Detection of storm losses in alpine forest areas by different methodic approaches using high-resolution satellite data

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ABSTRACT: Based on the detection of storm losses in Swiss alpine forest areas, two different digital classification approaches were compared. In contrast to the pixel based classification we investigated an object-oriented classification procedure. The eCognition software package of Definiens offers this possibility. The comparison was performed for images with different spatial resolution – very high resolution images of IKONOS, and images of SPOT in the sharpened mode. The evaluation of the IKONOS image indicated a significantly higher accuracy for the object-oriented classification approach than for the pixel-based method. The eCognition software handles the high level of detail and the associated high texture better than the pixel-based parallelepiped-algorithm. The quality of the pixel-based approach, which takes into account only the spectral information and some derived data-products is limited for very high resolution images. The classification of the SPOT presented approximately the same results for both methods.

1 INTRODUCTION

In Switzerland thirty-one percent of the area are covered by forests which are of vital importance and playing multifunctional roles. Forest management as well as forest monitoring with remote sensing data have a long tradition in Swiss research work (Kellenberger, 1996). Especially as a result of the hurricane Lothar at the 26.12.1999 the public interest in forest management was growing.

During the last decades the classification of forest was in the focus of many remote sensing supported investigations. The spatial resolution of the available systems (Landsat, SPOT, IRS) ranged between thirty and twenty meters for multispectral data. The new generation of satellite-systems, like the spaceborne IKONOS system, offers a spatial resolution between one and four meters which allows on one hand new perspectives in many applications but on the other hand needs more basic investigations (Manakos et al., 2000).

Most classification approaches are based exclusively on the digital number of the pixel itself. Thereby only the spectral information is used for the classification. Limitations arise through this way of thinking, especially for the new sensor generation (Steinocher, 1999). The images show a very high level of detail and are very strong textured (Manakos et al., 2000). A single tree in a Landsat image for example appears as a homogenous object. The same object in an IKONOS image is represented as several pixels with different reflections. Due to this, homogenous objects are not only characterised by their spectral signature but also by the texture and their local context.

In order to overcome these limitations, an object oriented way of data assessment is adopted in new image analysis methods. The eCognition software promotes this new perspective (de Kok et al., 2000). By this new software product not single pixels are classified but homogenous image objects are extracted during a previous segmentation step. This segmentation can be done in multiple resolutions, thus allowing to differentiate several levels of objects categories (eCognition, 2000).

The objective of this study was to test a pixel-based approach against the object-based classification approach by eCognition for the detection of storm losses in alpine forest regions. Classifications were performed for two different satellite systems representing different spatial resolutions, SPOT and IKONOS. Another objective of this project was to extract rules and needs for a successful classification of storm losses.

2 MATERIALS AND METHODS

2.1 *Testsite*

The testsite is located in the area of Bern in Switzerland between 7°42'03"E and 7°50'48"E longitude and 46°40'55"N and 46°52'15"N. The main part belongs to both the alpine and the prealpine region. The altitude elevates between 555 m (Thunersee) and 2060m (Gemmenalphorn). According to this difference in elevation different plant societies exist, corresponding the altitude.

2.2 *Satellite data*

One IKONOS image was at our disposal collected at August, 12th 2000. The spatial resolution is 4 m for the multispectral channels and one meter for the panchromatic band. For the classification only the multispectral bands blue, green, red, and near infrared were used. Furthermore we could get a SPOT image, recorded at July, 2nd 2000. The processing of this SPOT image was done as "pansharpened" which results in an image with a spatial resolution of 10m. Before the merge with the panchromatic band, the original spatial resolution of the multispectral bands were twenty meters. The image was collected by the SPOT4 serie including green, red, near infrared, and middle infrared bands.

2.3 *GIS-Data*

In addition to the satellite data the forest areas of the national map 1:25'000 were available. This thematic layer was an important input into the classification process, and was resampled on the spatial resolution of the satellite data.

2.4 *Groundtruth*

The groundtruth is based on the visual interpretation of aerial images, collected shortly after the hazard. The interpretation of the damages was performed by several independent engineering companies. The groundtruth was resampled on the spatial resolution of the satellite data.

2.5 *Software*

The object-oriented classifications were performed with Definien's software product eCognition. On the other hand the ERDAS Imagine was used as well for the pixel-based approach as for the accuracy assessment and all image pre- and processing steps. The classifications were performed with ERDAS Imagine's expert-classifier and the accuracy assessment was realised with Modelmaker.

2.6 *Image Processing*

All satellite images were corrected geometrically and georeferenced to the national map 1:25'000. The images were resampled using the nearest neighbour algorithm. This georeferencing was necessary to eliminate the topographic effects and to connect the satellite data with the GIS-data described in 2.3 which is used for the classification.

2.7 *Pixel-oriented classification method*

The measured electromagnetic energy per pixel serves as the base for the pixel-oriented multispectral classification. Each pixel is characterised by a special reflectance in the multidimensional feature space (spectral signature). Due to this spectral signature the pixel will be associated to a certain class (Leiss, 1998). In contrast to a visual image-interpretation it is not possible to take into account contextual or topological information.

In this investigation the parallelepiped classification algorithm has been chosen representing a supervised pixel-oriented classification approach. The parallelepiped algorithm is based on a deterministic approach. The classification of an object-class is set by rectangular "regions of decision" in the multidimensional feature space. Each class is explicitly defined by a minimum and maximum value for one or several bands. The pixel is assigned to a class only as a result of the spectral information (digital number) for the different spectral bands. For the extraction the most suitable bands has been chosen. For further detailed information see also (Kraus et al., 1988). The selection of the bands was based on the maximum separability. As a result of the training samples a histogram was generated for each class. Further the exact value of the separation was computed, by the maximum difference of the relative cumulative frequency of each class (Kellenberger, 1996). This means that only spectral information was taken into account in the process of classification. The entire classification process can be summarised as follows.

1st step
Differentiation of forest areas from the rest on the base of the forest mask (see also 2.3)

2nd step
Selection of training-samples which describe the different object-classes

3rd step
Selection of the most suitable bands and computation of the parallelepiped values

4th step
Building the classification rules

5th step
Classification of the entire image

6th step
Accuracy assessment

2.8 *Object oriented*

The eCognition software allows an object-oriented classification. The basic difference, especially when compared to pixel-based procedures, is that object-oriented classification methods does not classify single pixels but rather image objects, which are extracted in a previous image segmentation step. eCognition allows the segmentation into highly homogenous object primitives in any chosen resolution. These object primitives represent the image information in an abstract manner. Beyond the spectral information many other additional attributes can then be used for classification: shape information, texture information, relations to neighbouring objects and a good deal more. The basic part of the software is the previously mentioned segmentation.. It was developed to extract image objects in optional resolutions and high quality (eCognition, 2000; Baatz et al., 2000).

eCognition supports supervised classification-techniques and provides different methods to train and build up a knowledge base. The frame of eCognition's knowledge based classification of image object is the so called class-hierarchy. This class-hierarchy contains the classification rules to which the image will be classified. Each class is defined by a class-descriptor which offers a lot of different parameters and object attributes. This way the forest-mask can be incorporated into the classification rule for example (eCognition, 2000; Baatz et al., 2000). The entire classification process is summarised in Figure 1.

1st step
All bands including the thematic layer were segmented in different levels representing the level of detail.

2nd step
Definition of the class-hierarchy and class-description. The distinction between forest and non-forest areas is based on the thematic layer containing the forest mask. The object class forest area was subdivided into the classes possible forest and possible forest damage. Training-samples for both subclasses were gathered.

3rd step
Based on the classification hierarchy the entire image was classified. The correlation to one of the subclasses was performed by a nearest-neighbour function which was calculated on the base of the training-samples.
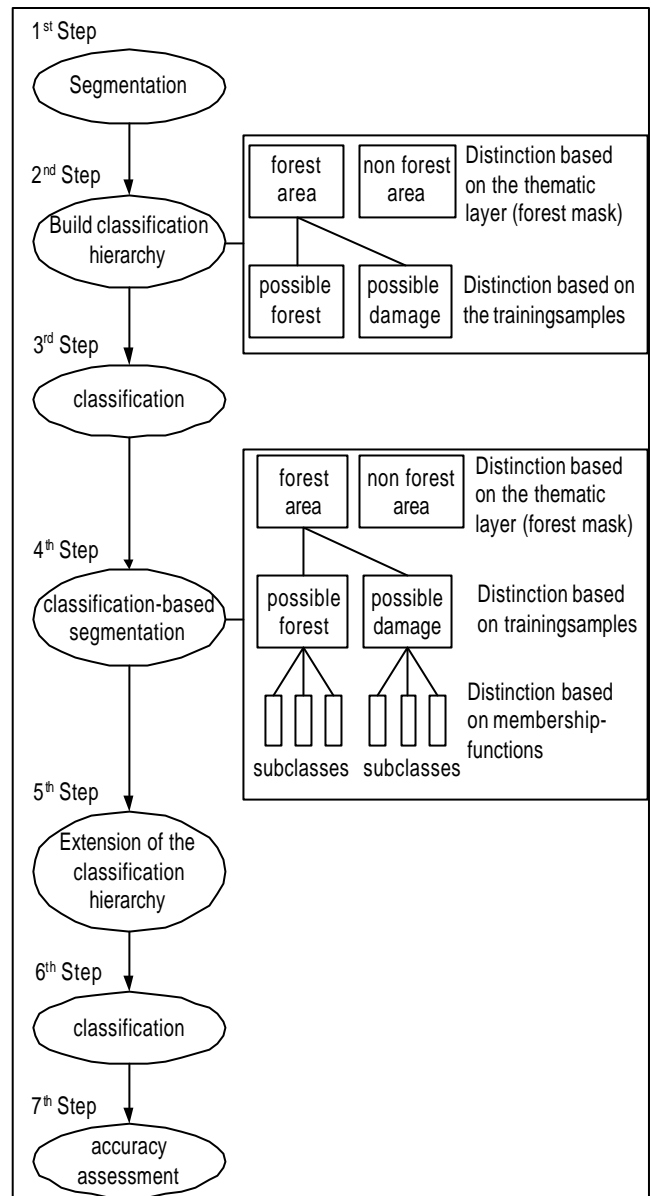

Figure 1. Classification process with the eCognition Software

4th step
Further a classification based segmentation was performed. In many cases image objects of interest cannot be extracted following a relatively general homogeneity criterion. For this reason, eCognition provides techniques for classification-based segmentation of image objects, merging neighbouring objects of the same structure group. The structure groups were built with the desired classes that were defined in the class hierarchy. All contiguous objects belonging to the same object class were merged to super objects. The advantage of this step presents the user driven segmentation. Figure 2 illustrates a part of the original IKONOS Image compared with the same part after a classification based segmentation illustrated in Figure 3. As a result of this step a new segmentation level was obtained.
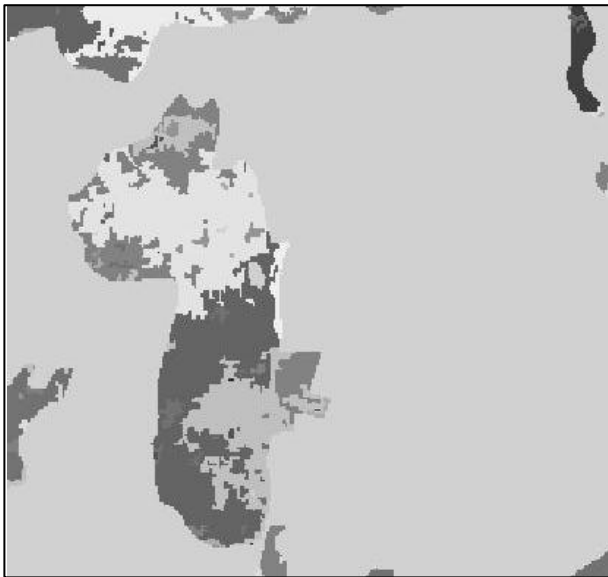
Figure 2. IKONOS Image (4m resolution)

Figure 3. IKONOS image after classification based segmentation

5th step
This new level was reclassified by defining a new class hierarchy. The classification was enhanced by using membership functions. The Membership functions allow the formulation of knowledge and concepts. They offer relationship between feature values and computed fuzzy values. The use of membership functions is recommended if a class can be separated from other classes by one or several features.

6th step
The classified image was imported into ERDAS Imagine where the accuracy assessment was performed.

2.9 *Accuracy assesment*

The classifications were compared to the groundtruth which is described in chapter 2.4 to assess the quality. An error matrix was computed based on the pixel to pixel comparison. Due to the error matrix, the following accuracy-parameters were calculated in order to obtain more reliable comments about the quality of the classification (Kellenberger, 1994).

Overall accuracy:
The sum of all correct classified pixels divided by the sum of pixels in the entire classification.

Producer accuracy:
The sum of all correctly classified pixels that belong to the class (x) divided by the sum of pixels in the ground-truth that belong to the class (x).

User accuracy:
The sum of all correctly classified pixels that belong to the class (x) divided by the sum of pixels in the classification that belong to the class (x).

Inclass accuracy:
The sum of all correctly classified pixels belonging to the class (x) divided by the sum of pixels belonging to the class (x) which are minor or surplus classified.

3 RESULTS

In this chapter, the results of the classifications are described. The creation of a difference-map proved to be a very useful tool for the analysis of the incorrectly classified pixels with respect to their spatial distribution. Therefore a difference map was calculated for each classification. Resulting classes were: correctly classified forest, correctly classified damage, surplus-classified forest, minor-classified forest. In the following figures each class is represented by the color described in Table1.

Table 1. Colortable for the difference-map

class	color
Not forest	white
Correctly classified forest	light grey
Surplus classified forest	dark grey
Minor classified forest	grey
Correctly classified damage	black

3.1 *Pixel-oriented classification results*

Table 2 presents the most important results of the accuracy assessment. For the IKONOS image the accuracy was slightly better as for the SPOT image. The IKONOS classification obtained an inclass-accuracy of 1.49 for the object class damage, compared to 1.31 for the SPOT classification. Within the testsite 43.5ha of damage-areas were found in the IKONOS image and

42.5ha in the SPOT image, compared to 44.1ha in the groundtruth. For both classifications the user accuracy and the producer accuracy were quite the same. This indicates that the classification was satisfying balanced. The best feature extraction was achieved by the green, red and near spectral channels. The derived Normalized Difference Vegetation Index (NDVI) could improve the results slightly but not significantly. The results shown in the table are the results without using the NDVI.

Table 2. Accuracy assessment of the pixel-oriented classification

Setting	SPOT		IKONOS	
	forest	damage	forest	damage
area [ha]	546.9	42.5	542.9	43.5
inclass-accuracy	22.26	1.31	24.20	1.49
user-accuracy	0.98	0.74	0.98	0.76
producer-accuracy	0.98	0.71	0.98	0.74
overall-accuracy	0.96		0.97	

3.2 Object-oriented classification results

In Table 3 the results of the accuracy assessment for the object oriented classification are shown. The accuracy for the IKONOS image was significantly better than for the SPOT image. The calculated inclass-accuracy for the object class damage is 1.29 for the SPOT image compared to 2.16 for the IKONOS image. Within the testsite 44.7ha of damages were found in the IKONOS image and 40.9ha in the SPOT image compared to 44.0ha in the groundtruth. For both images the user-accuracy and the producer-accuracy were quite the same, which means that the classification was satisfying balanced. The best feature extraction was achieved by the green, red and near spectral channels. The derived Normalized Difference Vegetation Index (NDVI) could improve the results slightly but not significantly. The results shown in the table are the results without using the NDVI.

Table 3. Accuracy assessment of the object-oriented classification

Setting	SPOT		IKONOS	
	forest	damage	forest	damage
area [ha]	548.9	40.5	541.8	44.6
inclass-accuracy	22.45	1.29	31.98	2.16
user-accuracy	0.75	0.98	0.81	0.99
producer-accuracy	0.69	0.98	0.81	0.98
overall-accuracy	0.96		0.97	

3.3 Pixel-oriented versus object-oriented approach (SPOT)

Both, the pixel-oriented and the object-oriented classification approaches revealed similar results with comparable accuracy. The inclass-accuracy varied from 1.31 for the pixel-oriented to 1.29 for the object-oriented classification method. The sources of errors were well recognised by analysing the difference images. Most

popular errors appeared at the borders of the damages. It seems that there still is a problem in the geometric accuracy of the georectification. Although all data were georeferenced a certain inexactness in the geometric position implicates some errors. Further a few small damages were not recognised which is due to the spatial resolution. Other errors are found in steep slopes, west to north-east oriented. These errors are mainly based upon the low solar radiation in those areas. A similar problem was detected by the shadows of the healthy trees which affect the areas located in the south of a damage section. Figure 4–5 show the Difference-Map for a part of the testsite with the object- and the pixel-oriented classification.

Figure 4. Difference-map with the pixel-oriented classification for the SPOT image (for color explanation see Table 1)

Figure 5. Difference-map with the object-oriented classification for the SPOT image (for color explanation see Table 1)

3.4 Pixel-oriented versus object-oriented approach (IKONOS)

The accuracy-assessment reveals a significant difference. The inclass-accuracy for example varies from 1.49 for the pixel-oriented approach to 2.16 for the object-oriented classification method. In addition to the errors described in the previous section, some misclassifications are implicitly due to the higher spatial resolution of

the IKONOS data with its increasing level of detail and texture. Trees or shrubbery are sometimes within obviously damaged areas. The digital number of these pixels are the same values as of the vital vegetation but in fact these objects should be grouped to the damage class. This problem can not be handled by the pixel-oriented approach but by the object-oriented method. A similar problem was recognised for unclenched forest stands: Figure 6 shows the noisy pixel-oriented classification in contrast the homogenous result with the eCognition software and the right hand side shown in Figure 7.
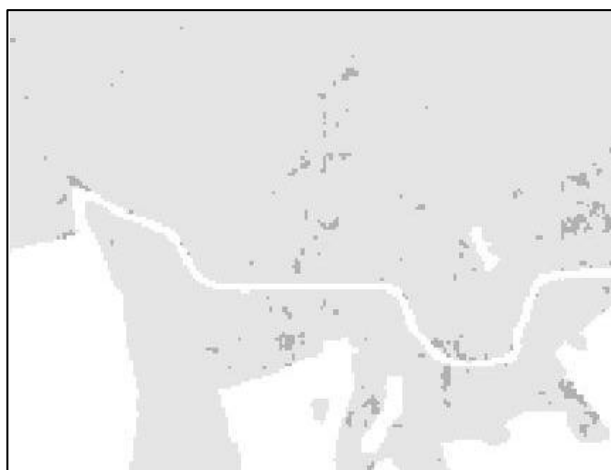

Figure 6. Difference-map performed by the pixel-oriented-approach for the IKONOS image (for color explanation see Table 1)
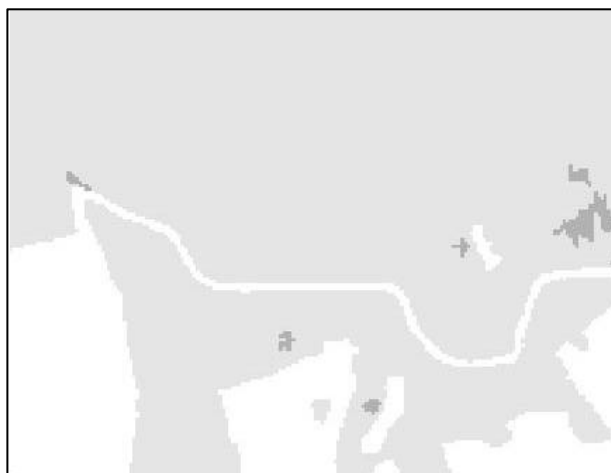

Figure 7. Difference-map performed by the object-oriented-approach for the IKONOS image (for color explanation see Table 1)

Due to the geometric inexactness some missclassifications along streets or along the border of forest with the pixel-oriented method were found (Figure 8). These missclassifications could avoided with the eCognition software as Figure 9 illustrates.

Figure 8. Difference-map performed by the pixel-oriented-approach for the IKONOS image (for color explanation see Table 1)

Figure 9. Difference-map performed by the object-oriented-approach for the IKONOS image (for color explanation see Table 1)

4 DISCUSSION AND OUTLOOK

In this study two different classification approaches were tested for satellite systems with different spatial resolutions. The investigation was based on the detection of storm losses in alpine forest areas.

The classification of the SPOT image shows that both, the pixel-oriented and the object-oriented classification approach revealed similar results and comparable accuracy. Both methods are available within software packages suitable for operational application in business or research work. As long as the spatial resolution ranges between ten and thirty meters no significant difference can be detected for the overall-accuracy.

Classifications of the IKONOS image show that the usage of eCognition results in a significantly higher accuracy. The pixel-based approach reached its limits of operational use because of the internal variance and the level of texture of the spectral image information. For this reason the pixel-oriented approach is not very helpful not only in terms of detection of recent storm losses but also of land-use classification in general. To overcome this problem, an object based analysis should be

preferred. Moreover the eCognition software allows good integration of GIS- and remote sensing data. With the possibilities to implement additional information about the geographic position, orientation and the relationship to neighbouring objects a better classification is guaranteed. The expert knowledge can be incorporated and the implicit richness of information can be fully exploited.

Further on a few general perceptions in terms of detection of recent forest losses could have been set up. A satisfying classification is only assessed by including external GIS-data for the rough boundaries of forests.. Areas with recent forest damage may have the same reflectance as parts of urban areas or bare agricultural land. The green, red and NIR are the spectral bands which are well suited for this kind of classification. In some cases the use of the normalised difference vegetation index NDVI could be a helpful additional information. For a proper classification result the satellite images should be collected during the vegetation period from mid May to mid October, otherwise deciduous forest will not be classified well enough.

For a more complex land-use classification the possibilities offered by the eCognition software will surely improve the results. The user friendly way to include spatial, contextual and internal object information will be the standard in image interpretation software for the future.

5 REFERENCES

Baatz, M. & Schäpe, A. 2000. Multiresolution Segmentation - an optimization approach for high quality multi-scale image segmentation. Proceedings, Angewandte Geographische Informationsverarbeitung (AGIT) XII. Salzburg: AGIT

Darvishsefat, A. 1995. Einsatz und Fusion von multisensoralen Satellitenbilddaten zur Erfassung von Waldinventuren. Dissertation, Remote Sensing Series Vol.24. Zürich: Remote Sensing Series

De Kok, R. & Buck, A. & Schneider, T. & Ammer, U. 2000. Analysis of image objects from VHR imagery for forest GIS updating in the Bavarian Alps. ISPRS 2000, Vol. XXXIII, Working Group III/5, Amsterdam: ISPRS

Ecognition, 2000. Ecognition User guide, München: Definiens

Kellenberger, T. 1996. Erfassung der Waldfläche in der Schweiz mit multispektralen Satellitenbilddaten. Dissertation, Remote Sensing Series Vol.28. Zürich: Remote Sensing Series

Kraus, K. & Schneider, W. 1988. Fernerkundung, Band 2, Auswertung photographischer und digitaler Bilder. Bonn:Dümmler Verlag

Manakos, I. & Schneider, T. & Ammer, U. 2000. A comparison between the ISODATA and the eCognition classification methods on basis of field data. ISPRS, Vol. XXXIII, Supplement CD. Amsterdam: ISPRS

Leiss, I. 1998. Landnutzungskartierung mit Hilfe multitemporaler Erdbeobachtungs-Satellitendaten. Dissertation. Zürich: Geographisches Institut Zürich, Switzerland

Steinocher, K. 1997. Texturanalyse zur Detektion von Siedlungsgebieten in hochauflösenden panchromatischen Satellitenbilddaten. In Dollinger, F. & Srobl, J. Proc. of Angewandte Geographsche Informationsverarbeitung, IX, Salzburger Geographische Materialien, No. 26. Salzburg: