Towards an automated estimation of vegetation cover fractions on multiple scales: Examples of Eastern and Southern Africa

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Abstract – Vegetation cover is one of the key parameters for monitoring the state and dynamics of ecosystems. African semi-arid landscapes are especially prone to degradation due to climate change and increased anthropogenic impact on different spatial and temporal scales. In this study, a multi-scale method is applied to monitor vegetation cover by deriving sub-pixel percentages of woody vegetation, herbaceous vegetation and soil. The approach is comparatively applied to two semi-arid savannas, one in Namibia and one in Kenya. The results in eastern and southern Africa demonstrate the applicability of the method to different semi-arid ecosystems and to different types of remote sensing data. The presented analysis could show that continuous cover mapping is a highly suitable concept for semi-arid ecosystems, as these show gradual transitions rather than distinct borders between land cover types. Different spatial patterns of vegetation cover depending on land use practices and intensities could be revealed.

Keywords: fractional vegetation cover, regression trees, degradation, semi-arid environments, Africa

1. INTRODUCTION

Climate change and an increasing anthropogenic impact can lead to both subtle modifications and severe transformations of terrestrial ecosystems. In this context, the analysis of semi-arid environments is particularly interesting since these ecosystems are especially vulnerable, and both conversion processes and climatic changes may lead to severe degradation (Lambin et al., 2005). At the same time, these systems are characterized by a strong natural variability on different spatial and temporal scales (e.g. Wessels et al., 2007; J.L. Dodd, 1994; Dube and Pickup, 2001). Human activities, such as forest clearing for agricultural land use and grazing, but also shifts in precipitation amount and variability can result in changed proportions of woody and herbaceous vegetation cover (Sankaran et al., 2005; Budde et al., 2004). Possible consequences are for example a decline in rangeland productivity, increased soil erosion and reduction of biodiversity. Moreover, globally relevant impacts are likely, such as altered carbon cycles as a consequence of changes in ecosystem biomass (Jackson et al., 2002). Any in-depth understanding of the involved large-area change processes requires an accurate and long-term monitoring of the land surface (Lambin et al., 2005; Coppin et al., 2004). Especially the quantification (Ustin et al., 2005) of the “slow variables” of change (Lambin et al., 2005) is necessary, which requires spatially explicit and reliable data. However, up to now, the distinction between woody and herbaceous vegetation in savannas has not yet been approached adequately (Archibald and Scholes, 2007).

The MODIS product *Vegetation Continuous Fields* (VCF, Hansen et al., 2003) is an example for a promising estimation of percentage tree and herbaceous cover at global scale. Here, like in few other studies (e.g. Hansen et al., 2002; Huang and Townshend, 2003; Yang et al., 2003; Xu et al., 2005), regression tree methods are applied to remote sensing data for sub-pixel estimation. These applications give evidence that regression trees are a valuable non-parametric tool for soft classification. However, the available global continuous cover products show ambiguities regarding woody and tree cover which are hard to separate in semi-arid environments and important small-scale patterns are not represented well at a resolution of 500 m.

In this study, the percentage cover of herbaceous vegetation, woody vegetation and soil in African savanna ecosystems is derived from remote sensing data with decision tree regression following Breiman et al. (1984). The analysis is performed on three different spatial scales: 1) QuickBird and aerial imagery, 2) Landsat TM/ETM+ and 3) MODIS data. The applicability of the approach is tested comparatively for a southern and an eastern African semi-arid ecosystem, both of which are typical African landscapes strongly affected by various change processes.

2. STUDY AREAS

The multi-scale regression tree approach for deriving fractional vegetation cover in semi-arid environments was applied to two study areas: the north-eastern Kalahari woodland in Namibia and the savanna on the Laikipia plateau in central Kenya. These landscapes are semi-arid savannas, which are both composed of a relatively continuous herbaceous stratum and a disconnected layer of trees and shrubs. However, regarding climatic conditions, species composition and land use, the regions show several differences.

Northeastern Namibia is characterized by a mosaic of savanna woodlands and thickets on deep, nutrient-poor Kalahari sands (Strohbach and Petersen, 2007). The annual precipitation of 450 to 600 mm falls during a single rainy season between October and April and declines from northeast to southwest. The northern part of the region (Kavango) is mainly communal land where strong settlement activities have taken place since the 1970ies. The main land use type in this region is subsistence farming and fire plays a major role; in contrast, the southern part of the region of study (Otjozondjupa) is dominated by farming on freehold land (Mendelsohn, 2006).

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The study site in Kenya is characterized by a strong rainfall gradient ranging from more than 1000 mm rainfall at the foot zone of Mt. Kenya towards less than 600 mm in the northwest on the Laikipia plateau and two main rainy seasons (Berger, 1989). Accordingly, land use and land cover varies from mountainous forests on the slopes of Mt. Kenya to agricultural fields at the foot zone and extensive cattle ranches and game reserves on the plateau. Over the last decades, population has increased drastically and land use has intensified by splitting up large scale farms into small scale farms, by increased livestock numbers and by the establishment of horticultural farms and additional game reserves (Kiteme et al., 1998).

3. DATA AND METHODS

The presented comparative analysis was performed on three scales using remote sensing data of three different spatial resolutions. The finest-scale analysis was based on pan-sharpened QuickBird data (spatial resolution: 0.6 m; coverage: 220 km^2) for Namibia and aerial images (spatial resolution: 1 m; coverage: 6.5 km^2) for Kenya. We took these aerial pictures with a digital camera Nikon D70 mounted on a small airplane, mosaicked them into sequences of 3 to 5 images and georeferenced them. The medium scale analysis was conducted at a spatial resolution of 30 m using Landsat TM and ETM+ data. For the Namibian study site, four Landsat TM acquisitions of the year 2007 (WRS-2 path 177 row 73; Feb 15, May 6, Jun 23 & Jul 25) were used and for the Kenyan study region, two Landsat ETM+ scenes (WRS-2 path 168, row 60; May 22 & Sep 11 2004) were utilized. MODIS time series with a spatial resolution of 232 m were the basis of the large scale analysis covering an area of 240000 km^2 and 108900 km^2 for Namibia and Kenya respectively. MODIS data of one year were utilized, starting in October 2006 for Namibia (in order to avoid a split-up of the vegetation period) and in January 2004 for Kenya. The time series of NDVI, EVI as well as of blue, red, NIR and MIR reflectances were derived from 16-day composites of the MODIS standard product MOD13Q1.

The sub-pixel fractions of herbaceous vegetation, woody vegetation and bare soil surface were estimated using decision tree regression following Breiman et al. (1984). Particular advantages of regression trees are that they can handle high-dimensional data and non-homogeneous relationships and that normal distribution is not a prerequisite. The multi-scale procedure was performed in the same way for both study areas.

Initial training data for the construction of regression trees were defined with the help of very high resolution data. For this purpose, the QuickBird data and aerial images were classified into discrete classes of woody vegetation, herbaceous vegetation and soil with a maximum likelihood approach. The resulting very high resolution classifications were aggregated to the Landsat pixel level of 30 m, resulting in continuous values of percentage woody cover, herbaceous cover and bare soil per pixel. For this upscaling procedure, the very high resolution classifications were overlaid with the Landsat grid. The contribution of each 60 cm or 1 m pixel to the upscaled value was weighted according to its occurence within the 30 m grid cell. From the resulting continuous cover values, training, pruning and validation samples for construction and validation of regression trees were extracted.

On the basis of these samples, the fractional vegetation cover was estimated for the full extent of the Landsat scene, similar as described in Gessner et al. (2007). The features used for constructing the regression trees were the reflectances of Landsat band 1-5 and 7, the NDVI, SR, SAVI and Tasselled Cap Greenness, Brightness and Wetness for all available acquisitions. Additionally, the median, mean, minimum, maximum, range, standard deviation and sum of all acquisitions were calculated for these reflectances and indices. Regression trees were built from the training and pruning data for each cover type (i.e. woody, herbaceous and bare) individually. In a bagging procedure (Breiman, 1996), a random fraction of the training and pruning samples was drawn in eight iterations, regression trees were grown and subsequently pruned. The results of the eight trees were combined in order to stabilize the predicted values.

The resulting percentage cover with a spatial resolution of 30 m was scaled to the 232 m MODIS grid and was used as training data for further regression trees to analyse MODIS time series. The procedure of upscaling, sampling and regression tree construction with bagging was performed in the same way as described above for Landsat data. Due to the differing data characteristics of multitemporal MODIS and multispectral Landsat data, different features were used for building the decision trees. The features derived from the annual MODIS time series were median, mean, minimum, maximum, range, standard deviation and sum of all bands. All features were calculated for rainy and dry seasons, as well as for the entire year. Due to the different precipitation regimes of the study regions, two seasons were considered for Namibia whereas in Kenya, four seasons were discriminated.

The validation of the percentage cover values was performed using the independent validation sample set. Root mean square errors between predicted and true cover values were calculated.

4. RESULTS AND DISCUSSION

Figure 1 shows the estimation of woody cover on three spatial scales for a subset of the Namibian and the Kenyan study areas. At the highest spatial resolution, both landscapes are well represented by discrete classes as e.g. trees, shrubs, roads and cultivated plots are objects of bigger size than the pixel resolution (Figure 1 a and d). At the intermediate and coarse resolutions, these objects become smaller than pixel size, resulting in smooth transitions between land cover types. These gradual transitions are characterized very adequately through the sub-pixel percentage cover estimations (Figure 1 b-c & e-f).

For the Namibian study region, apart from edaphic conditions, the most obvious spatial patterns of the landscape are related to fire and agriculture. Areas with low fire impact show spatially more homogeneous patterns with higher woody fractions and less bare soil than surrounding areas. An example for this is the fire-proof fenced plot in the western part of the subset in Figure 1 a-c. At the border between communal and freehold land of the north-eastern Namibian study region (not displayed in the Figure 1), no clear difference in woody and herbaceous vegetation cover could be depicted at resolutions of 30 m and 232 m.

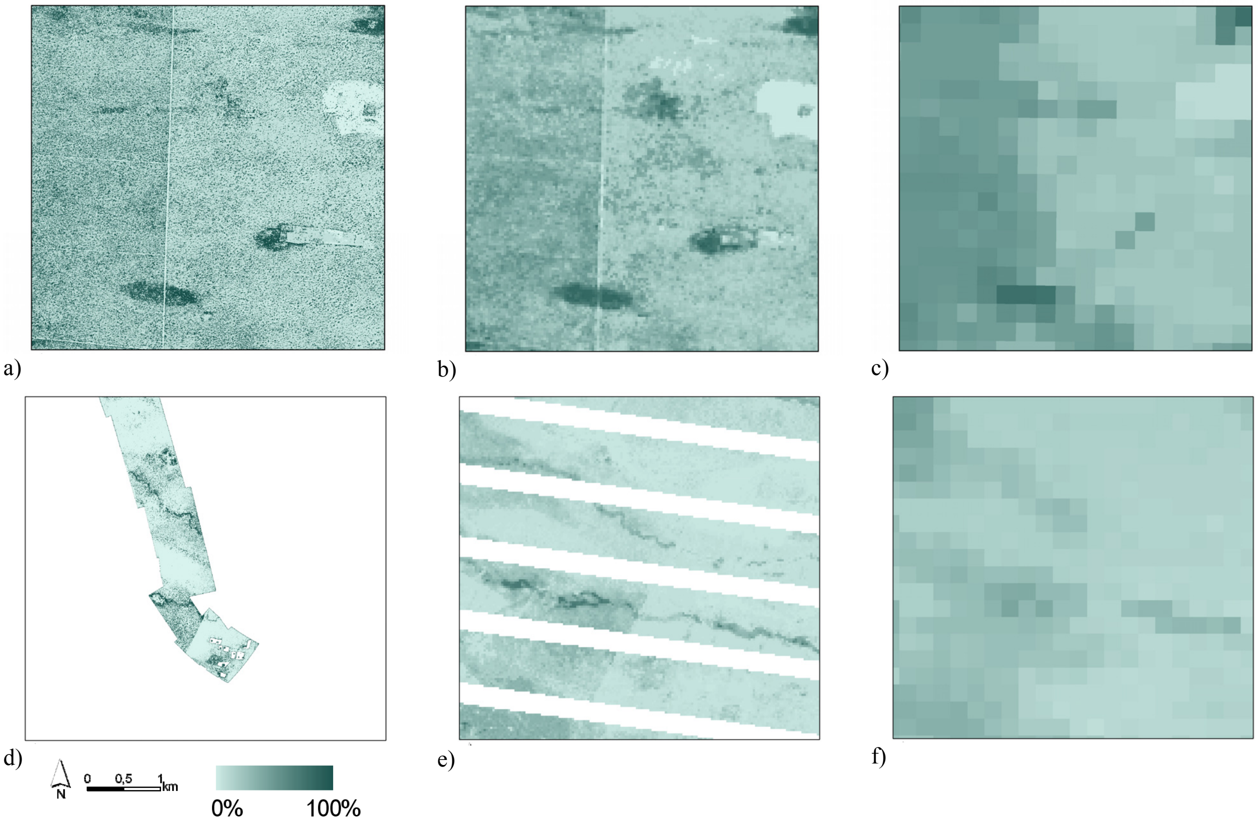

Figure 1. Estimated woody vegetation cover on three spatial scales.
a-c Subset of the Namibian study region at 60 cm, 30 m and 232 m resolution
d-f Subset of the Kenyan study region at 1 m, 30 m and 232 m resolution

In Kenya, the different land use types become apparent regarding the tree cover abundance (Figure 1 d-f). While within the large scale ranches, a relatively high degree of woody cover exists (eastern part in Figure 1 d-f), within the area of small scale farms, especially on the not yet settled plots, woody cover is highly reduced due to tree cuttings for fire wood and charcoal burning (western part in Figure 1 d-f).

Root mean squared errors (RMSE) for the Kenyan and Namibian study site are listed in Table A. The results are very realistic, showing RMSE values below 10 % for both scales in Namibia and for the MODIS scale in Kenya. RMSE values for woody and herbaceous cover at 30 m resolution in Kenya were somewhat higher, but still fall clearly below 13 %.

Table A. Estimations of root mean squared error for the fractional vegetation cover at spatial resolutions of 30 m and 232 m.

	woody	herbaceous	bare
Namibia (232 m)	9.22	7.76	6.13
Kenya (232 m)	7.90	8.10	3.30
Namibia (30 m)	9.21	6.81	5.59
Kenya (30 m)	11.45	12.19	9.21

The slightly lower accuracies for the 30 m resolution in Kenya can be due to the characteristics of the available aerial images. First, the potential to derive the exact surface cover from the aerial images was lower than for high quality QuickBird data, especially because of the missing near infrared band. In addition, the limited extent of the imagery resulted in a considerably smaller number of samples available for training, pruning and validation of ETM+ data. Especially the rarely occurring percentage cover values were not represented adequately by the very high resolution data. In very heterogeneous landscapes like the Kenyan study area, it becomes especially problematic to work with a small coverage of very high resolution data as it is likely that certain typical cover fractions are not comprised in the imagery. Additionally, it has to be considered, that if the missing ranges are at the extremes of the value range, the regression trees are not able to predict these extreme values. Thus the location and representativeness of the highest and high resolution data within the target region is crucial in order to attain reliable estimations for the whole area. However, the 30 m results for Kenya, with RMSE values below 13 % are very promising and well usable for continuative applications. This shows that it is also possible to take aerial pictures by oneself in case there are no other very high resolution data available or affordable.

The use of SLC-off ETM+ data for the intermediate scale in Kenya was due to the nonexistence of other high resolution data of the rainy season 2004. The disadvantage of large gaps in ETM+ data could be accepted as still a sufficient number of samples for the construction and validation of regression trees on MODIS scale could be derived, leading to good results at 232 m resolution

(Table A). However, the thematic interpretation of the fractional cover maps derived from SLC-off ETM+ data is limited (Figure 1 e).

5. CONCLUSIONS

The accurate results for both study areas affirmed the applicability of the method to different semi-arid environments within a range of environmental conditions. The approach could be successfully applied to both study regions in exactly the same way, even though different high resolution images were used. The only difference in the preprocessing was the number of rainy seasons considered for the calculation of MODIS metrics, according to the respective rainfall regimes. Thus, the method seems to be highly suitable for automated processing.

It was revealed that the representativeness and quality of the higher resolution training data has a considerable influence on the accuracy of the results. In this context, it was discussed that it is especially important that all cover ranges occurring in the landscape are well represented in the training data set.

In general, for analyses depending on very high and high resolution data, the transfer to other regions and dates is often restricted by the non-availability of adequate data. Here, it was shown that for the presented approach, the use of aerial pictures as well as the now freely available SLC-off ETM+ data are efficient alternatives.

For both regions, the results adequately reflect the gradual transitions of the landscapes and are congruent on all of the three spatial scales. Thus, it could be shown that when using MODIS data for large area mapping, it is still possible to monitor gradual transitions in vegetation cover. Moreover, different spatial patterns of vegetation cover depending on land use practices and intensities were revealed. It can therefore be concluded that the presented sub-pixel approach is capable to also monitor the gradual temporal changes in land cover which are induced by anthropogenic land use in semi-arid savannas.

Further work will concentrate on the improvement of the representation of the extreme cover ranges and on the estimation of error propagation in the bottom-up multi-scale approach.

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