

OBJECT-BASED APPROACH TO MAP SEMI-NATURAL AREAS IN MOUNTAIN REGION WITH HIGH SPATIAL RESOLUTION IMAGES

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ABSTRACT:

Semi-natural areas are characterized by cultivated and natural areas with continuous transition zones. Especially in the alpine regions, this type of land-cover is predominant. The paper presents a method to classify semi-natural alpine areas by combining the spatial detail of orthophotos with the spectral information of SPOT satellite images. As case study, an alpine region in South Tyrol (Italy) has been considered. A four step approach is applied: (1) object delimitation, (2) object information assignment, (3) data mining and (4) classification. First, a segmentation procedure on orthophotos is used for an accurate delimitation of spatial objects, namely the segment. In a second step, spectral information from SPOT data as well as textural information from orthophotos are assigned to the segments. In a third step, those information are inserted in a data mining procedure, reducing the information to the most relevant ones for the next step based on classification. The classification procedure is mainly based on a decision tree approach. The main aim of this study was to compare the results from standard pixel vs. object-based classification approach by combining and considering different attributes (spectral, textures, topography) with decision tree approach and by comparing two classification approaches (maximum likelihood, decision tree). The study shows the potential of mapping semi-natural areas by combining high geometric detail (orthophotos) with spectral information of satellites images (SPOT).

1. INTRODUCTION

Grasslands and mountain meadows represent about 25% of the alpine vegetation. Most are semi-natural, having been influenced by centuries of low-key farming practices (European Commission, 2009). They often represent environmental sensitive areas with considerable variation in ground cover, ranging from humid areas, bogs, dwarf-shrubs, semi-natural grassland mountain pine and conifers with mosaic of extensive and intensive grazing land and mountain pasture.

Detailed mapping and monitoring of these large areas by field surveys are generally difficult and expensive. Here, remote sensing (RS) techniques offers up-to date and cost effective opportunities by providing synoptic, objective and homogeneous data which can be geographically and temporally registered. Remote sensing can therefore be an efficient tool for providing standard, high quality information (Tsiligrades, 1998). Especially in the last decades, a lot of satellite sensors have been launched with very high spatial and/or spectral resolution, delivering the opportunity of detailed land cover mapping at a scale of 1:5000.

Pixel based classification approaches on high spatial resolution satellite images (e.g. SPOT, LANDSAT), however, often results in pixelised (salt and pepper) representation, which is even increasing when considering the new generation of very high spatial resolution data (e.g. IKONOS, QuickBird, GeoEye). In this context, object-oriented approaches (Baatz and Schäpe, 2000) have gained more and more interest, especially when dealing with very high spatial resolution satellite images.

The object-oriented classification approach is based on image segmentation and usually performed as a pre-processing step. Therefore, the image is divided into semantically significant

regions, also known as objects. In recent years, research in multi-scale or hierarchical segmentation approach has received a growing interest (Baatz and Schäpe, 2000; Guigues et al., 2006). This research offers new opportunities, not only for analysis of the image at several different scales, but also for working with hierarchical structures, by setting objects in relation to neighbouring objects, or even to sub or super objects (multi-resolution segmentation). Object-oriented classification approaches have shown their potential for identifying and differentiating thematic aspects of the real world. A good, clear delineation is particularly achieved when dealing with the new generation of very high spatial resolution satellites images (Blaschke and Strobl, 2001; Schiewe, 2002; Benz et al., 2004).

Oldeland et al. 2010 demonstrated the potential of high spatial resolution hyperspectral imagery for mapping semi-natural vegetation units. However, while the achieved accuracy delivers promising results, flight campaign for the acquisition of these data are quite cost intensive. Baker et al. 1991 have shown that spectral classification alone out of SPOT HRV is not a suitable tool for mapping semi-natural cover types. The spectral identification is not always feasible (e.g. mountain pine and conifers) and even increases, when dealing with a lot of classes.

Textural measurements, especially for very high spatial resolution, offer a new input of information. Textural related information can highlights this difference better than any spectral index. Haralick et al. (1973) defined 14 texture features that were derived from the GLCM among which six –angular second moment (ASM), contrast, variance, homogeneity, correlation and entropy – are considered to be the most relevant for remote sensing imagery analysis. GLCM stands for Grey Level Co-occurrence Matrix (also called the Grey Tone Spatial Dependency Matrix) and consist of a tabulation of how often different combinations of pixel brightness values (grey levels)

occur in an image. A precise definition of image texture is rather difficult to formulate. An often adopted description of it is the structure in the spatial variation of the pixel values (Rees, 2001). Their information content depends on the type of image analysed with regards to the spectral domain, the spatial resolution and the characteristics of the sensed objects (dimension, shape and spatial distribution) (Kayitakire et al., 2006). Several studies using textural classification inputs have already revealed the potential of textural derived information and its relative applications (Chen, 2004; Warner and Steinmaus, 2005; Kayitakire et al., 2006; Agüera et al., 2008). However, these studies focused on pixel-based, texture related classification approaches. Whilst these studies applied a fixed size mowing window approach, object based approaches gain their window size from the segmentation procedure, focusing afterwards on those significant regions (objects) and are therefore better able to obtain texture related information.

Over the last many years, a number of classifiers, both parametric and nonparametric, have been developed for classification of remote sensing data. The Maximum Likelihood Classifier (MLC), a probabilistic classifier, has been widely used for classification of remote sensing data to produce both hard and soft classification outputs. However, practitioners of MLC frequently assume that the data follow Gaussian distribution, an assumption which may not be tenable in remote sensing images containing mixed pixels. Therefore, non-parametric algorithms that use iterative procedures may be more appropriate than the statistical algorithms such as MLC (Xu et al., 2005). Quinlan See5 (Quinlan, 2003) software is one of those non-parametric algorithms, generating easily if-then rule sets out of decision tree. Several studies dealing with the decision tree have showed the potential of See5 for remote sensing applications as hard classifier (Landenburger et al., 2008, XiaoPing et al., 2008, Punia et al. 2008, Ke et al. 2010).

This study is based on previous work performed by the authors (Notarnicola et al., 2009). The added value of this study is mainly an accuracy improvement regarding the classes humid areas and mountain pine, the integration of orthophotos and a more intensive consideration of object based approaches and texture measurements.

2. METHODOLOGY

2.1 Study area



Figure 1. : Study area in South Tyrol, Italy.

The study site is located in South Tyrol, Italy (see Figure 1). The area of interest covers approximately 50 km² and is

characterized by a plateau at an elevation of almost 2000m a.s.l., called “Villanderer Alm”. Different vegetation types and agricultural uses overlaps here continuously. The area is covered with vegetation, showing continuous transition from semi-natural grassland, dwarf-shrubs, humid areas, bogs, mountain pine and conifers. The agricultural use is restricted to mowing and grazing of grasslands and mountain pasture.

2.2 Data used

The data used for this study were two SPOT scenes from May 2005 and September 2006 as well as orthophotos from 2006. Additionally, a digital elevation model (DEM) obtained from Lidar data of 2006 was considered. The initial very high spatial resolution DEM (2.5m) has been resampled to 10m to be consistent with the spatial resolution of SPOT data. As a reference map, a land-use classification covering whole South Tyrol with a minimum mapping unit of 1600 m² is taken. For the area of interest a more detailed biotope map based on ground survey was available, focusing on the land use classes, humid areas, extensive and intensive grazing land.

2.3 Pre-processing

2.3.1 Georeferencing: The two SPOT scenes were georeferenced to the orthophotos by thin plate spline using PCI Geomatica with the DEM. This georeferencing procedure was necessary to guarantee a correct overlapping of the two SPOT scenes with the orthophotos, allowing afterwards a segmentation on orthophotos by combining the obtained segments with the spectral information of the SPOT scenes.

2.3.2 Segmentation: The segmentation procedure was done by using a bottom-up segmentation approach of 3 levels, also known as multi-resolution segmentation (Baatz and Schäpe, 2000) with Definiens Developer 8. 4 Layers for the segmentation procedure have been considered: three spectral bands (red, green, blue) from orthophotos and an intensity band, delineated from the orthophotos by using the transformation of Intensity, Hue and Saturation (IHS) calculated from the Red, Green, Blue (RGB) composition (Lillesand et al., 2004). The latter was mainly created to consider a kind of panchromatic layer with the whole spectral information out of the orthophotos containing the main textural information. The segmentation procedure was performed by creating 3 segmentation levels, starting with scale parameter 30 on level 1, 60 on level 2 and 90 on level 3. In each segmentation step, different layer weightings were considered: 12 for the red band, 8 for the green, 4 for the intensity and finally 1 for the blue band. A weighting factor of only 1 was considered for the blue band as it was affected by noise effects. After having generated segmentation level 2, level 1 was deleted and level 2 was processed through a Morphology filter of Definiens. As parameterisation, the operation “close image objects” was considered with a width of 8 while creating circles. This was necessary to smooth the objects and reducing the branched effects. Finally, level 3 was generated above level 2 for the relational object information while the segments of level 2 were considered for the following classification.

2.3.3 Sampling: samples were collected on the basis of the segments, generated on level 2 and interpreted visually taking into account the orthophotos and the detailed biotope maps as described in section 2.2. Only segments above or equal the area of 300 m² were considered. For each class, at least 50 samples were collected. However, due to lower representation within the

area of interest, water surfaces and build-up areas had less than 50 samples. After the selection of relevant samples, a split into test and train samples was done, by considering about 65% as train samples and 35% as test samples. In order to compare the effect of segment based classification with pixel based classification, the samples were afterwards rasterized to the resolution of the SPOT scenes. This conversion assured that the initial samples, generated on the spatial resolution of the orthophotos, fitted after the conversion to the spatial resolution of the SPOT scene. The amount of samples remained the same and allowed therefore a comparison of the results.

2.4 Object information assignment

The objects (segments) of level 2 were used as objects for information assignment. Three main types of object information were considered: (1) spectral, (2) textural and (3) topographic. Additionally to these features, the same object information were derived on the segmentation level above (level 3) and set in relation to level 2 by using customized relational feature in Definiens. Each segment was finally described by 380 attributes. For level 2: 144 spectral, 40 textural and 6 topographic. The same information were derived on level 3 and set afterwards in relation to level 2.

2.4.1 Spectral: The spectral information was assigned to the segments, by considering the mean values of each band (SPOT and orthophotos). Additionally, more than 100 indices and ratios between the bands of the two SPOT scenes as well as the bands of the orthophotos with the two SPOT scenes were considered. These indices and ratios were defined in Definiens by using the customized arithmetic features.

2.4.2 Textural: Texture measurements were assigned to the segments by considering nearly all available textures taken from Haralick (1979) in DEFINIENS and their four spatial directions (0°, 45°, 90°, 135°). We used GLCM Homogeneity, GLCM Contrast, GLCM Dissimilarity, GLCM Entropy, GLCM Ang. 2nd moment, GLCM Mean, GLCM StdDev, GLCM Correlation, GLDV Ang. 2nd moment and GLDV Entropy (GLCM: Gray-Level Co-occurrence Matrix; GLDV: Gray-Level Difference Vector). GLDV Mean and GLDV Contrast were not considered, as they were identical to GLCM Dissimilarity and GLCM Contrast, respectively (Laliberte and Rango, 2008). In order to reduce the number of textural information, only the maximum value of the mean value of a specific texture measurement of each given direction, was considered. The procedure was introduced into the process tree of DEFINIENS by defining a “zonal mean max” variable for each texture measurements. Therefore the mean value of a specific texture measurement for each segment and for each given direction, was calculated. Finally, the maximum of the direction mean values for a give segment and for a given texture measurement was considered. The main expression used was the following:

Variable = Texture (0°)

If Texture (45°) > Variable then Variable = Texture (45°)

If Texture (90°) > Variable then Variable = Texture (90°)

If Texture (135°) > Variable then Variable = Texture (135°)

2.4.3 Topographic: Topographic information were considered by using the Topographic Modelling Option in ENVI. We derived all possible parameters out of ENVI and considered therefore 6 additional topographic bands (Profile convexity, Plan convexity, Longitudinal convexity, Cross

sectional convexity, Minimum curvature and Maximum curvature) on the basis of the DEM. The mean value of these topographic bands was considered for each segment and used as additional information.

2.4.4 Object relational information: Finally, of all object information (spectral, textural and topographic) for level 2, object relational information were also generated by deriving the same information on level 3. These features were afterwards related to the segments of level 2, by using the customized object relational settings in Definiens.

2.5 Classification

The classification was done by investigating three different combinations and approaches.

1) Comparison of a pixel-based and a segment-based maximum likelihood classification taking into account only the spectral information from the two SPOT scenes.

2) Use of a decision tree classifier (See5) on segments (objects) taking into account all spectral information including indices, textural information as well as topographic information.

3) Maximum likelihood approach based on a selection of attributes (spectral, textural, topographic) which have identified in step 2 as most promising for the classification.

2.5.1 Pixel vs. segments: The results of two different layer stacks (pixel vs. segments) with a standard maximum likelihood classification were compared. Therefore, on one hand a layer stack of the two SPOT scenes was considered. On the other hand, each band was exported separately from Definiens by considering the mean value for the given segment. Those segment-based bands were afterwards also stacked.

2.5.2 Decision tree: See5 is a decision tree builder, which generate classifiers called “rule sets”, that consist of unordered collections of (relatively) simple “if-then” rules. The rule sets are generated with the given attributes of the training samples and validated with the test samples. The Software See5 uses a statistical measure (e.g. an entropy) that tries to find the attribute with the most discriminatory power and then sets a threshold, which represents a node. This node contains only part of the data and can further be divided until an end node (leaf) is reached where no further splitting is possible or desired. To overcome the problem of decision trees as rather “weak” learners compared to parametric classifiers (maximum likelihood), a common strategy of boosting is used. The boosting approach uses a special set of weights for all training samples, by increasing the weight after each run for the misclassified samples and by decreasing it for the correct samples (Freund and Schapire, 1996).

See5 performs a validation by classifying the test samples, comparing it with the original class and summarizes the result into a confusion matrix, which indicates the expected overall accuracy, user and producer accuracy. Furthermore, an information for each attribute is given in how many percent of rule sets the attribute was used. This gives an indication on the importance of the respective attribute to delimit the given classes. The generated rules sets can be applied to the segments as a hard classifier which results in a assignment to a given class including the information of the probability to belong to this class.

Different settings regarding the sources of spectral information were compared: (1) orthophotos alone, (2) mono temporal

SPOT image or (3) the multi temporal SPOT approach. Within those main combinations, the improvement by considering spectral and/or textural and/or topographic information on level 2 (L2) were analyzed. Additionally, the results when adding also the combination of object relational features out of level 3 (+L3toL2) were compared. As classifier construction option rule sets of See5, 99 trials of boost was set.

2.5.3 Decision tree vs. maximum likelihood: Finally, we compared a segment based maximum likelihood classification with a decision tree hard classification. Therefore, only the attributes which contributed to more than 90% of all rule sets in See5 were considered (19 out of 380, see Table 1). The maximum likelihood classification was done by exporting the suggested attributes out of Definiens as individual bands and stacking them afterwards. As train and test samples the samples mentioned in section 2.3.3 were considered. The decision tree hard classification was derived, by appending to each segment the predicted class as well the probability obtained from the rule sets. This was done by using free available script, called "See 5 Sam".

SEE5 attribute usage above 90%
L2: SPOT 2006 GREEN / SPOT 2006 NIR
L2: SPOT 2006 NIR / SPOT 2006 RED
L2: SPOT 2006 RED / SPOT 2006 NIR
L2: SPOT 2006 RED - SPOT 2006 NIR
L2: SPOT 2006 SWIR / SPOT 2006 GREEN
L3toL2: SPOT 2006 RED - SPOT 2006 NIR
L3toL2: SPOT 2006 RED / SPOT 2006 NIR
L3toL2: SPOT 2006 GREEN - SPOT 2006 SWIR
L3toL2: Orthophoto RED / SPOT 2006 NIR
L2: SPOT 2006 RED
L2: SPOT 2006 GREEN - SPOT 2006 SWIR
L3toL2: SPOT 2006 SWIR / SPOT 2006 GREEN
L3toL2: SPOT 2006 NIR / SPOT 2005 RED
L3toL2: SPOT 2005 RED - SPOT 2005 NIR
L3toL2: SPOT 2006 GREEN / SPOT 2006 NIR
L3toL2: SPOT 2005 GREEN - SPOT 2006 NIR
L3toL2: SPOT 2005 GREEN / SPOT 2005 RED
L3toL2: SPOT 2006 GREEN / SPOT 2006 SWIR
L2: Orthophoto BLUE / Orthophoto RED

Table 1. : See5 attribute usage above 90% when considering all possible 380 attributes.

2.6 Results and discussion

2.6.1 Pixel vs. segments: The accuracy assessment of the two classifications is shown in Table 2. A clear accuracy improvement is highlighted, when comparing pixel-based to segment-based classification. While considering a multispectral maximum likelihood classification, the segment-based approach reaches better results than the usual pixel-based approach. The improvement in accuracy is probably due to the aggregation of the spectral information to the segments, reducing so the effect of outliers and their misclassification. Beside the aspect of better accuracy, the spatial resolution improves notably, in this case from 10m spatial resolution up to 0.5m spatial resolution of the segments. Beside this aspect, a generalization is also already given. While the pixel based classifications still results in salt and pepper effects, the segment based result is already smoothed to relatively compact and homogenous classes.

Class	pixel-based		segment-based	
	PA	UA	PA	UA
Rocks	83.92	88.48	92.89	96.20
Loose rocks	72.95	71.01	91.09	81.13
Water bodies	95.94	84.02	74.59	100
Humid areas	87.26	89.91	93.9	94.98
Build-up areas	85.52	42.14	85.26	77.97
Intensive grazing	96.84	95.52	99.12	97.15
Extensive grazing	86.71	72.39	82.16	83.56
Natural near grassland	74.66	92.03	89.73	91.16
Dwarf-shrubs	75.51	67.73	85.48	78.68
Conifers	81.15	88.23	94.61	90.05
Mountain pine	85.04	83.57	86.87	94.72
OA	0.83		0.90	
Kappa	0.81		0.89	

Table 2. : Main confusion matrix results of pixel-based vs. segment based classification (OA: Overall Accuracy, PA: Producer accuracy; UA: User accuracy).

2.6.2 Decision tree: The differences in improvement while considering spectral information of (1) orthophotos alone, (2) mono temporal SPOT image and (3) the multi temporal SPOT are illustrated in Figure 2, Figure 3 and Figure 4, respectively. Considering only information on Segmentation level 2 are marked by "L2". Considering additional data out of segmentation level 3 with object relational feature are marked by "+L3toL2". The legend of the x-axis is given in Table 3.

	Meaning
1	Spectral Bands
2	Spectral Bands & Topographic
3	Spectral Bands & Textures
4	Spectral Bands & Topographic & Textures
5	Spectral Bands & Indices / Ratios
6	Spectral Bands & Indices / Ratios & Topogr.
7	Spectral Bands & Indices / Ratios & Textures
8	Spectral Bands & Indices / Ratios & Topogr. & Textures

Table 3. : Legend of x-axis regarding the histograms.

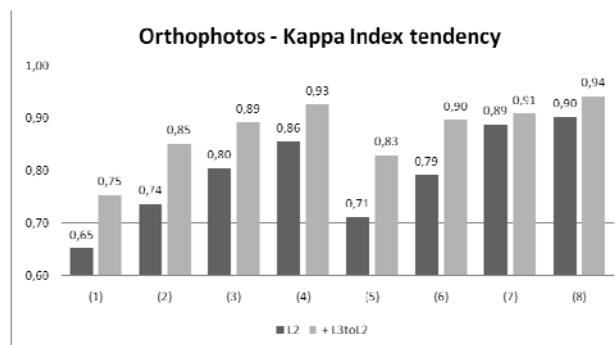


Figure 2. : Kappa Index tendency by considering only spectral information of orthophotos.

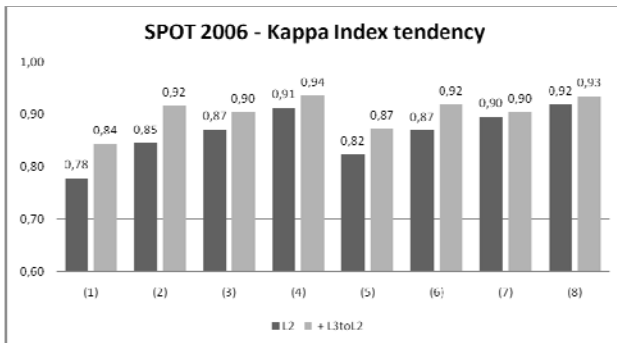


Figure 3. : Kappa Index tendency by considering only spectral information of SPOT 2006.

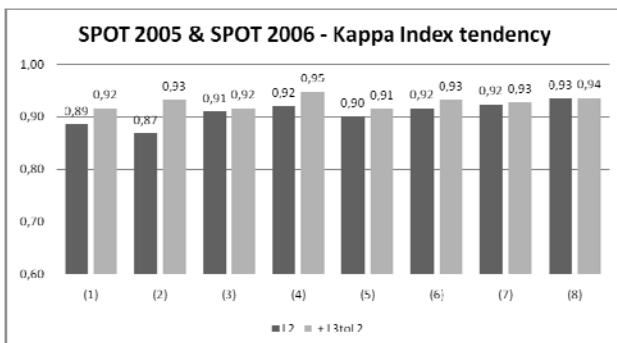


Figure 4. : Kappa Index tendency by considering spectral information of SPOT 2005 and SPOT 2006.

By comparing the different accuracies using orthophotos, one SPOT scene only and multi temporal SPOT classification, a clear improvement regarding all combination is given when the multi temporal SPOT approach is considered.

Substantial improvement is given when spectral, textural and topographic information (see Figure 2, Figure 3 and Figure 4: (4) and (8)) are taken into account. On the other side, considering also all possible combinations of indices and ratios, is not really improving the result. The spectral bands themselves contribute already with most of the relevant information. Considering relational object information of only spectral bands improves the accuracy (see Figure 2, Figure 3 and Figure 4: (4) +L3toL2), more than considering all possible spectral combination (see Figure 2, Figure 3 and Figure 4: (8) L2).

Textural and/or topographic information contribute to an improvement of the result (see Figure 2, Figure 3 and Figure 4: (2), (3), (4), (6), (7), (8)). Nevertheless, textural information are quiet process intensive, and topographic information only derivable when having an DEM. However, considering these two information in combination with spectral information from the orthophotos, yields in already quite satisfying results (see Figure 2: (4) L2, (8) L2). The results even improve when considering additionally object relation information ((see Figure 2: (4) +L3toL2, (8) +L3toL2).

The minor effort to reach acceptable results is achieved by considering only spectral bands of multi temporal SPOT scenes (see Figure 4: (1) L2). Considering additional object relational information of the spectral bands (see Figure 4: (1) +LtoL2) can result in an accuracy, that can still compete with the result of other combinations while not having to take into account process intensive textural information, or topographic attributes which are related to a DEM.

2.6.3 Decision tree vs. maximum likelihood:

The main results of the confusion matrix regarding the comparison of the segment-based maximum likelihood classification vs. a decision tree hard classification are shown in Table 4. The attributes or derived spectral bands we used are shown in Table 1.

Class	maximum likelihood		decision tree	
	PA	UA	PA	UA
Rocks	60.21	97.76	0.89	0.89
Loose rocks	92.26	82.42	0.92	0.84
Water bodies	96.67	32.36	0.56	1.00
Humid areas	84.06	95.05	0.87	0.91
Built-up areas	59.74	88.53	0.64	0.90
Intensive grazing	98.84	91.75	0.98	0.94
Extensive grazing	77.73	97.90	0.89	0.91
Natural near grass-land	98.01	92.99	0.97	0.91
Dwarf-shrubs	96.43	83.78	0.90	0.90
Conifers	97.38	89.76	0.95	0.95
Mountain pine	87.36	97.37	0.91	0.92
OA	0.90		0.91	
Kappa	0.89		0.90	

Table 4. : Main confusion matrix results of segment based maximum likelihood vs. decision tree classification (OA: Overall Accuracy, PA: Producer accuracy; UA: User accuracy).

Regarding the two classification approaches, the results doesn't differ so much. However, there is a slight improvement when considering the hard classification of the decision tree. This can be interpretive that hard thresholds, gained out of the rule sets, fits better for an differentiation of heterogeneous classes than cluster grouped classes gained out of the maximum likelihood classification. The reduction of outliers as well as wrong assignment of classes seems to be better reduced by hard classification thresholds, than by probability assignment of clusters.

3. CONCLUSION

The classification method applied here for semi-natural areas by combining the spatial detail of orthophotos with the spectrally information of SPOT satellite images, shows a high potential and improvements in classification procedures. Downscaling coarser spatial resolution with higher spectral information to higher resolution objects reduces salt and pepper effects and improves the accuracy. Furthermore, these procedures reflect better the given geometry by clear delineation and deliver vector products, ready to be directly incorporated into geographic information system (GIS).

Considering only information from spectral bands already contributes to good results. Taking additional indices and ratios into account, improves the result slightly. A further consideration of additional textural, topographic and object relational information leads to a net improvement but is time consuming and creates high processing demands. A good result with lower workload can be achieved by combining

multispectral and multitemporal information from high resolution data (SPOT in this case) with segments from very high resolution data (orthophotos) and combining them with object relational information from a higher segmentation level.

Problematic cases for classification are transition zones of overlapping classes (e.g. open conifers with natural near grassland misclassified as dwarf-shrubs)

Further research can be dedicated by considering more than two SPOT scenes, higher amount of segmentation level and the setup of object relational information to the most suitable segmentation level.

4. REFERENCES

- Agüera, F., Aguilar, F.J., and Aguilar, M.A., 2008. Using texture analysis to improve per-pixel classification of very high resolution images for mapping plastic greenhouses. *ISPRS Journal of Photogrammetry and Remote Sensing*, 63, pp. 635-646.
- Baatz, M. and Schäpe, A., 2000. Multiresolution Segmentation – an optimization approach for high quality multi-scale image segmentation. *Angewandte Geographische Informationsverarbeitung XII, Beiträge zum AGIT-Symposium Salzburg*, pp. 12-23.
- Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. and Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing*, 58, pp. 239-258.
- Blaschke, T. and Strobl, J., 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *Zeitschrift für Geoinformationssysteme*, 6, pp. 12-17.
- Chen, D., Stow, D.A., and Gong, P., 2004. Examining the effect of spatial resolution and texture window size on classification accuracy: an urban environment case. *International Journal of Remote Sensing*, 25, pp. 2177-2192.
- European Commission, 2009. Natura 2000 in the Alpine Region. <http://ec.europa.eu/environment/nature/natura2000> (accessed 08 Apr. 2010).
- Freund, Y. and Schapire, R.E., 1996. Experiments with a New Boosting Algorithm. In: *Machine Learning: Proceedings of the Thirteenth International Conference*, pp. 148-156.
- Guigues, L., Cocquerez, J.P. and Le Men, H., 2006. Scale-Sets Image Analysis. *International Journal of Computer Vision*, 68, pp. 289-317.
- Haralick, R. M., Shanmugan, K., and Dinstein, I., 1973. Texture features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, 3(6), pp. 610-621.
- Baker, J.R., Briggs S.A, Gordon, V., Jones, A.R., Settle, J.J., Townshend, J.R.G. & Wyatt B.K., 1991. Advances in classification for land cover mapping using SPOT HRV imagery. *International Journal of Remote Sensing*, Volume 12, Issue 5 May, pp. 1071 – 1085.
- Kayitakire, F., Hamel, C. and Defourny, P., 2006. Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery. *Remote Sensing of Environment*, 102, pp. 390-401.
- Ke, Y, Quackenbush, L.J. and Im, J., 2010. Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification, *Remote Sensing of Environment*, 114 (6), pp. 1141-1154.
- Laliberte, A.S., and A. Rango. 2008. Correlation of object-based texture measures at multiple scales in sub-decimeter resolution aerial photography. *The International Archives of the Photogrammetry, Remote Sensing, and Spatial Information Sciences: GEOBIA 2008: Pixels, Objects, Intelligence*, 6-7 Aug, 2008, Calgary, AB, ISPRS, Vol. No. XXXVIII-4/C1.
- Landenburger, L.; Lawrence, R.L.; Podruzny, S. And Schwartz, C.C., 2008. Mapping Regional Distribution of a Single Tree Species: Whitebark Pine in the Greater Yellowstone Ecosystem. *Sensors*, 8, pp. 4983-4994.
- Notarnicola, C., Frick, A., Kass, S., Rastner, P., Pulighe, G., Zebisch, M., 2009. Semiautomatic classification procedure for updating landuse maps with high resolution optical images. *IEEE International Geoscience & Remote Sensing Symposium*. Cape Town, South Africa, July 2009.
- Oldeland, J., Dorigo, W., Lieckfeld, L., Lucieer, A. and Jurgens, N, 2010. Combining vegetation indices, constrained ordination and fuzzy classification for mapping semi-natural vegetation units from hyperspectral imagery, *Remote Sensing of Environment*, 114, (6) pp. 1155-1166.
- Punia, M., Nautiya, V.P. and Kant, Y., 2008. Identifying biomass burned patches of agriculture residue using satellite remote sensing data, *Current Science*, vol. 94, n° 9.
- Quinlan, J.R. (2003). Data Mining Tools See5 and C5.0. St. Ives NSW, Australia: RuleQuest Research. <http://www.rulequest.com/see5-info.html> (accessed 08 Apr. 2010)
- Rees W. G., 2001. *Physical Principles of remote Sensing*. Second Edition. Cambridge University Press. 343 pp.
- Schiewe, J., 2002. Segmentation of high-resolution remotely sensed data - concepts, applications and problems. *International Archives of Photogrammetry and Remote Sensing*. 34(4), pp. 380-385.
- Tsiligirides, T.A., 1998. Remote sensing as a tool for agricultural statistics: a case study of area frame sampling methodology in Hellas. *Computers and Electronics in Agriculture*, 20, pp. 45-77.
- Warner, T.A. and Steinmaus, K., 2005. Spatial classification of orchards and vineyards with high spatial resolution panchromatic imagery. *Photogrammetric Engineering & Remote Sensing*, 71, pp. 179-187.
- XiaoPing, L., Xia, L., XiaoJuan, P., HaiBo, L. & JinQiang H., 2007. Swarm intelligence for classification of remote sensing data. *Science in China Series D: Earth Sciences*, Volume 51, Number 1.
- Xu, M., Watanachaturaporn P., Varshney P.K., Arora M.K., 2005. Decision Tree Regression for Soft Classification of Remote Sensing Data. *Remote Sensing of Environment*, 97, pp. 322-336.