ANALYSIS AND COMPARISION OF DIFFERENT HIGH-RESOLUTION DATA SETS FOR URBAN APPLICATIONS

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ABSTRACT:

The use of remote sensing for urban applications requires high resolution data with respect to geometry and spectral information in order to deal with the complexity and the variability of urban scenes. Unfortunately, the available sensors provide data of either high geometrical or high spectral information. Optical satellite sensors improved a lot with respect to the available ground sampling distance (gsd). Most prominent examples are IKONOS, QuickBird and OrbView. But this improvement was made at the expense of the spectral information by focussing on the visible and near-infrared using four spectral channels. Optical airborne sensors always had high geometric resolution. Nowadays hyperspectral sensors are available delivering almost continuous spectral information from visible to shortwave infrared with a resolution of a few meters depending on flying height and velocity. Such data offer the possibility to discern different surface materials showing differences in their spectral response not visible in multispectral data, but may not have the same high geometric resolution. This paper compares the use of different high resolution data for urban remote sensing applications focussing on hyperspectral data and its fusion with laser scanning data.

1. INTRODUCTION

Urban areas exhibit a high complexity and variability with respect to the present objects, their geometry and their appearance. Thus, high resolution data with adequate georeferencing is inevitable for the use of remote sensing in urban areas. With the increased availabilty of such data during recent years, an increase of remote sensing applications in urban areas can be recognised (cf. (Möller and Wentz, 2005) and preceding workshops and conferences). These applications range from simpler tasks as for example the assessment of urban green as indicator for the quality of urban neighbourhoods to more complex tasks as the extraction and characterisation of objects – geometry and material – in an urban scene. For both tasks, geometric high resolution data is a prerequisite. In addition the second task also requires data with high resolution spectral data in terms of number of bands with small bandwidths in order to provide detailed information. In a research project we investigated the use of hyperspectral and laser scanning data to derive geometric and material information about roof surfaces using a segment-based approach (Lemp and Weidner, 2005b). In this approach the laser scanning data is not only used to determine the geometry of the roof surfaces, but also for the classification of materials by data fusion on a decision level. The spectral and the geometric data are well suited for data fusion, because both types provide really complementary information about the objects. The combined use of both data for material classification improves the classification result significantly compared to the classification based only on the hyperspectral data. Of course, the availability of hyperspectral and laser scanning data is an optimal case. Therefore, it seems to be of interest to which extend other spectral data may be used for such an application. The institute collected different (optical) data over the last years besides the hyperspectral data, namely multispectral DAEDALUS data and high resolution satellite data from QuickBird, both used in our investigations.

Besides the data, the approaches have an impact on the results. Pixel-based classification schemes like Maximum-Likelihood are well known. The analysis is (normally) based on the information provided by the data for each pixel and do not incorporate information of each pixel's neighbourhood. Segment-based approaches allow for the introduction about relations to neighbour segments and context information. Although we preferred the segment-based approach in our research project on roof surfaces, we also investigated a pixel-based approach for this application, namely the Spectral Angle Mapper (SAM).

In order to give an overview of our research in urban remote sensing, we will start with a short description of the used data sets in Section 2.. Section 3. presents two applications. The focus is on the characterisation of roof surfaces, namley the results obtained by different analysis schemes based on the hyperspectral and laser scanning data and their quantitative evaluation. (Bochow, Greiwe, and Ehlers, 2003) is the closest related work to our approach. A similar approach of (Greiwe, Bochow, and Ehlers, 2004) is using HyMap data, high resolution orthophotos and a DSM - the latter both derived from HRSC-A data. Their focus is on fusing the high resolution data sets by a segment-based technique. Our approach differs from the above with respect to the input data, in particular the laser scanning data. The segmentation strategy used permits to incorporate geometric and spectral clues. For classification, we use eCognition, which allows a hierarchical classification and introduction of knowledge by using the different information sources for different decisions within a fuzzy classification scheme.

2. DATA

In this section, short descriptions of the data and remarks on the preprocessing are given starting with the laser scanning data followed by the optical data according to their geometric resolution.

Laser scanning: The DSM was acquired in March, 2002, with the TopoSys II system using the first and the last pulse modes. For ease of use within different software packages, $1\ m \times 1\ m$ raster data sets were generated. These data sets differ not only concerning the included objects, but also show systematic deviations. For further discussion on this topic refer to (Vögtle and Steinle, 2003) and (Lemp and Weidner, 2004).

QuickBird: The QuickBird data (Orthoready Standard) with $0.6\ m$ geometric resolution (resampling with nearest neighbour) for the panchromatic channel and $2.4\ m$ for the multispectral channels respectively was acquired in summer 2005 with an off nadir angle of about $11°$ and a target azimuth of about $34°$. A comparision with existing geodata indicated a linear constant shift of about $14\ m$ over the entire (almost flat) captured area of Karlsruhe. Therefore, a simple translation was performed in order to account for this shift.

DAEDALUS: The multispectral DAEDALUS data was acquired in summer 1997. It was georeferenced and orthorectified using a DSM, which was obtained from first pulse laser scanning data of the TopoSys I sensor of spring 1997, and has a geometric resolution of $2\ m$.

HyMap: The hyperspectral data was acquired in July, 2003, with the HyMap sensor during the HyEurope campaign organized by the DLR (German Aerospace Center). The data was preprocessed (atmospheric corrections, geocoding) by the DLR, Oberpfaffenhofen, using a Digital Terrain Model (DTM) on one hand and a Digital Surface Model (DSM) derived from first pulse laser scanning data on the other. The effects of the different underlying surface descriptions are clearly visible in the georeferenced data. The original data has a ground resolution of $4\ m \times 4\ m$. In order to use the data in combination with the DSM, the data was resampled to $1\ m \times 1$ m using nearest-neighbour interpolation.

Although the maximal time difference of the acquisition dates is more then 8 years, the different data sets can still be used in combination as changes fortunately only appear in some smaller areas. During classification based e.g. on optical and laser scanning data, these areas are revealed by inconsistent classification results. Besides the above mentioned data, aerial images taken in spring 2001 were used for the generation of a 3D model of the university campus including also information about the surface materials. This data serves as reference data for the evaluation of the roof surface classification.

3. APPLICATIONS

3.1 Urban green

The City of Karlsruhe is interested in determining the amount of urban green areas. Although the city has high quality geodata on use of parcels, this data does not necessarily indicate vegetation areas. An example for this are trees in streets: the landuse indicated by the geodata is *street*, location of trees may also be indicated in the geodata base, but no information on the *apparent green* is included. Therefore, the task is to determine the area of apparent green as seen from above based on data sets of satellite or airborne sensors, which is an easier task than the determination of sealed surfaces, which may be camouflaged by the trees. For this purpose, the QuickBird and the DAEDALUS data sets are suited, because they both provide information on vegetation by their near-infrared channels with almost the same geometric resolution. In this case the QuickBird data was choosen, because of its acquistion date in 2005. Based on the near-infrared and red channels, the NDVI was computed as the main criterion for the classification. The simplest way of classification is just thresholding the NDVI data set and thereby perform a pixel-based classification. The procedure was chosen for its simplicity and its applicabiliy for large data sets. The comparsion of the result with the existing geodata by the City of Karlsruhe is still pending. For the discrimination of low vegetation and trees, the laser scanning data provides the heights as additional information. In this case, a pixel-based classification based on NDVI and e.g. first pulse data would lead to a salt-and-pepper-like result of classification, because although in areas with trees first pulses may reach the

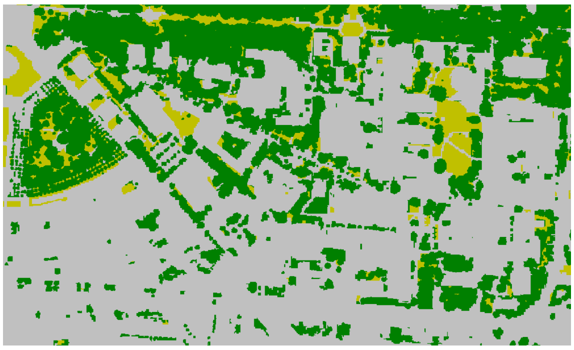

Figure 1. Urban green – Segmentation I and Classification by eCognition

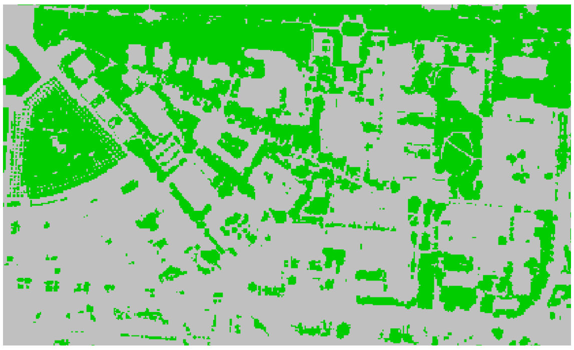

Figure 2. Urban green – Thresholding on NDVI

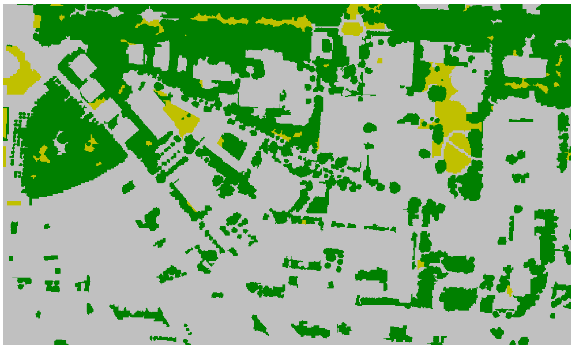

Figure 3. Urban green – Segmentation II and Classification by eCognition

ground. Therefore, a segment-based approach seems to be advantageous, although only the spectral and height information is used for classification and no relations among segments. This is partly due to the fact that we are only interested in vegetation areas (cf. (Möller and Blaschke, 2005)).

For the segmentation of the data sets with eCognition the red and near-infrared channels of QuickBird and the first pulse laser scanning data are used. The parameters for the segmentation with eCognition are set to consider mainly the layer information and not the shape of the segments with a small scale parameter. The result of segmentation and subsequent classification is shown in Fig. 1. *Dark green* indicates trees, *dark yellow* bushes and lawn. For comparison the result of NDVI thresholding is displayed in Fig. 2 (vegetation areas shown in *green*) and a result of eCognition with a larger scale parameter in Fig. 3. Besides the discrimination of vegetation type, the results of the pixel- and segment-based classifications do not differ significantly (visual inspection). The reason for this is the used segmentation: in order to capture also small vegetated areas and single trees, the scale parameter of eCognition was choosen to be small. Larger values for

Figure 4. Aerial image

the this parameter lead to larger segments, which represent vegetated and non-vegetated areas, thus *mixed segments*. Sometimes it is difficult to achieve a good segmentation result with respect to the application, but the quality of segmentation is decisive for the quality of the classification.

3.2 Roof Surface Characterisation

The aim of this project is the quantitative assessment of pollutants on urban surfaces with focus on roofs based on chemical analysis and remote sensing methods. For this purpose we have to characterise roof surfaces by their geometry and material. This characterisation is based on the analysis of laser scanning and hyperspectral data. The fact that we are focussing on the balance of contained pollutants in our application eases in some cases the requirements on the classification, e.g. a number of flat roof types consist of a bitumen sealing with a variable upper layer of different stonelike materials. In such cases the bitumen layer seems to have the main influence on pollution, while the stone cover is of minor importance. Therefore, a separation in different classes is not nessessary in this case.

Our first approach used the laser scanning data to derive geometric information about the surface patches. The subsequent material classification was solely based on the hyperspectral data. Despite the high spectral resolution of this data, it was not possible to discern the relevant classes for our application with high accuracy (Lemp and Weidner, 2004). Therefore, we extended this approach by integrating geometric information, namely the slope of the roof segments, into the classification, observing the fact that the slope is related to the material - at least qualitatively (Lemp and Weidner, 2005a). An example for this are the spectrally similar classes *slate* and *stonelike/bitumen*: slate roofs are normally sloped. Our data analysis is structured in two main parts: (1) the geometrical segmentation using an algorithm developed at IPF followed by a second segmentation step by eCognition including spectral information and (2) the classification using eCognition. The quality of segmentation is crucial as it impacts directly the classification result.

3.21 Segmentation The segmentation procedure within eCognition combines spectral and shape information using a region growing approach. The underlying model assumes constant values for each segment's channel, which is only adequate when dealing with flat (horizontal) roofs, but not when dealing with roofs consisting of planar (horizontal and inclined) faces, which is our assumed model, and using the laser scanning data as main information. In this case, the segmentation leads to elongated segments on sloped roofs (cf. Fig. 5 and Fig. 4 showing an aerial image for comparison). Such a segmentation may be used for classification, but does not represent meaning full segments with

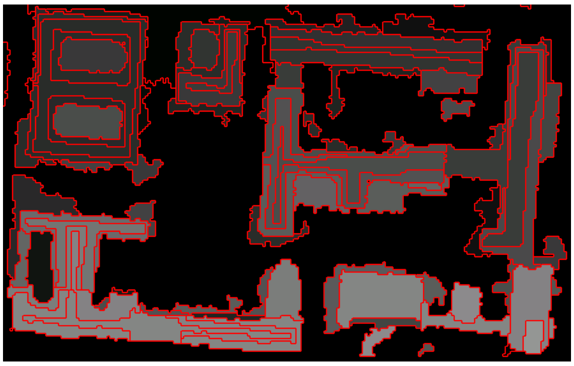

Figure 5. Segmentation eCognition (last pulse)

Figure 6. Segmentation eCognition (last pulse, spectral)

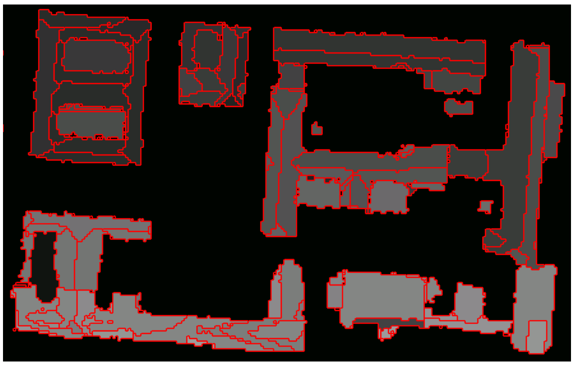

Figure 7. Segmentation IPF (last pulse)

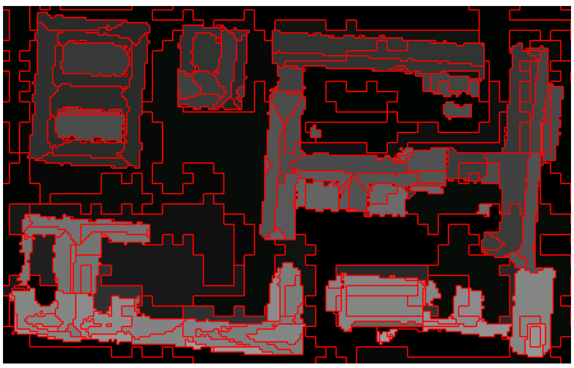

Figure 8. Segmentation IPF (last pulse, spectral)

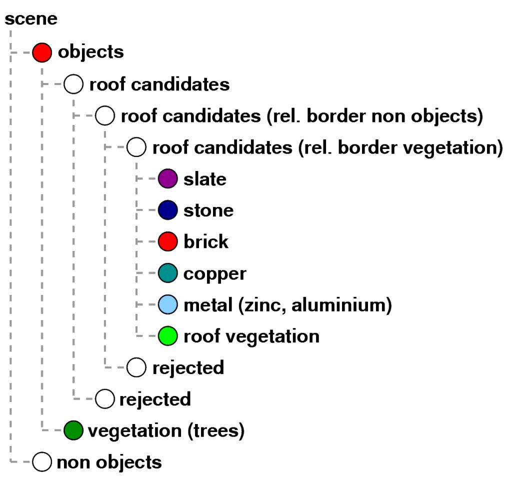

Figure 9. Class hierarchy

respect to the roof geometry. We therefore use a two step approach. First, we apply our segmentation procedure for laser scanning data which searches for planar faces by region growing. Details of the algorithm are given in (Quint and Landes, 1996) and the application for laser scanning data is already described in (Vögtle and Steinle, 2000). Parameters are set to include smaller roof extensions in the surrounding larger surface patch (cf. Fig. 7). The use of geometric data only may lead to problems, in case a planar roof surface patch consists of subareas of different materials. In a second step the first segmentation result is introduced into eCognition using the spectral data to split up the initial segments in order to take care of material changes. We use two spectral channels, which are also used for classification later on to refine the geometric segmentation. An example is shown in Fig. 8. For comparison the result of eCognition using last pulse and spectral data is given in Fig. 6.

3.22 Classification The main task is to identify specific characteristics of the spectra and the geometry to select an appropriate set of channels for classification. Besides the spectral channels, channels providing geometric information may be derived from laserscanning data. We actually use 20 hyperspectral channels manually selected based on the spectra of the surface materials and 3 geometric channels, namely height information from first and last pulse data as well as slope information.

The class hierarchy shown in Fig. 9 mainly reflects the sequence of fuzzy decisions. First, we classify *objects* and *non-objects* using the height information from laser scanning. In a second step we derive a set of candidate roofs by removing vegetation areas from the objects applying an NDVI (channel 25 and 15 of the HyMap-data) and smaller segments based on their size and their neighbourhood relations to segments of the classes *non-object* and *vegetation*. Thus, this classification procedure may in principal also be applied, if only a normalized DSM from first pulse data or derived from other sensor data is available. The roof segments are then classified according to their material and geometry. For this purpose, we have to define membership functions for each class and feature to be used, starting with those material classes with the most significant spectral differences to other materials. Tile brick roofs show an increase in the spectrum from the first channels to the last, which seems in our case to be independent from the age of the material. The spectrum of copper has a significant decrease from channel 8 to 20, while aluminum has high values in the first channels and shows some characteristic slopes in the spectrum, so we use the channels 1 and 2 and a channel ratio. Galvanized zinc is decreasing between channel

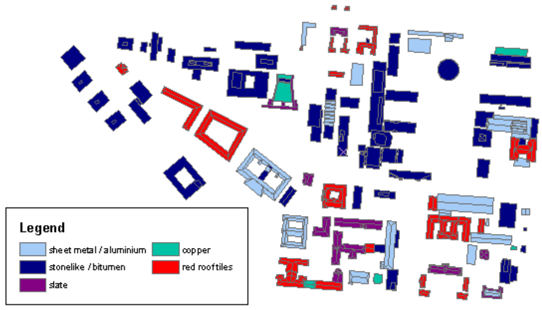

Figure 10. Reference

32 and 40. Slate can be separated from other stonelike surfaces with respect to the slope: slate surfaces usually have a significant slope, while surfaces of gravel and stone plates are flat. As mentioned above the better part of pollution related to gravel and stone plate surfaces is caused by a bitumen layer. Therefore, the three classes *gravel*, *stone plate* and *bitumen* are fused to one main class *stonelike/bitumen*.

3.23 Comparision of Results with Respect to Data and Approaches In this section we present and discuss the results for the central campus area using the approaches described above. We compare the results with the existing reference data (Fig. 10). Furthermore, we also present results by the pixel-based SAM-approach for the hyperspectral data and will discuss the limitations of DAEDALUS data for roof surface classification.

Fig. 11 displays the result of roof surface classification based on the combined geometric and spectral segmentation, again using the colour coding given in Fig. 9. The membership values of all classes are computed using the *fuzzy and(min)*, which means that all membership conditions must be complied. The stability as derived by eCognition based on the differences of membership values is lower for smaller segments. This problem is caused by the limited geometric resolution of the HyMap data. The class *stone like/bitumen* has a much higher stability than we could obtain using the subclasses *gravel*, *stone plates* and *bitumen* as in (Lemp and Weidner, 2004). Fig. 12 displays the comparison between classification and reference. The green segments represent the correct classified ones with about 90% of the total area of roof surfaces. Incorrect classified surfaces (red) are accumulating to approx. 8%. These include also roof surfaces for which the assignment of the reference – zinc or aluminium – is uncertain, because even by field checks, visual discrimination is sometimes impossible. The area with uncertain reference is about 3.4% of the total area, thus leaving 4.6% of total area as truely incorrect classified segments, most of them small with sizes $< 10\ m^2$. Zinc and aluminum surfaces are grouped to *metal surfaces*, because they are separated in the eCognition classification, but not in the reference data, due to the problems described above.

For comparison with the results given above Fig. 13 shows the classification results based on hyperspectral data only and Fig. 14 displays the comparison of this result with the reference data. A visual inspection already indicates the lower quality of the classification results. Most incorrectly classified segments are roof segments of classes for which the seperabilty based on the hyperspectral data is low. The overall accuracy is about 60% only. In order to investigate if the decrease is really due to the fact that no roof slope information is used for the classification, we performed a SAM classification based on the hyperspectral data. For this approach, we used a building mask derived from the laser

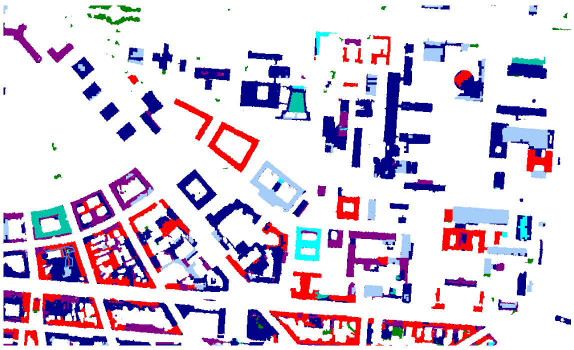

Figure 11. Classification A based on hyperspectral and laser scanning data

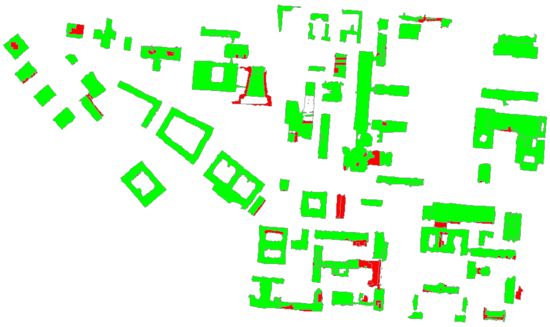

Figure 12. Comparison of classification A with reference

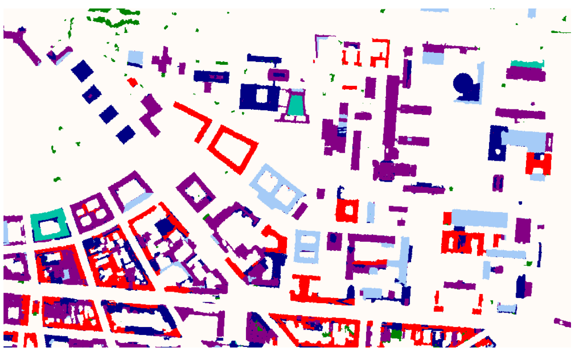

Figure 13. Classification B based on hyperspectral data only

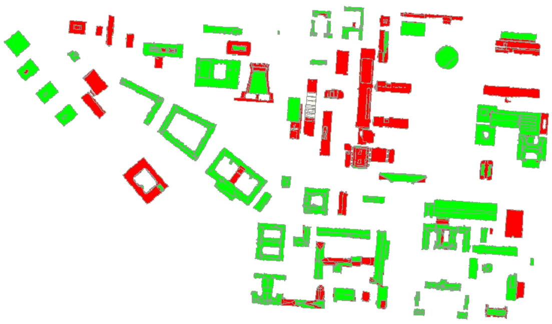

Figure 14. Comparison of classification B with reference

scanning data and then applied SAM for pixel-based classification within this mask. First of all, it was difficult to define endmembers due to the low resolution compared to the complexity of roof structures. We therefore introduced several endmembers for some material classes. The original result shows the typical salt-and-pepper-effect of pixel-based classification. In order to compare the results with those from the approach above, we aggregated the classes. The overall accuracy of the classification was in the same range of about 60% as for the segment-based classification using no roof slope information. Again, problems occured at borders of buildings, where pixels are not assigned to a class. For all approaches the use of either the DSM or the DTM as underlying surface for georeferencing the hyperspectral data was of minor impact on the results. In our opinion, this is also mainly due to the low geometric resolution of the hyperspectral data as compared to the laser scanning data. It definitely will have an impact with higher the geometric resolutions.

For comparison we also analysed the DAEDALUS and the laser scanning data for roof surface classification. As described above for the SAM-approach, we used the laser scanning data to identify building areas and applied Maximum-Likelihood classification within this building mask. Although the geometric resolution of the DAEDALUS data is higher by factor 2, the spectral resolution does not allow for the discrimintation of different materials.

4. CONCLUSIONS

In this paper we presented two applications of urban remote sensing – vegetation and roof material clasification – based on spectral and geometric information given by high resolution optical systems and airborne laser scanning. For both applications we applied different classification schemes and obtained similar results. For roof surface classification the results improved significantly by using the laser scanning data not only as basis to outline the building areas, but by using the geometric information, namely the slope of the roof segments, also for the classification in combination with the optical data. In our opinion hyperspectral data is mandatory in order to classify roof surface materials due to its high spectral resolution. Higher geometric resolution would certainly reduce the problems at segments' border, but it seems doubtful, if it would increase the overall accuracy, because in higher geometric resolution data more details of roofs are visible, which are generalized by the lower resolution. In both applications the segmentation as prerequisite for a segment-based classification is crucial also for the classification result. For roof material classification, we used a combination of an own segmentation approach using the laser scanning as input data and the segmentation of eCognition. This was essential as we need meaningful planar constant or inclined segments to derive the slope information.

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