Assessing changes of forest area and shrub encroachment in a mire ecosystem using digital surface models and CIR aerial images

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Abstract

This paper presents an approach to assess increase and decrease (2002-1997) of forest area and other wooded areas in a mire biotope in the Pre-alpine zone of Central Switzerland using logistic regression models and airborne remote sensing data (CIR aerial images, DSM derived from them). The present study was carried out in the framework of the Swiss Mire Protection Program, where increase and decrease of forest areas are a key issue. In a first step, automatic DSMs were generated using an image matching approach from CIR aerial images of 1997 and 2002. In a second step, the DSMs were co-registered and normalized using Lidar data. Tree layers from both years of various levels of detail were then generated combining canopy covers derived from normalized DSMs with a multi-resolution segmentation and a fuzzy classification. On the basis of these tree layers, fractional tree/shrub covers were calculated using explanatory variables derived from these DSMs only. Bias was estimated by analyzing the distribution of the fractional model differences. The corrected models reveal a decrease of tree/shrub probability which indicates a decrease of forest and other wooded areas between 1997 and 2002. The models also indicate real shrub encroachment in open mire. The detection of shrub encroachment may be helpful for selective logging purposes for sustainable mire habitat management. The study stresses the importance of high-resolution and high-quality DSMs and highlights the potential of fractional covers for ecological modeling.

Keywords: canopy cover, change detection, fractional tree/shrub cover, multi-image matching, General Linear Model, LiDAR, Swiss Mire Protection Program

Abbreviations: CIR (colour-infrared), DSM (digital surface model), DTM (digital terrain model), GLM (generalized linear model), nDSM (normalized digital surface model), NIR (near-infrared)

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This paper presents an approach to assess increase and decrease (2002-1997) of forest area and other wooded areas in a mire biotope in the Pre-alpine zone of Central Switzerland using logistic regression models and airborne remote sensing data (CIR aerial images, DSM derived from them). The present study was carried out in the framework of the Swiss Mire Protection Program, where increase and decrease of forest areas are key issues. In a first step, automatic DSMs were generated using an image matching approach from CIR aerial images of 1997 and 2002. In a second step, the DSMs were co-registered and normalized using LiDAR data. Tree layers from both years of various levels of detail were then generated combining canopy covers derived from normalized DSMs with a multi-resolution segmentation and a fuzzy classification. On the basis of these tree layers, fractional tree/shrub covers were calculated using explanatory variables derived from these DSMs only. Bias was estimated by analyzing the distribution of the fractional model differences. The corrected models reveal a decrease of tree/shrub probability which indicates a decrease of forest and other wooded areas between 1997 and 2002. The models also indicate real shrub encroachment in open mire. The detection of shrub encroachment may be helpful for selective logging purposes for sustainable mire habitat management. The study stresses the importance of high-resolution and high-quality DSMs and highlights the potential of fractional covers for ecological modeling.

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1. Introduction

This study focuses on assessing increase and decrease of forest area and area of other woody species in mire ecosystems between 1997 and 2002 by means of logistic regression and Digital Surface Model (DSM) data derived from CIR aerial images. The study was carried out in the framework of the Swiss Mire Protection Program which aims at conserving mire ecosystems of national importance and outstanding beauty in their present state. This implies no decrease of the mire area and no degradation of vegetation. To examine the effectiveness of the conservation status, a long-term monitoring program was set up in 1996. Within this program, monitoring based on a representative sample of 130 mires was established to determine whether and how far this aim has been reached.

The definition of mire comprises all wetlands with the exception of floodplains and fen woodland. To assess the state and condition of the mire ecosystems for the purposes of further management and conservation targets, the mire areas and their vegetation were described over time and space in significant detail (Grünig et al., 2004; Küchler et al., 2004).

Taking into account that changes in the extent of forests, as well as shrub encroachment, may alter a sensitive mire biotope, early detection and evaluation of increase and decrease of the entire wooded area is indispensable and may help the preservation of these biotopes. Change detection in general is a prerequisite for monitoring programs and also of high importance for conservation efforts in mires and for future protection planning tasks, since both natural (e.g. storm losses) and anthropogenic changes (e.g. logging) influence biodiversity in ecosystems (Nagendra, 2001). The fact that sustainability has become a primary objective in present-day ecosystem management has as one of its consequences the continuous need for accurate and up-to-date land resource data (Coppin et al., 2004). According to Turner et al. (2003), continuously accurate and up-to-date information on land cover is needed for present-day ecosystem management. However, several studies (e.g. St-Onge and Achaichia, 2001; Watt and Donoghue, 2005) revealed that using traditional methods of field survey or aerial photograph interpretation to gain information on exact forest area, canopy height, single tree and shrub occurrence, and tree growth is not feasible for larger monitoring programs because of costs and time constraints. By contrast, increase and decrease of forest area and occurrence of shrubs can be estimated using high-resolution remotely sensed data. According to Laliberte et al. (2004), shrub abundance mapping and encroachment in ecosystems is often performed using object-oriented image analysis. Furthermore, recent progress in three dimensional remote sensing mainly includes digital stereophotogrammetry, radar interferometry and LiDAR (Hyyppä et al., 2000). For example, canopy height models can be calculated by subtracting a DTM from a DSM. DSMs can be generated automatically by image matching methods, whereby most commercial packages use cross-correlation or matching of interest points. Meanwhile, several LiDAR systems are commercially available (e.g. Baltsavias, 1999; Heurich et al., 2003), enabling the derivation of DSMs and DTMs from such data as well. Some studies suggest the use of DSM data to detect changes in the forest stands (Lefsky et al., 2002; Schardt et al., 2002; Naesset and Gobakken, 2005; Yu et al., 2004) and to evaluate growth estimations including extent of forest area and shrub encroachment.

There is also a growing need for sensitive tools to predict spatial and temporal patterns of plant species or communities (Kienast et al., 1996). Spatially explicit predictive modeling of vegetation using remotely sensed data is often used to construct current vegetation cover using information on the relations between current vegetation structure and various environmental attributes (Davis and Goetz, 1990; Küchler et al., 2004). Guisan and Zimmermann (2000), Scott et al. (2002) and Guisan et al. (2002) point out that modern regression approaches such as generalized linear models (GLM) and generalized additive models (GAM) have proven particularly useful for modeling spatial distribution of plant species (Guisan et al. 2004) and communities. Since old CIR aerial images are often available to calculate DSM variables, retrospective analysis of changes in forest area and shrub encroachment in a mire biotope is feasible. Thus, airborne remote sensing data in combination with GLMs could be useful for modeling changes in mire ecosystems over time.

The objective of the present study is to assess increase (shrub encroachment) and decrease (forest loss, logging) of forest area and area of other woody species in a mire ecosystem between 1997 and 2002 using DSMs derived from CIR aerial images as explanatory variables in logistic regression models. The method consists of two steps. First, discrete forest masking from both years of two levels of detail were generated by combining canopy covers derived from normalized DSMs with a multi-resolution segmentation and a fuzzy classification. Second, on the basis of these tree layers, fractional tree/shrub covers are calculated using explanatory variables derived from these DSMs only. A fractional cover approach was chosen since it is widely known that the discretization of tree covers (Mathys et al., 2006) into a limited number of categories results in a loss of information and that fractional cover has higher potential to accurately describe land cover change over time (Hansen et al., 2002). The resulting shrub/tree cover maps contain the fraction of shrub/tree as a continuous variable and can be adapted easily and consistently to a range of protecting purposes as applied in the Swiss Mire Protection Program. For this modeling approach, a new image matching method (Zhang and Gruen, 2004) has been implemented.

2. Material and Methods

This section consists of several steps of processing (from the input data to the final models). As an overview the main steps of processing and the methodological workflow are given in Fig. 1.

Figure 1: Overview of the methodological workflow with main steps of processing.

2.1 Study Area

Models have been developed and tested for the mire “Eigenried-Oberallmig” which is located on a small plane in the East of Lake of Zug in the Pre-alpine zone of Central Switzerland (approx. 47°07’ N and 8°32’ E). The mire site covers an area of 2.61 km^2 whereas 1.72 km^2 belongs to the core area. The altitude varies from 850 m to 1000 m above sea level. The landscape is highly fragmented and characterized by pastures that are crossed by shrubs and broad-leafed woodland (see Fig. 2). The dominant vegetation types are moist and wet meadows and pastures (*Molinietalia caeruleae, Potentillo-Polygonetalia*), low sedge poor fen (*Caricetalia fuscae*), bog forest (*Sphagno-Betuletalia*) and broad-leaved woodland. The bordering forested area, with an extent of approx. 0.85 km^2, is mostly characterized by opened mixed forest (approx. 40%) and coniferous forest (approx. 60%). The most relevant changes for the present study between 1997 and 2002 are forest loss caused by hurricane *Lothar* (1999), permanent shrub encroachment in open mire land, and selective logging activities and cutting of shrubs as a result of conservation efforts.

Figure 2. Left: Overview of the test site (Pixelmap © 2006 Swisstopo JD052552); right: bog and fenland, broad-leafed woodland and shrubs typical for the mire.

2.2 Remotely sensed data

This study uses three different sets of input data: CIR aerial images, DSMs derived from it and LiDAR data. For the present study, all data sets were resampled to 0.5 m.

1. The first data set consists of CIR aerial images: 4 (1 strip) of 1997 and 12 (2 strips) of 2002. Table 1 gives an overview of the scanned image data used in this study. The 1997 film images had severe scratches on the emulsion side, causing artifacts in the digitized images and DSM errors in the automated DSM generation. Image orientation was established with 15 ground control points measured by a differential GPS survey and using bundle adjustment. RMS of image residuals was 0.198 image pixels for 1997 and 0.227 for 2002, respectively. The orientation error characteristics for 1997 and 2002 differed, and especially for 2002 some of the border images had significant errors and differences with their neighboring images, causing jumps in the generated DSM (see section 2.4.2). Two CIR orthoimages of 1997 and 2002 with ground pixel size of 0.5 m were produced.

Table 1. Characteristics of the CIR aerial images.

2. The DSMs have a spatial resolution of 0.5 m. Both were generated automatically from the above images of the years 1997 and 2002, respectively (see section 2.4).

3. National LiDAR data of the Swiss Federal Office of Topography (Swisstopo) was acquired in 2001 with leaves-off. From the raw data, both a DTM and DSM are generated by Swisstopo (as raw irregularly distributed points and regular grid; the first dataset was used in this study). The average density of the DSM data was 1-2 points / m^2 and the height accuracy was (1 sigma) 0.5 m for open areas and 1.5 m for vegetation and buildings. The DTM has an average point density of 0.8 points / m^2 and height accuracy

was (1 sigma) of 0.5 m (Artuso et al. 2003). The DTM was interpolated to a regular grid with 0.5 m grid spacing for reasons explained below.

2.3 Ground truth

Ground truth data to validate the different outputs of the current study (tree layers and fractional models) was produced using digitized samples from stereo-images. Three types of samples were distinguished and a total number of 3 x 65 samples were digitized from the aerial images of 1997 and 2002: 1) Tree/shrub-less areas in 2002 that belonged to tree/shrubs in 1997 (decrease, 0.0283km^2), 2) Tree/shrub-less areas in 1997 that are covered with trees/shrubs in 2002 (increase, 0.0469km^2) and 3) Tree/shrub areas and tree/shrub-less areas that are unchanged between 1997 and 2002 (equal, 0.0319km^2).

2.4 Automatic generation of digital surface models

2.4.1 Matching

Since accurate surface information in forested and open mire land is indispensible for modelling, a matching method was applied which is described in detail in Zhang (2005) and in Zhang and Gruen (2004).

The matching method first performs pre-processing to reduce noise without smoothing edges and enhances the contrast. It combines the matching results of the three primitive types (feature points with good texture for high-accuracy matching, edges for good modelling of surface discontinuities, and grid points for bridging over areas with poor texture) at each pyramid level with probability relaxation matching to ensure local consistency and detect matching blunders. The method combines two matching algorithms: sum of modified cross-correlation, and at the last pyramid level optionally least squares matching that slightly increases accuracy and detects additional blunders. From the raw match points, a regular grid is interpolated. The matching method is implemented in the operational, quasi-complete photogrammetric processing package Sat-PP which supports satellite and aerial sensors with frame and linear array geometry. The matching method used the interior and exterior orientation. The resulting DSMs had a grid spacing of 0.5 m. In a first run, panchromatic images derived from averaging the RGB channels were used for matching. In a second run, the channel that would best allow modelling the vegetation surface was selected. Through visual inspection, it was determined that the blue channel (showing actually information in green) showed more details on vegetation canopy, while in open surfaces and buildings it was similar or slightly worse. More contrast and texture are obtained in areas of forest openings (even if they are covered with shadows) where the ground is often covered with grass and/or small bushes (Fig. 3). This might also be due to specific spectral characteristics of the film, the spectral characteristics of the used scanner and the scanning parameters. Thus in all further investigations, the blue channel DSM was used.

Figure 3. Colour-coded matching DSM from averaging the RGB channels (left) and using only the blue channel (right). The right DSM shows a better modelling of tree individuals and small openings (circle) between trees.

The 1997 DSM was quite noisy due to the film scratches that caused several artifacts during the digitization. The noise was especially apparent in homogeneous areas (like grassland and pastures), causing surface discontinuities that could be partially misinterpreted as shrubs and has to be considered when modeling changes of tree/shrub area between 1997 and 2002 (see Fig. 4). It was also of inferior quality compared to the 2002 DSM due to the larger ground pixel size. The 2002 DSM showed some stripes (Fig. 4), probably caused by film scanner errors, which were corrected for the 1997 image scanning after performing a new scanner calibration.

Figure 4. Detail of the 1997 (left) and 2002 (right) DSMs. The noise in the 1997 DSM is clearly visible in bare ground areas. Some stripes are visible in the 2002 DSM again on bare ground. Shrub encroachment in 2002 is clearly visible on the top right.

2.4.2 Co-registration

The matching DSMs of 1997 and 2002, and the LiDAR DSM and DTM were co-registered, using a point cloud co-registration procedure described in Akca (2005), Gruen and Akca (2005) and Akca and Gruen (2005). This co-registration uses a 7-parameter 3D similarity transformation to remove systematic differences (bias) between two datasets, e.g. due to different image orientation. To estimate these parameters, control surfaces such as DSM features that did not change in the two datasets such as bare ground were used while large differences due to matching errors were removed by robust filtering. Among the seven parameters, only the three X, Y, Z shifts were significant. After co-registration, the Euclidian distances between the two datasets and the X, Y, Z components were calculated, the latter being more important for these investigations. After co-registration of the 1997 and 2002 DSMs, the Z-component of the Euclidian distances (sigma a posteriori) was 3.4 m, showing a clear reduction of trees and other wooded plants from 1997 to 2002. The difference between the DSMs minus the LiDAR DTM gives the normalized DSMs (nDSMs), i.e. the 3D objects and especially the canopy models. The LiDAR DSM was also subtracted from the 2002 DSM in spite of the small time difference. This could give a comparison between the two DSMs and also an indication to what extent LiDAR penetrates the tree canopy more compared to matching, a characteristic that was observed in previous studies (see Baltsavias et al., 2006). After co-registration, the Z-component of the Euclidian distances (sigma a posteriori) was 0.8 m, however, there is no indication as to whether the LiDAR or the matching DSM is more accurate, especially since the LiDAR data were acquired with leaves off.

Results are shown in Fig. 5.

Figure 5. a) Z component of the Euclidian distances 1997 - 2002 DSM showing clearly areas of deforestation and shrub encroachment. **b)** Z component of the Euclidian distances LiDAR DSM - 2002 DSM. At the top and bottom, the effect of the stripes in the matching DSM due to film scanner miscalibration is visible. The orange areas at the top left are probably due to differences in image orientation between the two flight strips and within each strip causing discontinuities in the 2002 DSM. These areas are also visible in Fig. 5. a) but have less sharp boundaries due to the noise of the 1997 matching DSM. Due to software limitations regarding computer memory, the LiDAR DSM and DSM were sub-sampled to a 2.5m grid

2.5 Tree layers

Two levels of generalization for tree layers serve as the basis (response variable) for the fractional modeling approach. Two canopy covers were calculated by a multistage procedure using slope data of the nDSMs of 1997 and 2002. This simple but robust algorithm incorporates a slope threshold, minimum area for tree canopy and minimum area for forest gaps in the nDSM data. In a second step, non-tree objects (buildings, rocks etc.) of the canopy covers were removed by an object-oriented image analysis using CIR orthoimages spectral information. This implies a two stage process with a multi-resolution segmentation of the canopy cover and the CIR orthoimages (1997 and 2002) and a fuzzy classification using eCognition (Baatz and Schäpe, 2000). The resulting tree layers have a spatial resolution of 0.5 m and have most previous errors removed.

For the purpose of the present study, a total of four tree layers (two for 1997 and two for 2002) were produced using different slope thresholds, minimum tree canopy area and minimum gap size. Tree layers that lie in between these thresholds have different levels of generalization of the forest area but are appropriate for the fractional modeling approach.

The thresholds for the three parameters were set empirically but have been successfully tested for fine-scale modeling of forest area in mire ecosystems by Küchler et al. (2004). For the more detailed tree layers, *trees97_detail* and *trees02_detail*, all slope values of higher than 15 degrees, a minimum tree canopy area on single tree level (1.25 m^2) and a maximum gap size of 120 m^2 were considered. For the more generalized tree layers *trees97_general* and *trees02_general,* only pixels with slope values higher than 25 degrees, a minimum tree canopy area on single tree level (7.5 m^2) and a maximum gap size of 150 m^2 were considered. This means that less tree–like objects are extracted and the resulting tree area is smaller than in the first tree layers.

2.6 Quantifying changes in tree and shrub occurrence

Coppin et al. (2004) and Lu et al. (2004) present various change detection algorithms and techniques in ecosystem monitoring. Ideally one would like to use imagery from the same sensor to keep the sensor characteristics as consistent as possible. It should be noted that even using imagery from the same sensor is no guarantee that the sensor characteristics will be equal. A straight forward approach to quantify the changes in tree and shrub occurrence would be just to compute the difference between tree layers from two survey times (e.g. *trees02_detail – trees97_detail*) after the co-registration of the two data sets. However, a possible bias may result from different data quality of the CIR aerial images from the two survey times, e.g. different spatial resolution, different image scanning facilities, varying radiation, and different acquisition data (different status of phenology of trees and shrubs). Thus, in the present study estimation of such bias and its reduction or elimination is a key issue.

2.6.1 Model choice: logistic regression

According to Toner and Keddy (1997), logistic regression is often used to predict probabilities for presence/absence of a specific vegetation type at each point. Shrub/tree occurrence maps can be constructed by analysis of these probabilities' actual occurrence.

The logistic regression model is a special case of the generalized linear model (GLM) and is adapted for modeling such data (see e.g. McCullagh and Nelder 1983). The formula of the logistic regression function is given in Hosmer and Lemeshow (1989). Whether a pixel belongs to a tree layer or not can be attributed to a binomial variable. The result is a fractional tree/shrub cover, i.e. a probability for each pixel to belong to the class "tree/shrub". The training data for the model were selected in a way to enable estimation of bias: pixels were only used which belong to the same class in both surveys, i.e. that were either corresponding tree pixels or open land pixels in the 1997 and 2002 layers.

The explanatory variables consist of five commonly used topographic parameters derived from nDSMs: slope, aspect, curvature, and local neighboring functions; see Table 2 and for further details see Burrough (1986). Most of these parameters have been successfully applied for ecological modeling purposes in mires (Küchler et al., 2004) or in biodiversity studies (Waser et al., 2004).

Two pairs of fractional tree/shrub covers per year (1997 and 2002) were produced using the tree layers described in section 2.5: one pair based on more detailed layers, the other pair using the more generalized layer version.

Table 2. Overview of the five explanatory variables (derived from nDSM) used to generate the fractional shrub/tree covers.

2.6.2 Bias estimation

In the context of predictive modeling, bias denotes a systematic error in predicted values which might be misinterpreted as a change. Küchler et al. (2006) present a method of estimating bias arising from different data quality in two surveys. This method works for metric response variables in a multiple linear model. In the present study however, one has to deal with a categorical response variable in a nonlinear regression.

The problem in estimating bias is to discern between real change (increase and decrease of forest area) and model error. The model error consists of two components: the random error and the systematic error or bias. To estimate bias, random error and real change has to be estimated as well. At the level of single pixels, the random error is much greater than change or systematic error. This can be managed by smoothing the generalized and the detailed fractional tree/shrub covers of the years 1997 and 2002 with a moving window before computing the difference. A window size of 5 x 5 m with the arithmetic mean as the focal function was chosen. If no change has occurred and no bias is involved, the differences between the smoothed fractional covers are random. For small ranges within the response variable space, one assumes these random errors to be normally distributed around a mean of 0. If bias is involved, the mean of the error will shift away from 0. In addition, there can be a real change. If this change does not affect the entire area homogeneously, then only a part of the differences is affected by the change. The distribution of the differences will then be long-tailed, or if the changes in one direction are predominant, the distribution will be skewed or even bimodal. As long as the pixels with real change are in the minority (see Fig. 7b), bias can be estimated by the mode of the distribution. That is, mean minus mode would then be a corrected estimation of the change. In the present study, bias is estimated by the following procedure: The probabilities of each pixel of the corresponding smoothed fractional covers (i.e. *model_general_uncorr* and *model_detail_uncorr*) were added together and the sums stratified into 20 classes. The lowest class (0.0 - 0.1) of model sums corresponds to "non-tree/shrub" whereas the highest class (1.9 - 2.0) corresponds to "tree/forest". Intermediate classes represent either partly forested areas or areas that have been deforested or areas where shrub encroachment occurred. Then the smoothed fractional covers of 1997 were subtracted from the smoothed fractional covers of 2002. The distributions of the resulting differences were analysed separately within each of the 20 classes. As result, discrete bias estimations for each class were obtained. To have a continuous bias estimation the discrete values were smoothed by Loess regression with a span of 0.3. Bias correction was performed by subtracting the values from the differences between the fractional tree/shrub covers.

To summarize this section, the main steps of processing and the methodological workflow are given in Fig. 1.

3. Results

3.1. Tree layers

Visual image analysis revealed some differences between the two different tree layers in forest clearings and in some parts of the open forest areas of the mire. In these areas the fractional tree/shrub covers based on the detailed tree layers (*trees97_detail* and *trees02_detail*) seem to be more precise. Fig. 6 a-d visualizes the difference between the two tree layers of both years in a typical part of the mire where small shrubs and single trees are present. Tree/shrub area estimation depends on the three threshold values used in tree layer estimation. The tree area extracted by the four layers *trees97_general* *(trees02_general)* is 0.9184km^2 (0.7299km^2) and by *trees97_detail (trees02_detail)* 0.8534km^2 (0.8112km^2) respectively.

Figure 6. a) CIR orthoimage with generalized tree layers of 1997 and **b)** of 2002, **c)** and **d)** more detailed tree layers, **e)** and **f)** corresponding fractional tree/shrub covers. The two circles on the left side mark areas with decreased tree/shrub cover due to deforestation/logging. The two circles on the right side mark increased tree growth / shrub encroachment.

Visual image inspection revealed that several shrubs and small single trees are still not extracted in the remaining open mire land.

3.2. Fractional tree/shrub covers

Two pairs of fractional tree/shrub covers per year (1997 and 2002) were produced using the tree layers described in section 2.5. A tree/shrub cover stratum of 0.1 - 1 (10-100%) means that all pixels with a probability higher than 10% are assigned to the shrub/tree class. Fig 6.e-f) shows the five predicted tree/shrub cover strata for a typical part of the mire. Tree/shrub area that is previously missed by the detailed tree layers is extracted by dependence on the threshold of probability. Area of extracted trees/shrubs increases with lower probability thresholds. At the same time errors increase as well. For example, visual stereo image analysis revealed that a cover stratum of 10-100% also considers vegetation other than shrubs such as tall grass or herbs. By contrast, considering only a cover stratum of 0.5 – 1.0 (50-100%) leads to a significant underestimation of shrubs and trees in the open mire land.

3.3 Bias estimation

Suspicion of bias arises when analysing the logistic regression lines on the variables of the normalized DSMs for the detailed fractional tree/shrub covers. The intercept and the regression coefficients are different for the two surveys (1997 and 2002). Given the well-defined training data, the most plausible explanation for different coefficients (different steepness of the lines) is the different quality of the nDSM's. Pixels of the 1997 model with low slope values show higher probability for tree/shrub than in the 2002 model. This is due to a slightly rougher surface of the nDSM in open mire land and might be a result of scale, quality and date and time of acquisition of the 1997 CIR aerial images.

Bias was estimated by subtracting the smoothed fractional covers and analysing the distribution of the differences within 20 classes of the model sums (i.e. *model_general_uncorr* and *model_detail_uncorr*, respectively). Distributions of model differences within four typical classes of model sums are displayed in Fig. 7.

Figure 7. Distribution of differences between the fractional tree/shrub covers from both surveys in four different classes (x). Y-axis: number of counts. **a)** class 0 - 0.1, **b)** class 0.8-0.9, **c)** class 1.2 - 1.3, **d)** class 1.8 - 1.9.

Fig. 7a shows the distribution of differences in the lowest class of model sums. The differences follow a normal distribution, but the mode is negative, which points to apparent deforestation. As tree-like objects were never present in the area concerned, this deviation from 0 must be bias. Fig. 7b displays the distribution of differences in a class of model sums which corresponds to locations that were partly forested in 1997 and 2002, or areas that meanwhile have been deforested or where shrub encroachment occurred.

The mode of the distribution is near 0 which can be interpreted as a small bias. There is a second local maximum of differences at about -0.7 that can be attributed to deforestation. Fig. 7c shows the distribution within a class of model sums which denotes a relatively dense forest in common in the two surveys. The mode of the distribution is greater than 0 which can be interpreted as a bias (apparent density increase). The distribution is skewed at the negative end which can be attributed to deforestation. Fig. 7d displays the distribution of differences in a high class of model sums which corresponds to locations that were forested in both surveys. The mode of the distribution is markedly above 0 which denotes a bias (apparent density increase).

Estimated bias, the uncorrected mean differences and the corrected mean differences (i.e. changes) within all of the 20 classes, are visualized in Fig. 8. The two upper curves show the bias when using the models based on more general or detailed tree layers. Bias is negative in lower classes of model sums (areas with low trees/shrub probabilities, e.g. grassland, open mire land). Bias arises and is positive in higher classes of model sums (areas with high tree/shrub probabilities such as forests). Since uncorrected models contain bias they indicate an apparent increase of the tree/shrub area in areas which correspond to approx. classes between 1.2 – 1.8. Since both corrected models (based on the general and detailed tree layers) indicate similar decrease of the tree/shrub areas (nearly congruent curves), the chosen fractional cover approach can be regarded as robust.

Figure 8. Mean differences, bias (estimated by mode) and corrected differences of smoothed fractional tree/shrub covers for 20 classes of model sums. Lowest class (0.0 - 0.1) of model sums corresponds to “non-tree/shrub” whereas the highest class (1.9 – 2.0) corresponds to “forest”. Intermediate classes

represent either partly forested area or areas that have been deforested or areas where shrub encroachment occurred.

3.4 Decrease and increase of forest area and other wooded area (1997-2002)

Changes of tree/shrub probabilities between 1997 and 2002 are summarized in Table 3. Both the generalized and the more detailed tree layers reveal a decrease of tree/shrub pixel portion of -0.073 and -0.018 between 1997 and 2002 respectively. The different results are due to the different input parameters (minimum slope threshold, tree canopy area, and gap size) used for the tree layer-algorithms. One assumes that the decrease is in the same range in both tree layers but the increase in small trees/shrubs is detected less by the more generalized tree layers. Also, both fractional cover approaches revealed a decrease of tree/shrub probability in the range of -0.036 to -0.039 between 1997 and 2002 respectively. The scores of the uncorrected models are given in Table 3.

Table 3. Variations of change estimations for tree/shrub (1997-2002) as obtained by different methods.

The differences of tree/shrub probability as obtained by the corrected model (detailed fractional shrub/tree covers) are shown in Fig. 9. Decrease of trees and shrubs due to logging are displayed in red whereas increase due to shrub encroachment is displayed in green; non-changed areas are displayed in yellow.

Figure 9. a) CIR orthoimage 1997, **b)** CIR orthoimage 2002 **c)** corrected changes of tree/shrub probability of forest and other wooded areas with decrease (red), no change (yellow) and increase (green).

3.5 Validation

Changes of tree/shrub pixel portion between 1997 and 2002 on the digitized sample areas between the tree layers and the changes of tree/shrub probability of the corrected fractional covers is summarized in Tables 4-7. An accuracy assessment of the tree layers and the fractional tree/shrub covers was performed by means of statistical measures: kappa coefficient (K), the correct classification rate (CCR) and the correlation coefficient (r). For details see Congalton (1991). Both tree layers and fractional covers reveal no decrease/increase between 1997 and 2002 concurring with sampled no-change areas. Both tree layers and corrected models show a substantial decrease in tree/shrub probability in delineated areas where tree/shrub area declined between 1997 and 2002. Good information on deforestation is given by tree layer *trees97_02general*. Shrub encroachment and growth of small trees in open mire land is not or only slightly detected when using the generalized tree layers (+0.052). In contrast, both the detailed tree covers (+0.490) and the models (+0.150, +0.174) show shrub encroachment (general increase of tree/shrub probability in areas that were delineated as increase).

Results based on tree layers substantially differ depending on the threshold values used for their generation. Alternatively, the model based approach seems to be more robust; the result differ only little depending on the training data used (generalized and detailed tree layers). *Kappa, CCR* and r are also only slightly different. A comparison of digitized samples with tree layers and fractional tree/shrub covers is given in Tables 4 - 7.

Table 4. Comparison of digitized samples with generalized tree layers.

Table 5. Comparison of digitized samples with detailed tree layers.

Table 6. Comparison of digitized samples with corrected models based on the generalized tree layers.

Table 7. Comparison of digitized samples with corrected models based on the detailed tree layers.

4. Discussion and Conclusion

The objective of this study was to assess decrease and increase of forest area and other wooded area and to estimate shrub encroachment between 1997 and 2002 using normalized DSM data and tree layers in logistic regression models. Combining remote sensing data with regression analysis as it is performed in many studies for land cover mapping (Guisan and Zimmermann 2000; Ju et al. 2003; Mathys et al. 2006) is shown to be appropriate for fractional tree/shrub cover mapping and assessing changes of tree area in a mire biotope. The use of standard explanatory variables as already applied in other studies (e.g. Küchler et al. 2004; Waser et al. 2004) derived from the nDSM, proved to be a good approach for fractional modeling. With a fractional cover approach, subtle changes of forest area and of other wooded area have been detected before reaching a discrete value which may be an advantage for mire habitat management. The present study reveals that different quality of the scanned CIR aerial images and the nDSMs, different scale and also different acquisition time from the two surveys 1997 and 2002 caused systematic errors in the predicted values of the models which could be misinterpreted as a change of tree area and could therefore not simply be ignored. In fact, bias proved to occur at a scale which would, without correction, making a reproducible statement as to whether the removal of trees and shrubs or the encroachment by growing bushes was predominant in the survey time impossible. Estimation and correction for bias is essential if any change has to be assessed by statistical modelling.

Overall, the present study reveals a decrease of forest and other wooded areas since 1997 although shrub encroachment occurred in some parts of open mire land. This general decrease has two reasons: 1) most forest clearings in this region were caused by hurricane *Lothar* in 1999 and 2) selective logging of groups of trees, single trees, shrubs in open mire land in the frame work of the regeneration program. The difference in the corrected fractional tree/shrub cover indicate the magnitude of changes and spatial distribution of tree area between 1997 and 2002. Local experts assume that changes in the mire "Eigenried" may not considerably alter this sensitive biotope provided that current selective logging and deforestation measures will continue in the same range. Areas showing shrub encroachment may present a risk of disappearance of sensitive plant species communities by changing habitat conditions. Early detection of shrub encroachment is therefore essential for assessing possible changes of moisture, nutrient and light (e.g. drier conditions with less light and more eutrophication). Different environmental conditions may then lead to changes in species distribution.

Our future work will include the retrieval of the type of trees/shrubs which gives important information on the magnitude of growth. We also plan to compare the decrease and increase of forest area with new field data and to assess possible changes in species distribution.

However, both the accuracy of the tree layers and the fractional tree/shrub covers strongly depend on the accuracy of the DSM data. Thus, DSMs derived from newly developed, high-quality matching methods are indispensable. The use of dense and accurate DSMs are absolute prerequisites in order to derive accurate topographic parameters which in turn can be used to derive the tree layers and the fractional tree/shrub covers. The existing national LiDAR DSM has small point density and only partly penetrates the canopy and is therefore not appropriate for accurate shrubs/tree detection and vegetation canopy modeling (see also a comparison of ETHZ DSM and LiDAR DSM with reference measurements in Baltsavias *et al.* 2006). Regarding the matching DSM, a larger side overlap could reduce occlusions and lead to better modeling of small openings between trees while increasing the number of image rays per measurement and leading to higher accuracy and reliability. Use of modern digital photogrammetric sensors would lead to avoidance of scanner and film problems, providing better radiometric quality, and enable the use of the NIR for classification, all factors that would result in a more accurate mapping and change detection of trees and shrubs.

Acknowledgements

The study was carried out in the frame of the Swiss Mire Protection Program initiated in 1996 at the Swiss Federal Research Institute WSL and funded by the Swiss Agency for the Environment, Forest and Landscape (BAFU) and WSL. We acknowledge the support of Ruedi Boesch for providing the LiDAR data and Peter Longatti for linguistic improvements (both WSL) and Devrim Akca (ETH Zurich) for the co-registration of the DSMs.

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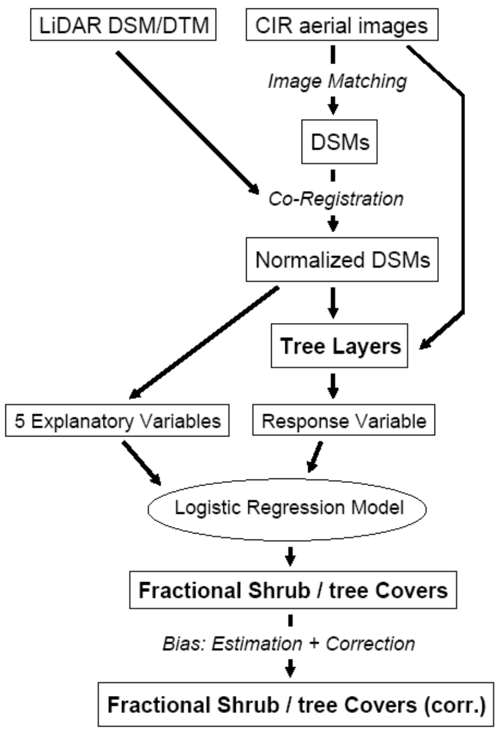

Figure 1. Overview of the methodological workflow with main steps of processing.

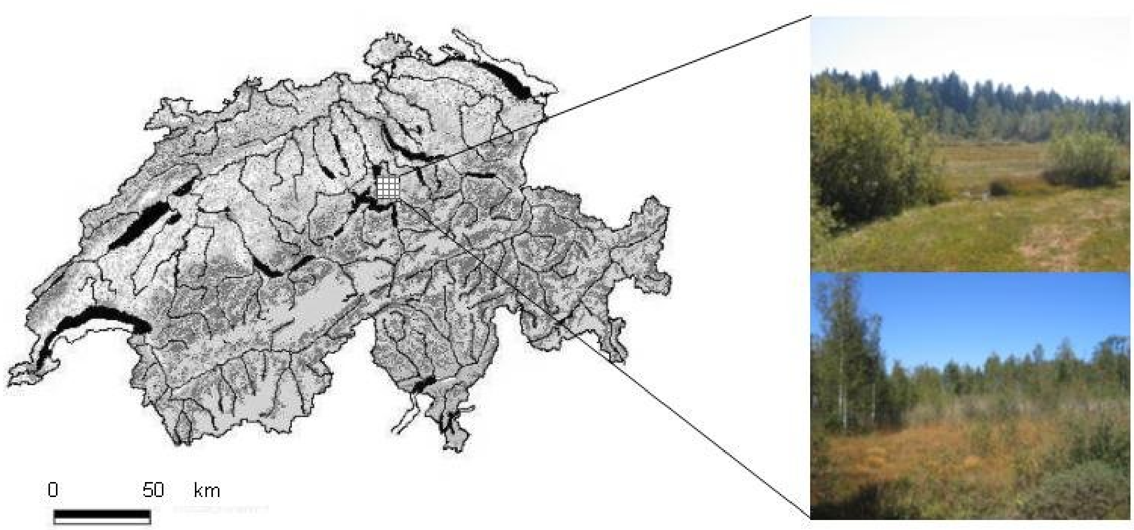

Figure 2. Left: overview of the test site (Pixelmap © 2006 Swisstopo JD052552); right: bog and fenland, broad-leafed woodland and shrubs that are typical for the mire.

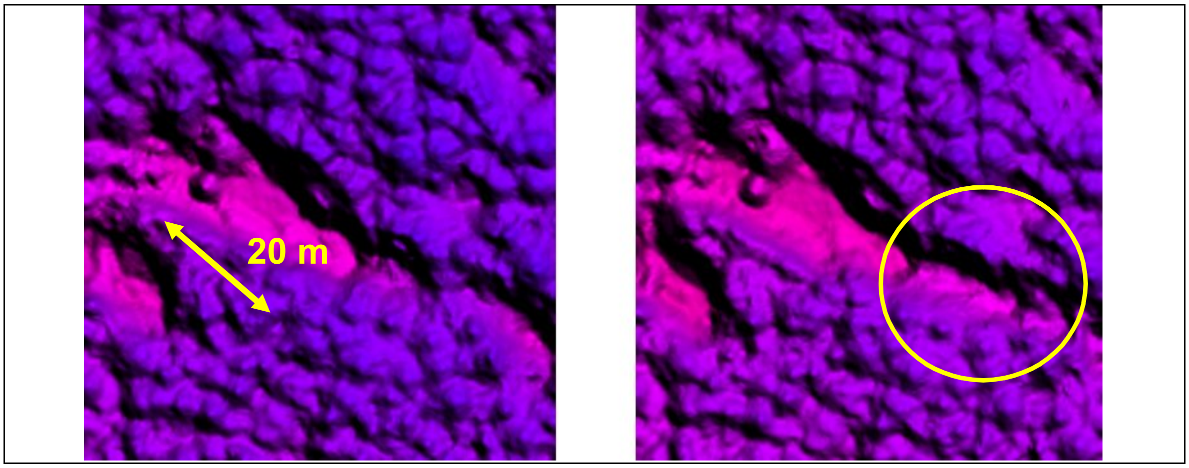

Figure 3. Colour-coded matching DSM from averaging the RGB channels (left) and using only the blue channel (right). The right DSM shows a better modelling of tree individuals and small openings (circle) between trees.

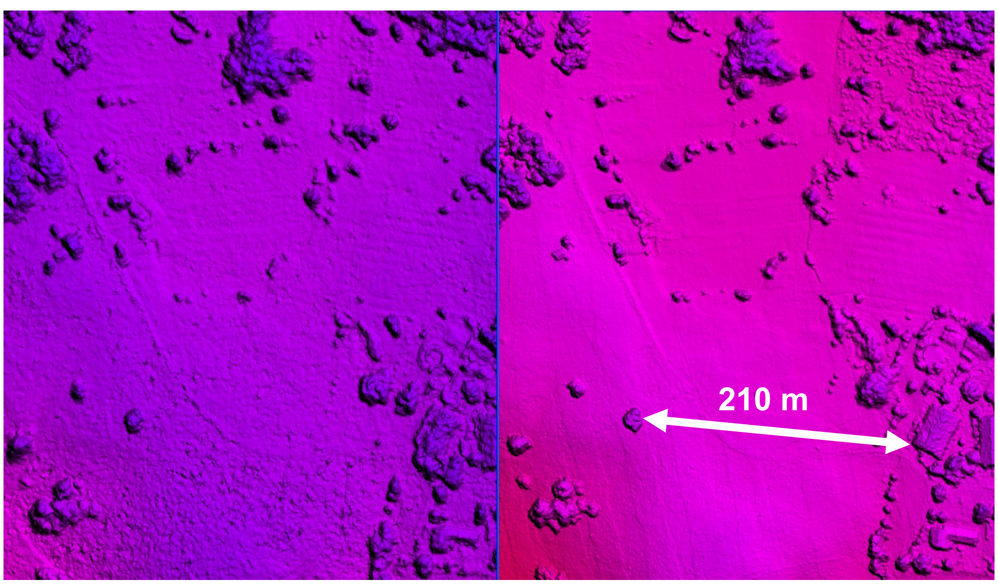

Figure 4. Detail of the 1997 (left) and 2002 (right) DSMs. The noise in the 1997 DSM is clearly visible in bare ground areas. Some stripes are visible in the 2002 DSM again on bare ground. Shrub encroachment in 2002 is clearly visible on the top right.

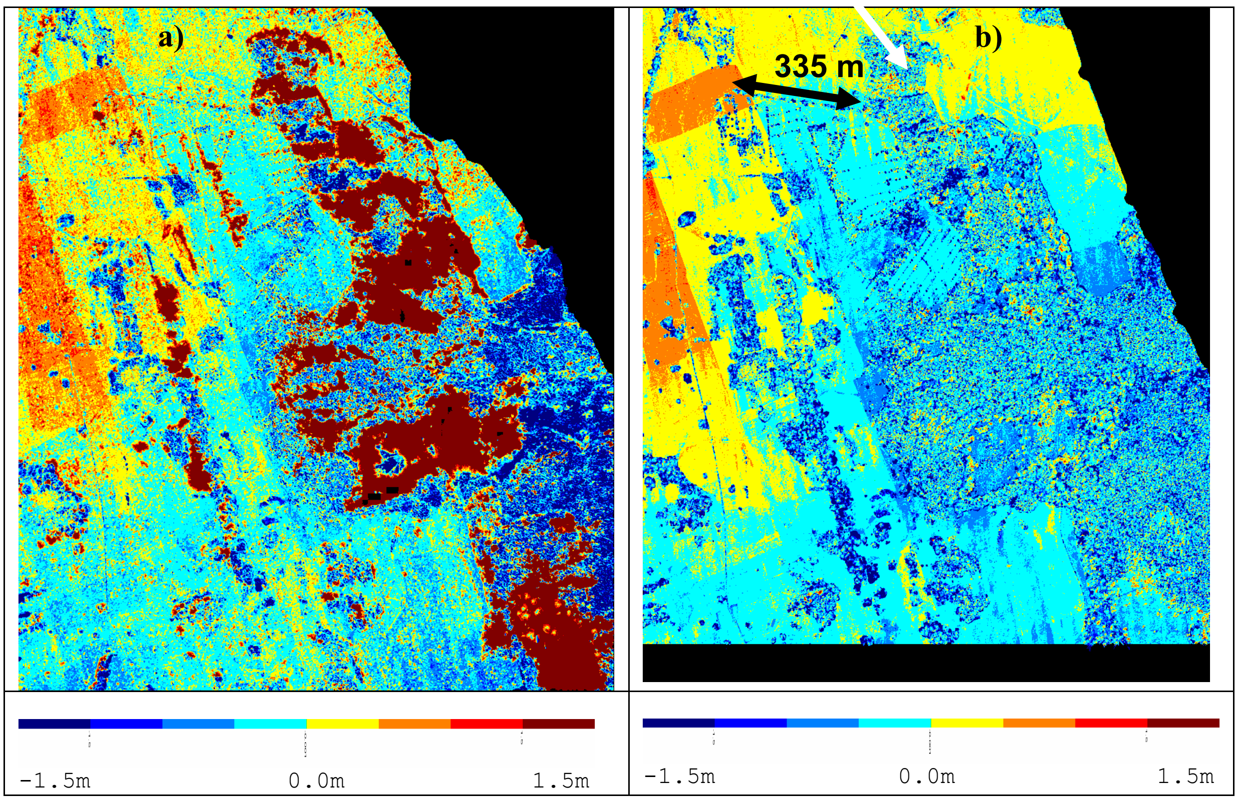

Figure 5. a) Z component of the Euclidian distances 1997 - 2002 DSM showing clearly areas of deforestation and shrub encroachment. **b)** Z component of the Euclidian distances LiDAR DSM - 2002 DSM. At the top and bottom, the effect of the stripes in the DSM due to film scanner miscalibration is visible. The orange areas at the top left are probably due to differences in image orientation between the two flight strips and within each strip causing discontinuities in the 2002 DSM. These areas are also visible in **Fig. 5 a)** but have less sharp boundaries due to the noise of the 1997 DSM. Due to software limitations regarding computer memory, the LiDAR DSM and DSM were sub-sampled to a 2.5m grid

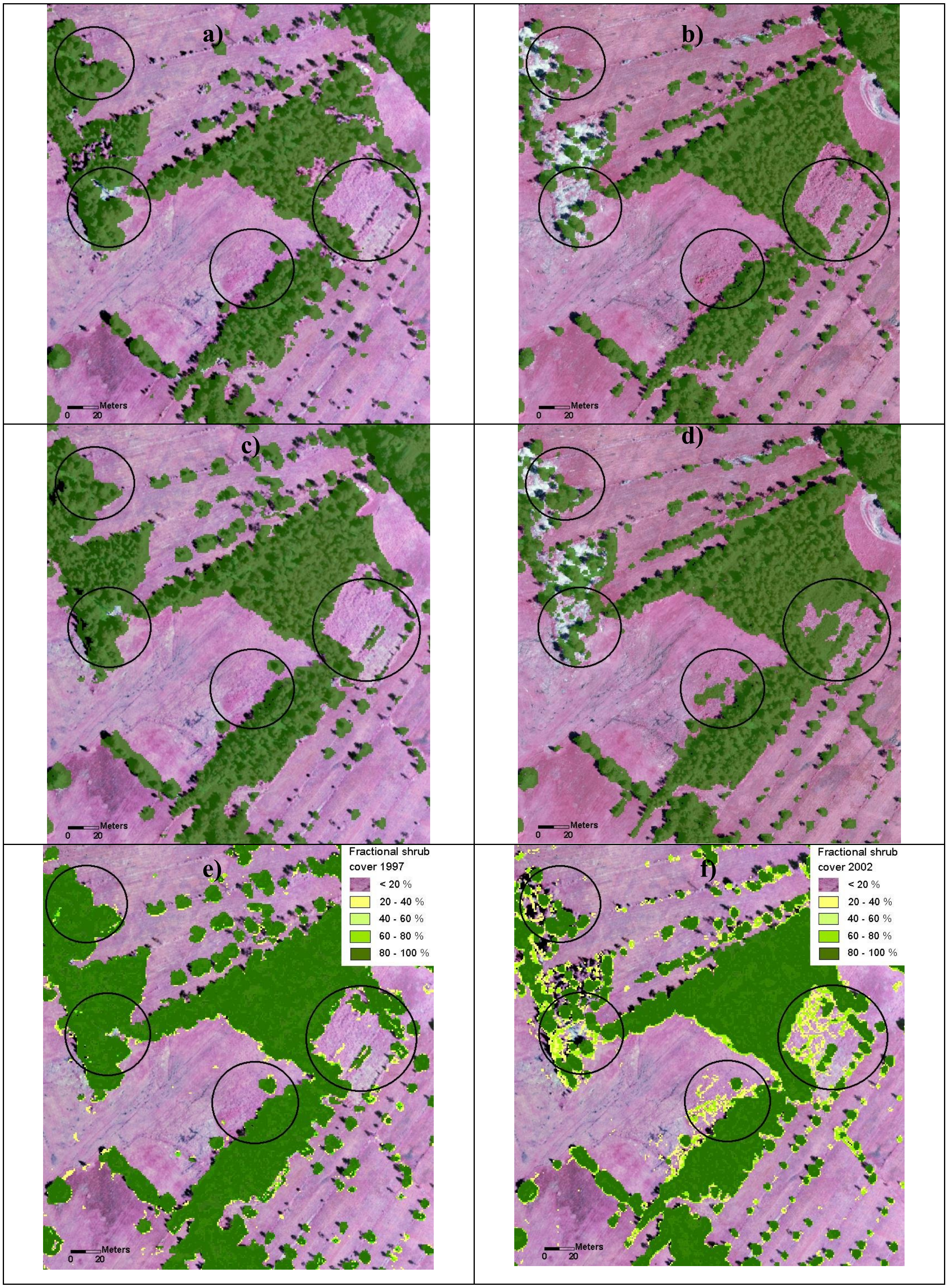
a)
b)
c)
d)
e)
f)
Meters
0 20
Fractional shrub cover 1997
< 20 %
20 - 40 %
40 - 60 %
60 - 80 %
80 - 100 %
Fractional shrub cover 2002
< 20 %
20 - 40 %
40 - 60 %
60 - 80 %
80 - 100 %

Figure 6. a) CIR orthoimage with generalized tree layers of 1997 and **b)** of 2002, **c)** and **d)** more detailed tree layers, **e)** and **f)** corresponding fractional tree/shrub covers. The two circles on the left side mark areas with decreased tree/shrub cover due to deforestation/logging. The two circles on the right side mark increased tree growth / shrub encroachment.

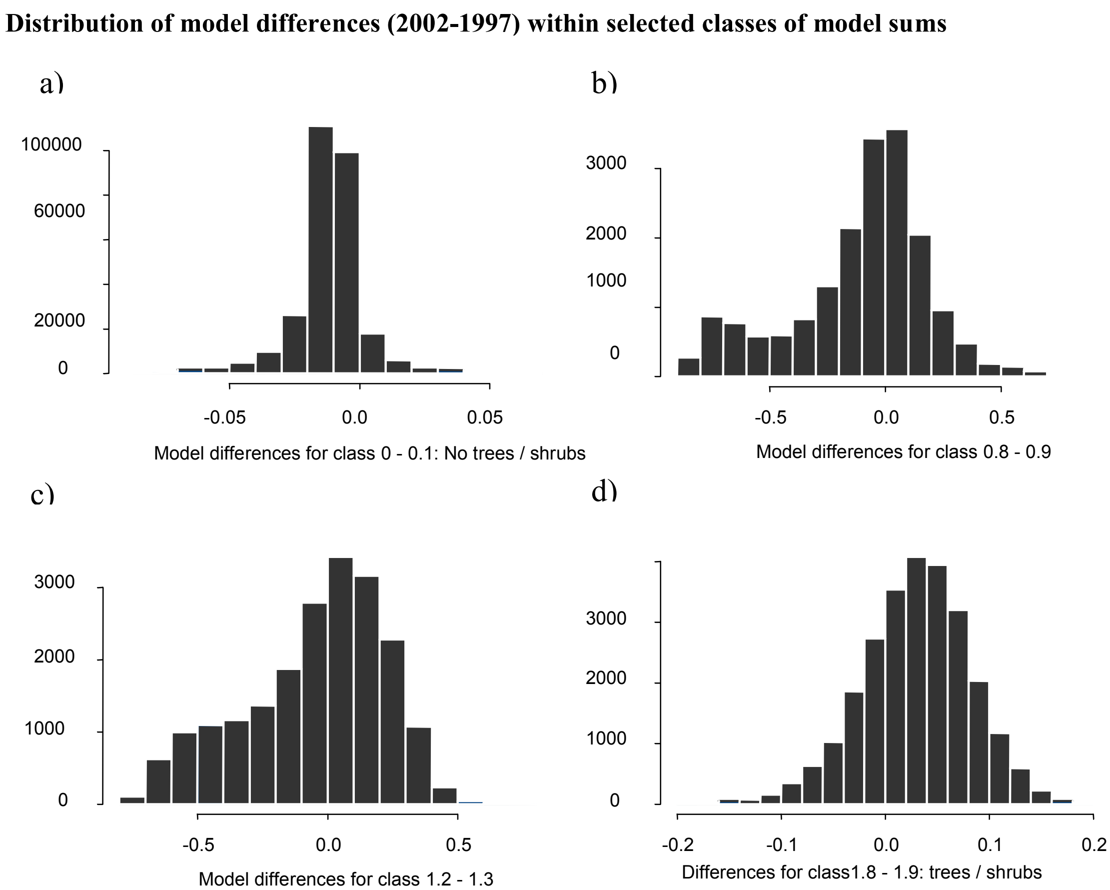

Figure 7. Distribution of differences between the fractional tree/shrub covers from both surveys in four different classes (x). Y-axis: number of counts. **a)** class 0 - 0.1, **b)** class 0.8-0.9, **c)** class 1.2 - 1.3, **d)** class 1.8 - 1.9.

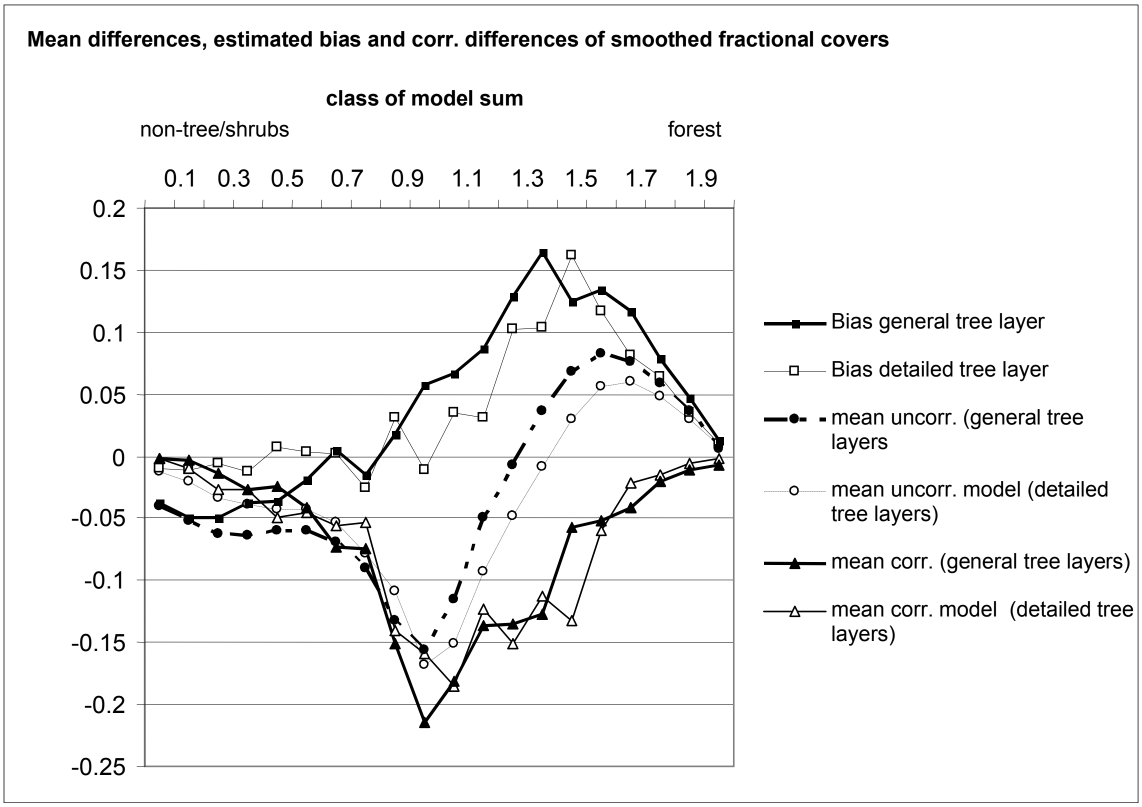

Figure 8. Mean differences, bias (estimated by modus) and corrected differences of smoothed fractional tree/shrub covers for 20 classes of model sums. Lowest class (0.0 - 0.1) of model sums corresponds to "non-tree/shrub" whereas the highest class (1.9 – 2.0) corresponds to "forest". Intermediate classes represent either partly forested area or areas that have been deforested or areas where shrub encroachment occurred.

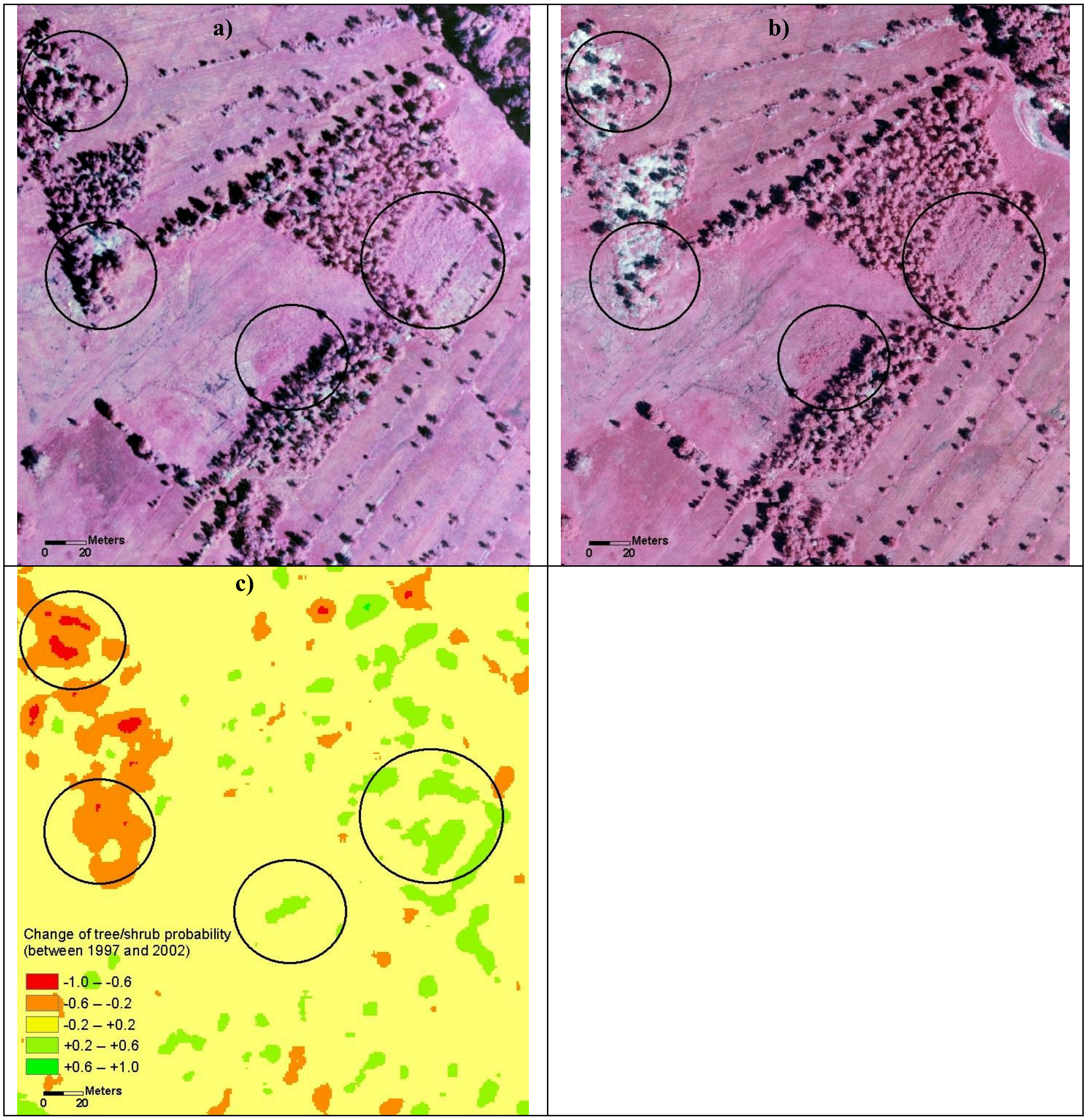

Figure 9. a) CIR orthoimage 1997, **b)** CIR orthoimage 2002 **c)** corrected changes of tree/shrub probability of forest and other wooded areas with decrease (red), no change (yellow) and increase (green).

Table 1. Characteristics of the CIR aerial images

Sensor	**CIR aerial images 1997**	**CIR aerial images 2002**
Type	RC 30	RC 30
Acquisition date	04/08/1997	08/07/2002
Scale	1:10,000	1:5,700
Focal length	21 cm	30 cm
Spectral resolution	Green: 500-600 nm Red: 600-700 nm Near infrared: 750-1000 nm	
Scan pixel size	15 µm	15 µm
Ground pixel size	15 cm	8.5cm
Radiometric resolution	8 bit	8 bit
Overlap	Forward: 75%	Forward: 75% Side: 30%

Table 2. Overview of the five explanatory variables (derived from nDSM) used to generate the fractional shrub/tree covers.

Name	**Derivation**
curvature	curvature of the surface at each cell center (3x3 window)
plan	curvature of the surface perpendicular to the slope direction, referred to as the planform curvature (3x3 window)
prof	rate of change of slope for each cell, curvature of the surface in the direction of slope (3x3 window)
slope	rate of maximum change in z value from each cell
top	assessment of topographic position (4 classes: ridge, slope, toe slope and bottom), the resulting grid displays the most extreme deviations from a homogenous surface

Table 3. Variations of change estimations for tree/shrub probability (1997-2002) as obtained by different methods.

Differences 2002 - 1997	**Description**	**Mean change of tree/shrub pixel portion**
Trees97_02general	Generalized tree layer 2002 - 1997	-0.073
Trees97_02detail	Detailed tree layer 2002 - 1997	-0.018
		Mean difference of tree probability
Model_general_uncorr	uncorrected modeled change (based on general tree layers), bias included	-0.029
Model_detail_uncorr	uncorrected modeled change (based on detailed tree layers), bias included	-0.016
Model_general_corr	Corrected modeled change (based on general tree layers)	-0.039
Model_detail_corr	Corrected modeled change (based on detailed tree layers)	-0.036

Table 4. Comparison of digitized samples with generalized tree layers by means of statistical measures: classification rate (*CCR*), Kappa (*K*) and correlation coefficient (*r*).

Generalized tree layers (*trees97_02general*)					
		dec.	eq.	inc.	∑
Digitized samples	dec.	**44258**	12256	40	56554
	eq.	14	**63676**	0	63690
	inc.	6796	75190	**11708**	93694
	∑	51068	151122	11748	
	CCR				**0.560**
	K				**0.591**
	r				**0.626**
Mean change of tree / shrub pixel portion		-0.782	-0.000	+0.052	

Table 5. Comparison of digitized samples with detailed tree layers.

		Detailed tree layers (*trees97_02detail*)			
		dec.	eq.	inc.	∑
Digitized samples	dec.	**32936**	22862	756	56554
	eq.	16	**63654**	20	63690
	inc.	1792	44178	**47724**	93694
	∑	34744	130694	48500	
	CCR				**0.675**
	K				**0.519**
	r				**0.696**
Mean change of tree / shrub pixel portion		-0.569	+0.000	+0.490	

Table 6. Comparison of digitized samples with corrected models based on the generalized tree layers.

		Model_general corr.			
		dec.	eq.	inc.	∑
Digitized samples	dec.	**33206**	20454	5788	56554
	eq.	190	**63270**	230	63690
	inc.	3314	61146	**29234**	93694
	∑	36710	144870	32358	
	CCR				**0.588**
	K				**0.612**
	r				**0.572**
Mean diff. of tree / shrub probability		-0.518	-0.000	+0.150	

Table 7. Comparison of digitized samples with corrected models based on the detailed tree layers.

		Model_detail corr.			
		dec.	eq.	inc.	∑
Digitized samples	dec.	**33970**	19968	2616	56554
	eq.	180	**63320**	190	63690
	inc.	3472	60656	**29566**	93694
	∑	37622	143944	32372	
	CCR				**0.593**
	K				**0.620**
	r				**0.582**
Mean diff. of tree / shrub probability		-0.562	-0.000	+0.174	