IMAGE DATA AND LIDAR – AN IDEAL COMBINATION MATCHED BY OBJECT-ORIENTED ANALYSIS

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Commission VI, WG VI/4

KEY WORDS: IKONOS, LiDAR, object-oriented classification, dasymetric mapping

ABSTRACT:

In this paper, object-oriented image analysis, on the basis of eCognition, is used to classify an IKONOS-2 image together with data derived from an aerial laser scanner. After the initial classification of different land cover types, a subset containing only buildings was integrated with zoning as well as population data. Zoning data was used to assign the classified buildings to different land use types, thus allowing the identification of buildings designated for residential use. On these were mapped population data, available on a 250 m grid basis while taking into account the height of each building, allowing a differentiated presentation of where people live within in each grid cell. Although at this stage no data was available for validation, the result suggest a high potential not only for further dasymetric mapping applications, but other applications as well.

1. INTRODUCTION

The classification of optical images has always been hampered by the missing third dimension. With the increased availability of LiDAR (Light Detection And Ranging) data classification can be significantly improved both in terms of accuracy as well as automation. Object-oriented classification is an obvious choice as a tool for an analysis with its ability of integrating and processing data with very different properties. In the first part of this paper an IKONOS-2 image will be analysed together with a normalised Digital Surface Model (nDSM) and a difference model between first- and last pulses (ΔH_{FL}) derived from airborne laser scanner data. The second part looks at an application that can now be performed due to the superior quality of the classification and the available height information. This application examines an improved mapping of population data to houses based on building height. Zoning information is used to identify those buildings belonging to residential areas, making a move from land cover to land use. This is followed by an outlook examining how the integration of different data bases can support the creation of further improved land use maps.

LiDAR data in combination with optical remote sensing images have already been used for classification in urban/suburban area in a number of studies. Zeng, et al. (2002) use a maximum likelihood classifier (MLC) after creating three different datasets for high, low and shadow areas. Haala and Walter (1999) use a maximum likelihood classification to separate buildings, trees, roads and grassland from a colour aerial image with a nDSM as an additional band. The classification result could be considerably improved by this method. Syed et al. (2005) compare MLC to object-oriented classification. MLC resulted in a "salt and pepper" and limits in successfully classifying shadows, a problem not encountered with object-oriented classification. Hofmann (2001) examined the detection of buildings and roads from and IKONOS-2 data and elevation

data, using object oriented classification, confirming its suitability for the data used.

Linking remote sensing with demographic data from census have been subject of a number of studies. Harvey (2002) estimated populations from Landsat TM imagery in Australia using a recursive algorithm to re-calculate population from the census zone according to a pixel's spectral vector. The correlation between census dwelling data and residential densities derived from remote sensing were analysed in Chen (2002) combining classified image data and population from census tracts. Spatial disaggregation of population based on housing densities on a regional scale was discussed in Steinnocher et al. (2006). The relationship between population density and vegetation cover in urban areas was investigated in Pozzi & Small (2005) in order to improve differentiation of urban land use classes. Liu et al (2006) compared population density with texture measures from IKONOS images. All these analyses have in common that they link population with (1) spectral or textural image features, (2) index images such as NDVI or (3) thematic classes such as residential areas or housing densities. In the present paper mapping will be taken one step further, not only going on a building or building block level but by including height information as well.

2. DATA AND STUDY AREA

The study area lies in the province of Upper Austria, in the north of the City of Linz, covering approximately 3.7 x 3.5 km (see Figure 1). It features mixed land cover/land use with large parts being covered by fields and forest. Residential areas comprise both single houses as well as large building blocks. In addition some commercial districts and a motorway are situated in the south and a university complex in the east.
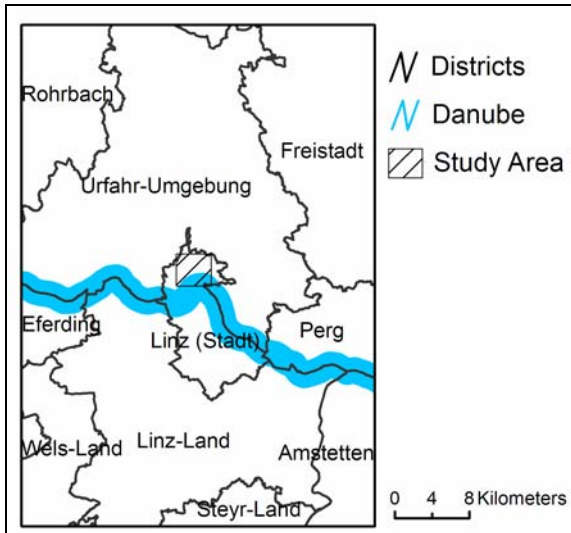
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Figure 1. Study area

Two remote sensing data sets were used for the study. One is subset of an IKONOS-2 scene, recorded on 15th June, 2002 (see Figure 2). It is a fusion product of the four multispectral bands (4 m spatial resolution) and the panchromatic band (1 m spatial resolution), resulting in four multispectral band with 1 m spatial resolution. The multispectral bands cover blue, green, red and part of the near-infrared of the electromagnetic spectrum.
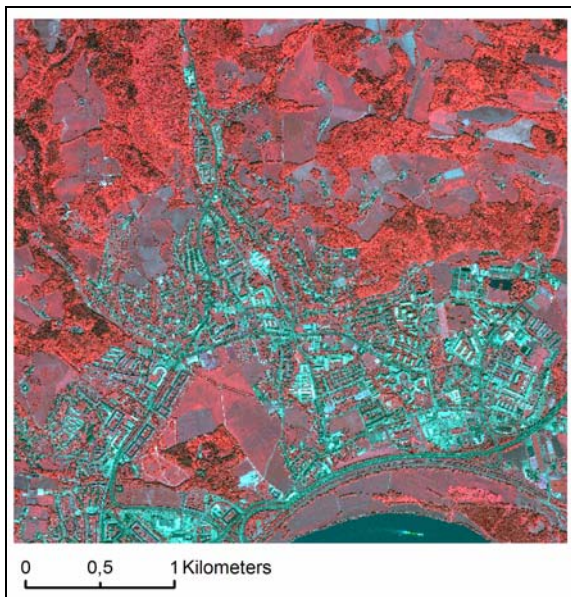

Figure 2. False-colour-infrared IKONOS-2 image of study area

The second data set is from an airborne laser scanner (ALS), acquired on 24th March, 2003, at a flying height above ground of 1,000 m and an average point density of 1 point/m². From this two different models were generated. One is normalised digital surface model (nDSM), containing height information above ground (see Figure 3). Buildings and forests can be clearly seen in this image while flat areas such as water bodies, roads, meadows, and so forth cannot be spearated. The other is a difference model between first and last pulses (ΔH_{FL}), which has a height of zero for sealed areas and a height similar to that of the nDSM in forested areas, thus aiding the identification of trees.
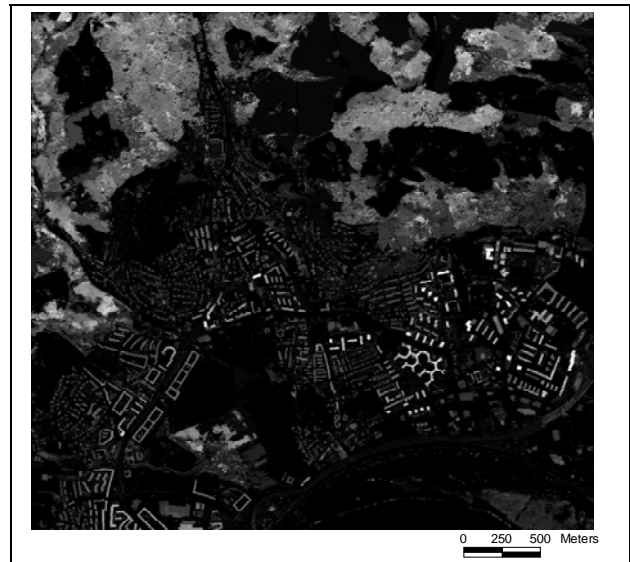

Figure 3. Normalised digital surface model (lighter tones represent greater heights)

For the integration of ancillary data, two data sets were available. One is the generalized zoning plan, as defined by the upper Austrian Land Use Planning law. The generalized zoning plan (see Figure 4) covers 5 classes (residential areas, mixed use, industrial areas, commercial areas, green areas), aggregated from its original 15 classes.
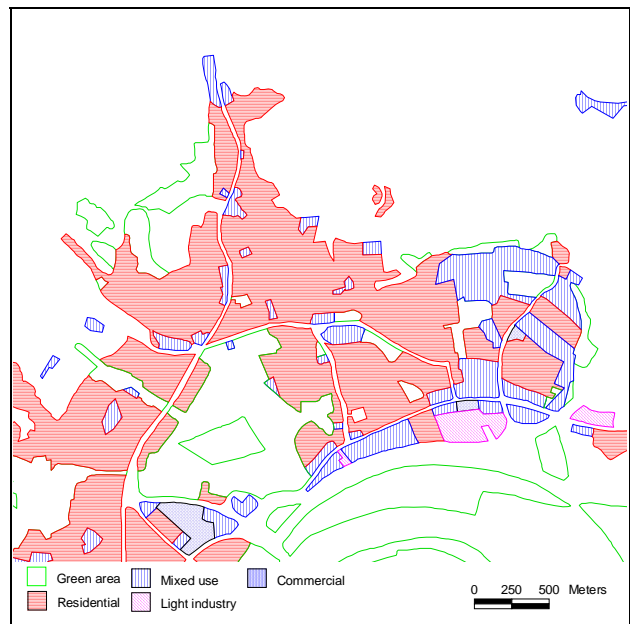

Figure 4. Aggregated zoning data

The other data set contains population data collected by the Statistik Austria[1]. The data are from the census 2001, aggregated to a raster with a cell size of 250 x 250 m (see Figure 5). Its advantage to the original representation on the level of census tracts is that the cell size is fixed and does not change over time. In addition these cells are generally smaller than census tracts, especially outside urban core areas. In the

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[1] http://www.statistik.at/

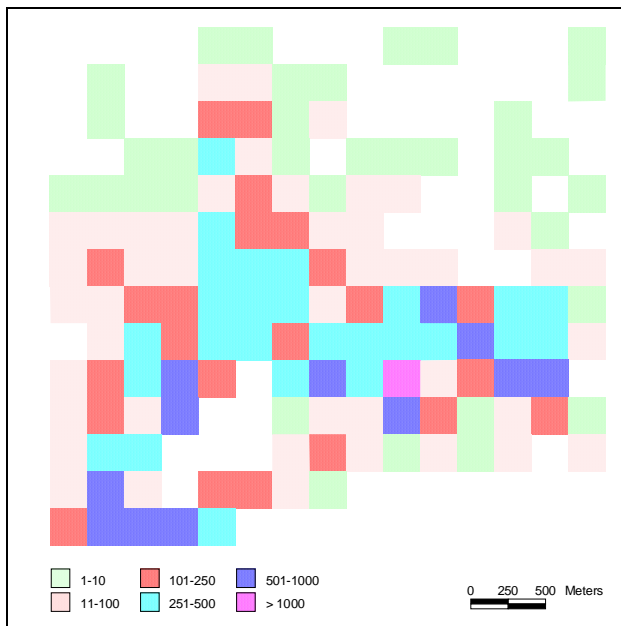future an improved version will beavailble with a cell size of 125 x 125 m.

Figure 5. Statistical population data on 250 m grid

It can be seen that some of the squares show population outside of those areas designated as buildings zones, especially in the Northeast. This is mainly due to individual farms that are not part of the zoning plan.

3. METHODOLOGY

For the classification of the satellite image and the ALS data an object-oriented approach as implemented in eCognition 4.0[2] was used. For the analysis two processing steps can be distinguished. One is the segmentation of the data into homogenous segments, the other is the assignment of these segments to discrete classes. These steps can also be used alternately, i.e. the classification results of one processing step can be input for a subsequent segmentation. In the following sections, image segmentation and classification will be examined followed by the integration of ancillary data.

3.1 Image Segmentation

Aim of this processing step is to identify homogenous image segments. Depending on the data and goal of the analysis, different degrees of homogeneity can be desirable. Segmentation is controlled by parameters scale, colour and shape, selected by the user (Baatz and Schäpe, 2000). Scale controls the maximum allowed heterogeneity per segment. Leaving all other parameters constant a larger scale will result in larger segments. The parameters colour and shape sum to one and determine how much colour and shape information is used for the segmentation process. The shape parameter is further divided into compactness and smoothness. A high value for compactness leads to smaller and very compact segments, more suitable for manmade objects, while a high value for smoothness leads to segments optimised to have smooth borders, more suitable for natural objects.

Different data sets such as laser and satellite images can be segmented simultaneously and their influence to the segmentation process can be adjusted by weights. Nevertheless, a stepwise approach was chosen here due to the very different information content as well as different scaling of the data, allowing more control over the segmenation process. An initial segmentation was carried out on the basis of the satellite image as its information content is larger that that of the laser image. Discrimination of different land cover types, especially of vegetation and built-up areas can be done very easily using this data A second segmentation was performed one level below the initial segmentation and here only the laser information was used. This allows a separation of both built-up areas and vegetation on the basis of height, improving both the identification of roads as well as that of shrubs and grassland. In a third segmentation level between level 1 and 2 a segmentation was performed based only the abosolute height difference while at the same time staying within the boundaries defined by the original segmentation of the satellite image.

3.2 Image Classification

For each segment, identified in the previous processing steps, a large number of features are available for the classification. In order to combine the relevant information and establish the necessary classification rules, a class hierachy has been set up. At this stage eight classes were identified (water, shadow, meadow, shrub, tree, soil, road and buildings). In addition a class for unclassified segments was introduced. Four types of features were used for the classification: mean, ratio, brightness and normalised difference vegetation index (NDVI). Mean refers to the mean value of all pixels present in a segment, e.g. mean nDSM is the mean height of all pixels within a segment. Ratio refers to the mean spectral values of one band divided by the sum of all spectral values, e.g. ratio blue is the ration of the IKONOS blue band with the sum of all other IKONOS bands. Brightness is the mean of all spectral bands and the NDVI is an index calculated from the red the near-infrared bands, giving an indication as to the vegetation intensity (Lillesand and Kiefer, 1994).

Each class was described by one or more of these features. Thresholds for each feature are given in the form of fuzzy functions. Classification is performed in a hierarchical manner, examining each segment whether its membership is high enough for a classification or not. If it is, then the segment is assigned to the appropriate class, all remaining segments are examined for the next class until all segments are classified. Table 1 shows an overview of the features used for each class. A combination of spectral as well as height information was used to successfully assign the different classes.

3.3 Integration with Ancillary Data

Of the classification result only the identified building objects are used for the integration with ancillary data. In a first step the buildings are intersected with the zoning data, making a first move from land cove to land use, assigning each building to one of the five zoning classes. These were then the edited to further separate buildings with public use and those that belong to allotments (typically in a green zone).

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[2] www.definiens-imaging.com

Class	Features used
Water	Mean nDSM
	Ratio infrared
Not water	Not *water*
Shadow	Brightness
Not shadow	Not *shadow*
Vegetation	NDVI
	Brightness
	Ratio blue
Meadow	Mean nDSM
Shrub	Not *shrub*
	Mean nDSM
Tree	Not *meadow*
	Not *shrub*
	Mean ΔH_{FL}
Not vegetation	Not *vegetation*
Sealed-flat	Mean nDSM
Soil	NDVI
Veg_flat	NDVI
Road	Not *soil*
	Not *road_veg*
Not Sealed-flat	Not *sealed-flat*
Building	Ratio blue
Unclassified	Not *building*

flp: first and last pulse
nDSM: normalised digital surface model
NDVI: normalised difference vegetation index

Table 1, Features used for classification

With this added information the next step, the integration of the population data, can be greatly improved. Population data, whether on a raster or on a census tract basis, provide no information as to the distribution on a building block level. This can be approximated by projecting the population data only on those buildings designated as residential or mixed use based on the area covered by them. An even better approximation can be derived by considering building height as well. In order to perform this mapping, for each building its volume is calculated. Based on this volume the population of each grid cell is map onto the buildings belonging to that cell. If a building occupies more than one gridcell then the population is averaged, arriving at one population value for the whole building. This is necessary as the whole population of a building is always assigned to only one grid cell in the census data.

4. RESULTS

4.1 Segmentation and Classification

Before a classification can be performed the data must be segmented. The initial segmentation was carried out using only the IKONOS-2 scene (scale: 20, color/shape: 0.5, smoothness/compactness 0.5). A second layer was created based on a spectral difference of 40. The result is the separation of spectrally distinct land cover types. Before the next segmentation can be carried out, the first layer must be deleted. Below the remaining layer a new segmentation is performed only on the basis of nDSM data (scale 3, colour 1). Here no shape information is used for the segmentation. The borders of the segments, derived in the segmentation of the satellite image limit how much a segment may grow. From this follows that spectrally simliar image object can be separted on the basis of

height (e.g. roof and road) but spectrally different object not combined based on heigth (e.g. a tree next to a house). The final segmentation level is created between level one and two, again only based on nDSM data and using a spectral difference value of 1, again within the boundaries defined by the segmentation of the satellite image..
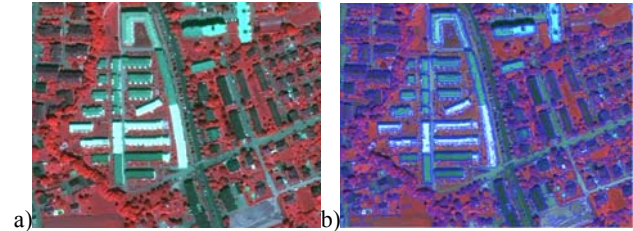

Figure 6. a) original b) final segmentation

The result of the segmentation (see Figure 6 a) and b) for a subset) is basically a product of two separate segmentation procedure, where the first limited the extent as how far a segments may grow in the later segmentation. This assumes that basic land cover types can be separated successfully in the first segmentation stage and only need refining, based on the LiDAR data within each land cover type. An example are sealed areas, which in most cases can be separated very well from non-sealed areas. A differentiation of different types of sealing is much more difficult. and often impossible using only optical data. Here LiDAR gives us the opportunity to identify land cover types such as roads and building with a high degree of accuracy.

Classification is performed on the final segmentation level using the features defined in Table 1. Seven land cover classes were differentiated plus shadow and one for unclassified segments (see Figure 7).

Water | Shrub | Road | Soil | Unclassified
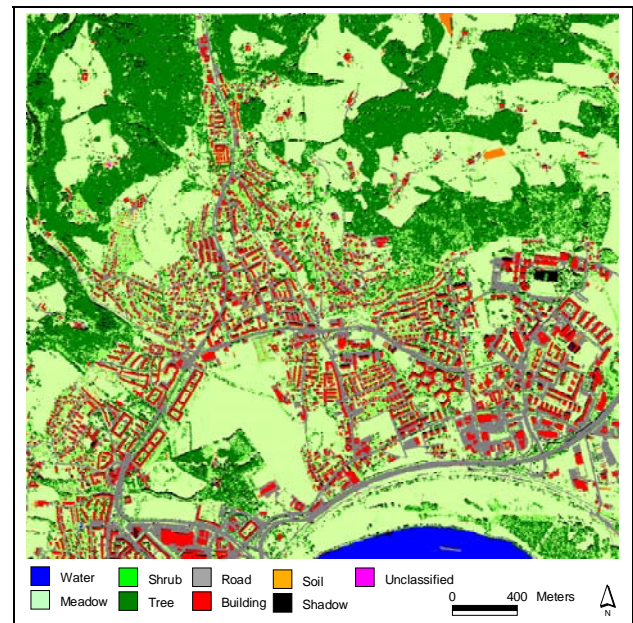Meadow | Tree | Building | Shadow | 0 400 Meters

Figure 6. Classification result

Vegetation and sealed areas were differentiated relying only on spectral information derived from IKONOS-2. Vegetation was further separated using nDSM information for meadow (light

green) and shrub (green). Trees were identified both on the basis of height as well as first-last pulse information (dark green). Sealed areas were divided into roads (grey) and buildings (red). Here the nDSM information greatly improves their differentiation, the quality being mainly dependent on the resolution of the data but not on any ambiguity within the data. The only time where a manual editing was necessary was in the case of road bridges, which were classified as buildings during the initial classification (sealed areas with high nDSM). With the use of a road network this problem could certainly be overcome to a large extent, if the degree of automation were to be increased.

4.2 Integration

For the data integration, only the identified buildings or building blocks were use. The first involves the integration with zoning data. This allows the separation of buildings based on the use allowed in a particular zone. This is an important step to facilitate the following integration of the population data, as then the data can be projected only on those buildings which, according to the zoning plans, are actually residential areas. The buildings were assigned to one of five classes. Light industry (magenta), residential (red) and mixed use (orange) were taken directly from the zoning data. Public use (cyan) such as schools and university buildings was manually assigned based on local knowledge, although in the future, automation for this step can be foreseen as well. Allotments were defined as houses built in green zones.

Figure 7. Classified buildings

For each building or building block a mean height is available, allowing the calculation of volume, assuming that all buildings have a flat roof. Based on this data the population of each grid cell could be mapped to the buildings (see Figure 8). At this stage no data representing the "truth" is available with which the result could be validated. Discrepancies will also occur because of the time difference of the data sets (census from 2001, IKONOS-2 from 2002 and from LiDAR in 2003) as well as because of the assignment of the population of a building to one grid cell of the population data, irrespective of how many cells is spans.
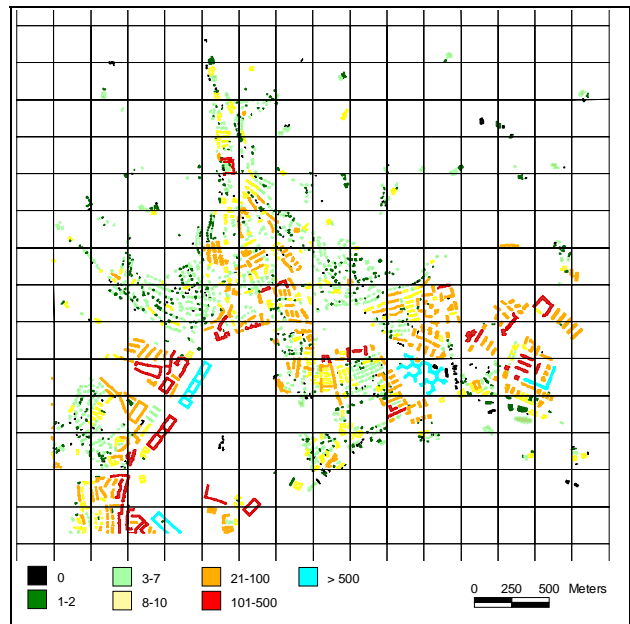

Figure 8. Population data mapped on residential and mixed use buildings

However, a comparison with a mapping based only on the area occupied by each building, does show some differences (see Figure 9). It can be seen that smaller buildings are not affected by the inclusion of height in the calculation, with a maximum deviation of plus/minus one (green). Larger and thus often taller buildings tend to be assigned more population by the mapping when the height is considered as well (dark red), while lower buildings, especially when close to taller buildings tend to show less population (dark blue).
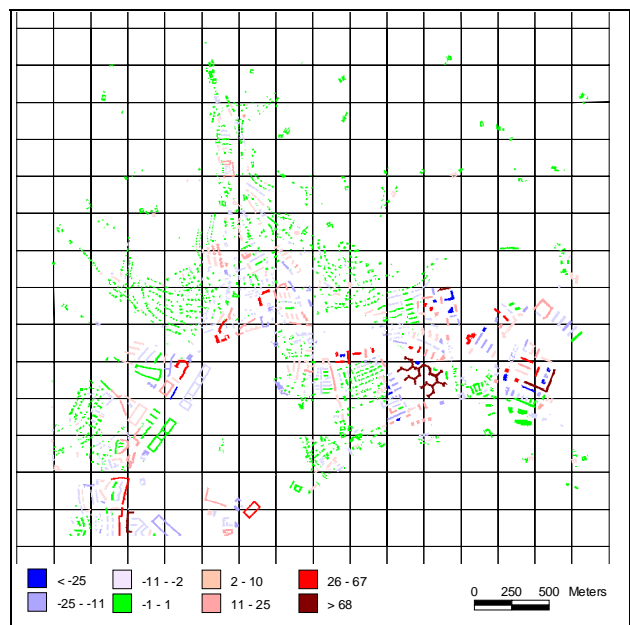

Figure 9. Difference of population distribution when mapping is based on volume compared to area

5. CONCLUSION AND OUTLOOK

In this paper object-oriented classification of LiDAR (nDSM and ΔH_{FL}) and multispectral IKONOS-2 data (pansharpened to 1 m spatial resolution) using object-oriented classification was examined. The use of both data sets allowed an easy separation of the basic land cover types present in the study area. LiDAR data are especially beneficial for the separation of flat sealed areas from buildings, while optical data allows a good separation of vegetation and sealed areas. Very little manual editing of the land cover classification was needed, mainly limited to correcting road bridges, which were classified as buildings.

The next step was the integration of the classification results with statistical data and the information provided by LiDAR. Aim was the mapping of population data, available on a 250 m grid basis, not only on the basis of areas covered by the buildings but also on the height of these buildings. As not all buildings are residential they building mask was first intersected with a zoning map of the area. This allowed the identification of those buildings which are not used for residential purposes. Using local knowledge this was further improved by manually identifying those buildings which lie in mixed use areas but are not used as residential buildings (e.g. churches, university, etc.). On the remaining buildings the population data was mapped, allowing a more detailed view of how many people live in each building. With this method especially larger buildings show more population compared to when only the area of a buildings is considered for the mapping. This is especially important when mapping how many people may be affected by certain measures such as the building of a new road, changed in air traffic patterns, and so forth) At this stage no validation of the results could be carried out as the necessary data, such as population data on a building level, is not generally available.

With the integration of the zoning data a fist step had been made from land cover to land use. The next will be the linking of the identified building blocks to address data, thus allowing a mapping of any kind of data, indexed by address. This way the identification of different uses of a building can be further improved. Depending on the accuracy of the address data and the various data bases used, very detailed land use maps could be created.

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