CHANGE DETECTION BASED ON FRACTIONAL TREE COVER DERIVED FROM MODIS DATA

Markus Schwarz[a], Lars T. Waser[a] & Niklaus E. Zimmermann[a]

[a]Swiss Federal Research Institute WSL, Zürcherstrasse 111, CH-8903 Birmensdorf – (markus.schwarz@wsl.ch)

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ABSTRACT:

Knowledge about the land cover of large areas is important for monitoring and modeling of ecological and environmental processes and for land cover change detection. Considerable efforts have recently resulted in the development of global continuous fields for different land cover types at large spatial scales based on NOAA-AVHRR, SPOT-VEGETATION, and TERRA-MODIS data. Researchers have applied a range of techniques to depict the sub-pixel fraction of land cover types from remotely sensed data. As a result, such products have a high potential to accurately monitor land cover and its change over time. In this study, we assess the potential of MODIS-derived fractional tree cover for change detection. Based on the uncertainty-model of our method to map land cover continuous fields we describe a methodology to quantify the statistical certainty of detected changes, thus adding statistical significance levels. The presented study is carried out in Switzerland a central part of the European Alps with a complex topography and a highly fragmented landscape. Based on MODIS data (MOD09) at a spatial resolution of 500m we derived fractional tree cover using a generalized linear model (GLM). The advantage of this model is quantitative availability of the model error for all predicted observations. This information can be used to calculate the interval of tolerance for each observation and for each year individually. Based on these intervals the probability of an occurred change of the fractional cover between two years can be calculated. For purpose of evaluation we first modelled the fractional tree-cover for the years 2001 and 2003 on MODIS 500m data using Landsat-data for training resampled to the spatial resolution of 500m. In a second step we calculated the fractional tree cover change for Landsat and MODIS and compared it to each other. Finally, we mapped the fractional tree cover of 1999 based on a Landsat-image of summer 1999. The calculated change between 1999 and the Landsat respectively MODIS-based fractional tree cover were compared to severe storm damages occurred in December 1999 over large parts of Europe. In Switzerland these damages were mapped by visual air photo interpretation. The correlation between Landsat based and MODIS based fractional tree cover change was 0.52.The correlation between air-photo based storm damages and the calculated fractional change was 0.43 for the Landsat respectively 0.45 for the MODIS fractional tree cover. The automatic classification of significantly changed pixels based on the probability revealed that on the 95% confidence interval only observations with a change of approx. 30% were detected. A decrease of the confidence level to 75% revealed only a few misclassifications and showed that the approach is very promising. Generally we conclude that our approach based on MODIS MOD09 data is appropriate for 1) mapping fractional tree cover and 2) monitoring its temporal change.

1. INTRODUCTION

The environment of the European Alps with its characteristic complex topography and its fine-scale and often traditional land use regime is exposed considerably to both natural environmental threats and human impacts and exploitation (Tasser & Tappeiner, 2002). For sustainable use and management and for large-area monitoring and modeling of these Alpine terrestrial habitats, consistent land cover information across national borders is indispensable for many aspects of Earth Sciences and analyses of global change, including resource management or biodiversity assessment (Townshend et al., 1994). Therefore, reliable land cover information and data sets are needed for a successful monitoring. Remotely sensed data, such as Landsat, SPOT, NOAA-AHVRR or TERRA-MODIS have become the major data sources for monitoring aspects during the past decades (Lu et al., 2004). This is because of the advantages of repetitive data acquisition, its synoptic view as well as digital format, which is suitable for computer processing. However, tree cover change is an important input for the monitoring modeling of ecological and environmental processes at various scales.

Considerable efforts have recently resulted in the development of global and continental land cover data at small spatial scales based on the Advanced Very High Resolution Radiometer (NOAA-AVHRR) and the Moderate Resolution Imaging Spectroradiometer (TERRA-MODIS) (Mucher et al, 2000, Hansen and Reed, 2000; Townshend et al., 1994; Belward et al., 1999; Friedl et al., 2002). The paradigm for describing the characteristics of the surface covered by these data sets is to classify each pixel into a land cover type based on a predefined classification scheme (DeFries & Townshend, 1994). However, this approach has certain limitations. Alternatively, a number of techniques to depict the sub-pixel fraction of landscape components from the same remotely sensed data have been applied. So far statistical approaches used (Hansen et al., 2002) 1) fuzzy membership functions (Foody, 1994), 2) artificial neural networks (Atkinson et al., 1997), 3) regression trees (DeFries et al., 1997), 4) decision trees (McIver & Friedl, 2002), 5) linear mixture models (Adams et al., 1995) and 6) generalized linear models (Schwarz & Zimmermann, 2005). The resulting continuous field maps – containing the fraction of landscape components as a continuous variable – offer the advantage of summarizing the effects of spatial heterogeneity better than the discrete land cover maps based on the same data sources. As a result, such products have a higher potential to accurately monitor land cover change over time (Hansen et al., 2002).

Good change detection research should provide information about the accuracy of the detected change. A systematic study and knowledge about the quality of the results are indispensable to assure the worth of the data and to ensure that the appropriate conclusions were drawn (Lu et al., 2004).The accuracies of change detection results depend on many factors, including 1.) precise geometric registration, 2) availability and quality of ground truth data 3) complexity of landscape, 4) algorithms used, as well as 5) calibration and normalization of the satellite images (Coppin et al., 2004). All the previous mentioned sources of uncertainties are incorporated in the process of modeling, leading to the predictions of the fractional tree cover. A critical part of prediction is an assessment of how much a predicted value will fluctuate due to the noise in the data. Without that information there is no basis for comparing a predicted value to a target value or to other predictions of the same pixel. Fortunately the data used to fit the model to a process can also be used quite often for computing the uncertainty of predictions and therefore calculating a prediction interval. This interval gives both the range of plausible values for a single prediction based on the parameter estimates and also the noise in the data for a given level of significance (Sachs, 2003).

In this study, we investigate the potential of MODIS based fractional tree cover for change detection. The presented procedure uses MODIS reflectance data at a spatial resolution of 500m for the years 2001 and 2003. The procedure is optimized at the regional scale of the European Alps using generalized linear models (Schwarz & Zimmermann, 2005). For purposes of comparison we test the resulting predicted MODIS based change against Landsat based change. In order to do this two Landsat based tree cover maps of the years 2001 and 2003 serve as "ground-truth". Further we incorporate the uncertainty of predictions into the model calculating prediction interval for each pixel. Based on these intervals the probability of a predicted change can be calculated. The benefit of such a model is that the uncertainty can be quantified. This helps to establish accurate information about the change enabling more precise change detection. For further analyses we tried to correlate storm damages as occurred in 1999 with a MODIS based predicted change. Since TERRA was launched in 2000 there are no MODIS data available for the year 1999. Due to this fact the fractional tree cover of the year 1999 based on Landsat served as a "simulated" MODIS 1999 data to calculate the difference between the years 1999 and 2001.

2. METHODS

2.1 Study area

The Alps of Southern Central Europe extend over 1000km from the Mediterranean coast of France and North-western Italy through Switzerland, Northern Italy, to Southern Germany, Austria, and Slovenia. The highest peak is the Mont Blanc at 4807m. The Alps are characterized by an extraordinary biodiversity and a variety of landscapes, which are influenced by geological, morphological and climatological factors and by a long history of varying traditional land management. One third of this mountainous landscape is covered by forest. Due to the large spatial extent and the wide altitudinal range a multitude of vegetation zones is present. In the South of the Alps the Mediterranean climate and increasingly warmer winter temperatures are responsible for evergreen broadleaf trees. The more northern areas of the Alps are affected by a moderate climate, with colder winters. The forests are formed by broadleaf deciduous and coniferous trees, depending on elevational belt and specific site conditions.

2.2 Modis based Tree cover

In order to calibrate the model of fractional tree cover, we used atmospherically corrected (6S code) and georeferenced surface reflectance data from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the TERRA satellite at a spatial resolution of 500m. In particular we used the MODIS level 3 surface reflectance product, MOD09_L3_V004, as an 8-day composite. We used all tiles of h18v04 for the year 2001 and 2003. The data were transformed to UTM coordinate system with WGS 1984 datum (Zone North 32). Further, the Normalized Difference Vegetation Index (NDVI = (nir-red)/(nir+red)) was calculated for each 8 day composite. To reduce the negative effect of cloud contamination we synthesized the 8-day composites to monthly images based on the maximum NDVI value per month (Holben, 1986). Based on these datasets a number of metrics representing the seasonal and/or annual phenological characteristics of vegetation were derived according to DeFries et al. (1997) using the 8 months with the highest NDVI-value. These metrics include the minimum, maximum, mean, range, and standard deviation per reflectance band. Finally, from these calibration dataset (i.e. area-wide maps), sub-samples of 15'838 pixels within Switzerland reflecting a regular lattice were re-sampled for calibrating the model. This represents 1/9th of the total surface of Switzerland. The omitted 8/9th of the Swiss data were treated as an independent reference dataset (for a more detailed description see Schwarz & Zimmermann (2005)).

A training data set is required to calibrate the model. In our case we used training data from high-resolution satellite imagery for Switzerland combined with forest inventory data and data from the "Swiss areal statistics 92/97". The resulting high resolution tree cover map was re-projected to UTM coordinate system with WGS 1984 datum (Zone North 32) and aggregated to the resolution of the MODIS (500m) data.

2.3 Reference data

2.3.1 Landsat based tree cover maps

Landsat Enhanced Thematic Mapper Plus (ETM+) data of the year's 1999, 2001 and 2003 were available for a part of the study area. For each Landsat image an accurate tree cover was calculated and aggregated to the spatial resolution of MODIS (500m). Generally the tree cover is modeled by linking data of the national Swiss forest inventory (NFI) with the spectral information of the Landsat image using a generalized linear model.

2.3.2 Storm damage map of the year 1999

In December 1999 the storm Lothar caused severe damage to forested lands over large parts of Europe. Based on the interpretation of aerial photos for Switzerland a map with the classified forest is available. This dataset contains all damages caused by the storm Lothar and was aggregated to the spatial resolution of MODIS (500m). Since TERRA was launched in 2000 there were no MODIS data for the year 1999 available. Due to this fact the fractional tree cover of the year 1999 based on Landat served as a "simulated" MODIS 1999 data to calculate the difference between the years 1999 and 2001.

2.4 Change detection

In this study we used the Post-classification comparison, sometimes referred to as "delta classification", involving independently produced classification results from two images, followed by a pixel-by-pixel or segment-by-segment comparison for the purpose of change detection (Howarth & Wickware, 1981). Hence, in a first step we calculated the change on the basis of the predicted MODIS fractional tree cover of the year 2001 and 2003, respectively the fractional tree cover maps based on the two Landsat images of the year 2001 and 2003. Further we compared the predicted change (MODIS) to the observed change (Landsat). In order to do so a handful of statistical measurements can be calculated, (1) the mean absolute error (*MAE*), (2) the bias, (3) correct classification rate (*CCR*), (4) the weighted kappa (κ_w) and (5) the pearson's correlation-coefficient. (*r*). Measures 3 and 4 were calculated based on a confusion matrix with the continuous difference of the change aggregated to strata of 5% width. Additionally, a correct sign rate (*CSR*) was calculated. For each single pixel we tested whether the direction of the predicted change (increase or decrease of the fractional tree cover) corresponds to the observed one (Landsat).

In a second step we calculated the statistical probability of the change by calculating the interval of tolerance for each single pixel. Generally, the goal of prediction is to determine the value(s) of the response variable that are associated with a specific combination of explanatory variables. A critical part of prediction is the assessment of the amount of fluctuation of a predicted value due to the noise in the data. Without that information there is no basis for comparing a predicted value to a target value or to another prediction. As a result, any method used for prediction should include an assessment of the uncertainty in the predicted values. Fortunately the data used to fit the model to a process can also be used quite often for computing the uncertainty of predictions and therefore calculating a prediction interval. This interval gives both the range of plausible values for a single prediction based on the parameter estimates and also the noise in the data for a given level of significance (Sachs, 2003).

The formula for constructing prediction intervals is given by

$$\tilde{y} \pm t_{1-\alpha/2,\upsilon} * \tilde{\sigma}_p \qquad (1)$$

where $\tilde{\sigma}_p = \sqrt{\tilde{\sigma}^2 + \tilde{\sigma}_f^2}$
(2)

and $\tilde{\sigma}^2 = \frac{(x_0 - \bar{x})^2}{SSQ^{(x)}}$ (3)

The confidence level of an interval is usually denoted symbolically using the notation , with denoting a user-specified probability. This so-called significance level indicates the interval's incapability to capture the true value of the regression function.

The standard deviations of the predicted values ($\tilde{\sigma}_f$) of the estimated regression function depend on the standard deviation of the random errors in the data, the experimental design used to collect the data and fit the model, and the values of the predictor variables used to obtain the predicted values. These standard deviations are not simple quantities that are directly presented by the output-summary of the fitted model. However, they can often be obtained from the software used to fit the model (Sachs, 2003).

The estimate of the standard deviation of the predicted value, , is obtained as described earlier. Because the residual standard deviation describes the random variation of the prediction in each individual measurement or observation, , the estimate of the residual standard deviation obtained when fitting the model to the data, is used to account for the extra uncertainty needed to predict a measurement value. Since the new observation is independent of the data used to fit the model, the estimates of the two standard deviations are then combined by "root-sum-of-squares" or "in quadrature", according to standard formulas for computing variances, to obtain the standard deviation of the prediction of the new measurement.

Based on the two prediction intervals for each calibrated model (2001 & 2003) the probability of a change is calculated by the given formula

$$t_{1-\alpha/2,\upsilon} = \frac{(\tilde{y}_{m3} - \tilde{y}_{m1})}{(\tilde{\sigma}_{p_{m3}} + \tilde{\sigma}_{p_{m1}})} \qquad (4)$$

3. RESULTS

We first describe the basic statistical accuracy measurements for the comparison of the predicted change (MODIS) versus observed change (Landsat). In a next step we show the results based on the calculated probability. Finally we present the analyses of suitability in detecting storm damages of the year 1999.

3.1 Basic statistical Performance

In Table 1 the basics statistical measurements were summarized. The frequency distribution of the predicted changes (MODIS) shows more pixels with a high change compared to the observed change (Landsat). Both, the maximum / minimum and 1st/3rd quarter are higher for the predicted change (MODIS) compared to the observed change (Landsat). The average change lies for both datasets around 3%. This means that an overall a decrease of the fractional cover is stated. The MAE between predicted change (Modis) and observed change (Landsat) is 6%. The κ_w calculated on the basis of 5%-strata is 0.844 while the *CSR* and *r* are 0.701 respectively 0.51.

	MODIS (y. 2003 – y. 2001)	Landsat (y. 2003 – y. 2001)
Mean	2.7%	2.8%
Max	50.9%	18.0%
Min	-41.6%	-31.0%
1st quarter	-2.6%	-1.0%
3rd quarter	8.5%	7.1%
Bias	0.08%	
MAE	6.2%	
CCR	0.233	
K_W	0.844	
r	0.515	
CSR	0.701	

Table 1. Basic statistical measurements for the comparison between the predicted change (MODIS) and the observed change (Landsat) of the fractional tree cover.

When assessing the accuracy measurements more in detail along the "observed change"-axis (assigned to 2.5% strata-intervals), we see that *CSR* is decreasing for lower changes and arising for high changes. The lowest rate shows the stratum -2.5% - -5% with 0.53. For strata with an absolute change of more than 15% the *CSR* is higher than 0.95.

The mean predicted change (MODIS) per stratum shows a nearly linear relation with the mean observed change (Landsat) for the strata -15% to 7.5%. For strata with a high change rate the mean predicted change (MODIS) underestimates the absolute change for both decrease respectively increase of the fractional tree cover. The variation of the predicted change within each strata is indicated by vertical bars in Figure 1 and is nearly constant for all strata.

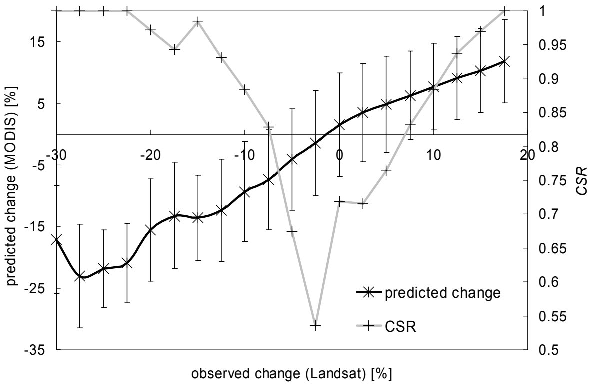

Figure 1: *CSR* and mean predicted fractional tree cover change (MODIS) in dependency to the observed change (Landsat)

3.2 Analyses of the probability

Based on the calibrated models we calculated for each pixel the probability of the predicted change. In Figure 2 the *CSR*, absolute mean predicted (MODIS) and absolute mean observed (Landsat) change are displayed in dependency to the calculated absolute probability. The probability is assigned to strata of 2.5% width. The absolute mean predicted change (MODIS) is increasing with an increase of the probability. For a probability of more than 95% this value corresponds to an absolute change of 45%. The corresponding curve of the observed change is significantly lower for a high probability (>0.4) and higher for low probability (<0.2). This means that the slope is lower. The *CSR* is increasing from 0.68 for low probabilities (0-0.2) to 1 for high probabilities (>0.75). The level of 0.95 is reached by a probability of 0.70. The variation of the observed change (Landsat) within each stratum stays nearly constant for all strata and is about 10%.

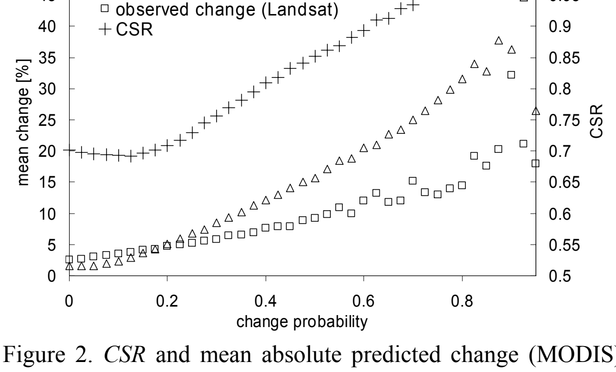

Figure 2. *CSR* and mean absolute predicted change (MODIS) and absolute mean observed change (Landsat) in dependency to the calculated probabilities of change (based on model calibration)

3.3 Analyses of storm damages

In Figure 3 respectively 4 the observed storm damages for MODIS and Landsat of December 1999 and the change of the fractional tree cover between 1999 to 2001 are displayed. For better visualization the true damages were classified to strata of 3% width and for each strata only 20 randomly sampled points were displayed. Both scatterplots show similar distribution patterns as well as a strong correlation between observed damages and predicted damages.

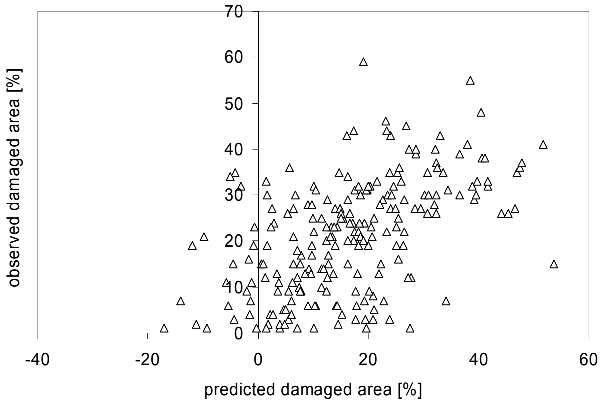

Figure 3. Observed storm damages of December 1999 and the change of the fractional tree cover between 1999 to 2001, based on MODIS

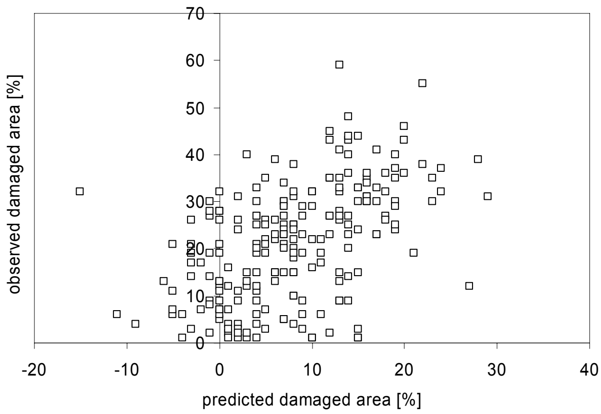

Figure 4. Observed storm damages of December 1999 and the change of the fractional tree cover between 1999 to 2001, based on Landsat

In Figure 5 the storm damages of the year 1999, assigned to predefined strata, and the mean predicted change (MODIS and Landsat) are displayed. The MODIS predictions overestimate the quantity of pixel damages, where the damaged area is less than 12% respectively underestimate pixel damages, where the damaged area is greater than 15%.The Landsat predictions underestimate the actual damages in general.

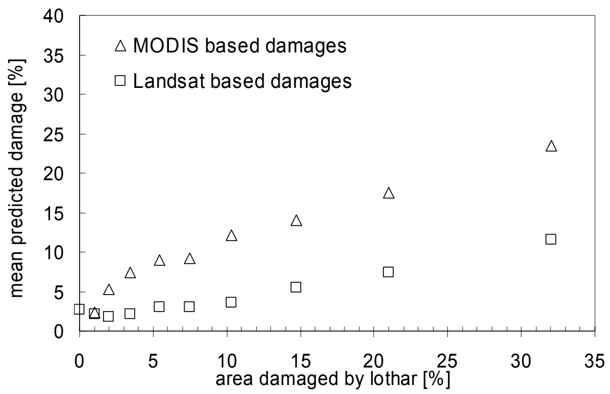

Figure 5. Storm damages of the year 1999, assigned to predefined strata and the mean predicted change (MODIS and Landsat)

4. DISCUSSION

The results show that a predicted change of the fractional tree cover based on MODIS data for the years 2001 and 2003 are well correlated with the observed change based on two Landsat fractional tree cover maps of the year 2001 respectively 2003.

The mean predicted change (MODIS) for predefined strata shows a nearly linear relation compared to the mean observed change based on Landsat fractional tree cover. Obviously (Figure 1) the predicted change (MODIS) tend to underestimate high observed changes (Landsat). Although these results are at a first glance very impressive, the error variation turns out to be fairly high. These variations mean that small changes between two time steps get lost in the uncertainty of the model and can not be detected sufficiently. This fact has to be taken into account for the interpretation of a predicted change. The calculated *CSR* shows that predicted changes of more than 15% are classified, with less than 5% misclassifications (on the basis of the *CSR*). This means that the uncertainty for predicted changes of less than 15% is increasing. Figure 2 tells us that the calculated probability of change, when higher than 0.7 leads to a misclassification rate less than 5% with an associated mean predicted change for this level of about 22%.

For the pixelwise interpretation this means, that for all predictions for which the calculated probability is less than 0.7, the variation lies within the uncertainty of the model and the probability for a misinterpretation is increasing. The proportion of pixel with a significant change is 0.6% of all Pixels. For the rest of the pixels the predicted change has not been proven. Nevertheless the interpretation of the probabilities allows to discover the pixel with a attested change.

The analysis of the storm damages shows that storm damages can be detected with the MODIS based fractional tree cover. For better identification of the potential of the MODIS based fractional tree cover we compared it to the Landsat based tree-cover. The results in Figure 3 respectively 4 show, that there is a high correlation between storm damage and predicted damage for both MODIS and Landsat. The mean predicted damage size for the MODIS-predictions is significantly higher than for the Landsat based damages. The Landsat damages underestimate the "true damages" in general. This is probably caused by the Landsat tree cover being based on a single Satellite image of the summer 2001. Two Years after the storm the young growth and shrubberies are dominating on most parts of the damaged forested areas, leading to a higher proportion of tree cover on this area. In contrast it seems, that for the MODIS-Predictions which are based on synthetizised multitemporal data, the effect of young growth and shrubberies is smaller. In contrast to the higher bias of Landsat the *MAE* of Landsat is smaller for damaged area less than 15%. Only for large changes the *MAE* of MODIS is higher. In addition and independently of the damaged area the *CSR* of MODIS is higher compared to the one of Landsat.

5. CONCLUSION

Ecosystems are in a state of permanent flux on a variety of spatial and temporal scales. Moreover, since that sustainability has become a primary objective in present-day ecosystem management, the continuous need for accurate and up-to-date resource data becomes apparent as one consequence. For sustainable use, optimal management and for large scale monitoring and modeling of the Alpine terrestrial habitats, it is critical to first obtain homogeneous, consistent and as far as possible highly accurate information across national borders. As several prior efforts have shown (DeFries et al, 1999, Hansen et al., 2002, Schwarz & Zimmermann, 2005), fractional tree cover mapping based on Modis data provide a useful and promising approach to detect land cover change. For a correct and accurate interpretation of the results, a systematic study and knowledge about the quality of the results are indispensable to assure the worth of the data and to ensure that the appropriate conclusions were drawn.

The results show that MODIS based fractional tree covers are well suited for change detection and accurate results can be obtained for the spatial resolution of 500m. Although the uncertainties of the models based on spatial errors and quality of model calibration data are leading to a significant variability of the predictions the quality of performance of the interpretation is increasing considering of the calculated probability of a predicted change. On the basis of the 500m resolution absolute changes of more than 20 % can be detected with a sufficient certainty. Such rapid changes between two years appear seldom in a highly fragmented landscape such like the European Alps and can only be caused by dramatic interferences on the tree cover. This holds especially when we consider that there is a strict fire suppression strategy and also a low intensity of timber harvesting (no large area clear-cuts). The major causes of tree cover change of the mentioned quantity are wind throw and forest expansion due to land abandonment or clearcuts. Nevertheless, after a dramatic incident the described method offers a good possibility to detect and monitor such changes over large regions and to locate these hotspots with high spatial accuracy. However, for monitoring slow changes of the tree cover, which is a typical phenomenon in the natural environment of the European Alps, a reduction of the spatial resolution may be necessary. The methodical approach to calculate the probability of a change is very useful and offers a more precise interpretation of the results. In this way the uncertainty of the prediction can be incorporated in the process of interpretation and the quality is improved.

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