is 55.13% and the sensitivity value is 72.69%. For both, the dispersion of the values is quite high. The precision scatters between 39.13% and 77.71%, and the sensitivity values between 60.45% and 91.88%. It is evident that a high precision is correlated with a low sensitivity as well as a high urbanization rate and vice versa. Thus it can be assumed that further improvement potential is on the parameterization of the change detection rule set.

### 6.2 Infrastructure Integration

The second aspect of the evaluation was to analyze the integration of the results into the infrastructure of the State Bureau of Surveying and Geoinformation Schleswig-Holstein, in the sense of a cost-benefit analysis. Therefore, a standard update project as well as the prototype of the above mentioned ArcMap-Add-In (chapter 3) was used. This Add-In enables an optimized screening of the change indicators in a project area of 9 square kilometers, using the ArcGIS core for the ATKIS® update. The net processing time of 369 change indicators was about 6:21 hours. This includes more than just the screening time. But also included is the time for updating the respective ATKIS®-objects, which affects 53.47% of all the change indicators (precision). The sensitivity in the project area was even 99.3%, due to the fact that it is a more rural area. Processing of the remaining ATKIS®-objects and the quality control lasted about 2:29 hours. The preparation time and processing the change indicators by the prototype took 0:40 hours. Thus, the gross processing time was 9:30 hours. This allows a slight acceleration, compared to the regular update process, of approximately 10%. Thus the capability to put the prototype into practice is proved.

## 7. CONCLUSION

The project ‘DLM-Update’ demonstrates time-saving and quality-assuring aspects of earth observation technologies and the usability of remote sensing data for a semi-automatic update of the ‘ATKIS® Basis-DLM’. It has to be taken into account, that due to availability restrictions of the SENTINEL-2 data during project, the classification was mainly based on LANSAT-8 images and orthophotos. Nevertheless, the quality of the change indicators must be improved in future implementations. Serious improvements can be expected by the integration of a digital surface model and the collection of more experiences with the multitemporal analysis of the new SENTINEL-2 satellite data. Still the evaluation results show, that the presented change detection approach can already support the periodical update work flow of the ‘ATKIS® Basis-DLM’ at the State Bureau of Surveying and Geoinformation Schleswig-Holstein. Due to its flexible rule-based design for the detection of change indicators, the implemented approach can be easily transferred to the needs of other survey authorities.

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