Estimating vegetation parameter for soil erosion assessment in an alpine catchment by means of QuickBird imagery

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Soil erosion rates in alpine regions are related to high spatial variability complicating assessment of risk and damages. A crucial parameter triggering soil erosion that can be derived from satellite imagery is fractional vegetation cover (FVC). The objective of this study is to assess the applicability of normalized differenced vegetation index (NDVI), linear spectral unmixing (LSU) and mixture tuned matched filtering (MTMF) in estimating abundance of vegetation cover in alpine terrain. To account for the small scale heterogeneity of the alpine landscape we used high resolved multispectral QuickBird imagery (pixel resolution = 2.4 m) of a site in the Urseren Valley, Central Swiss Alps (67 km²). A supervised land-cover classification was applied (total accuracy 93.3%) prior to the analysis in order to stratify the image. The regression between ground truth FVC assessment and NDVI as well as MTMF-derived vegetation abundance was significant ($r^2 = 0.64$, $r^2 = 0.71$, respectively). Best results were achieved for LSU ($r^2 = 0.85$). For both spectral unmixing approaches failed to estimate bare soil abundance ($r^2 = 0.39$ for LSU, $r^2 = 0.28$ for MTMF) due to the high spectral variability of bare soil at the study site and the low spectral resolution of the QuickBird imagery. The LSU-derived FVC map successfully identified erosion features (e.g. landslides) and areas prone to soil erosion. FVC represents an important but often neglected parameter for soil erosion risk assessment in alpine grasslands.

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1. Introduction

One of the most crucial factors to determine soil erosion rates is vegetation cover. Vegetation cover prevents soil erosion by reducing the impact of falling raindrops, increasing infiltration of water into the soil, reducing the speed and the force of the surface runoff, stabilizing the soil mechanically and improving the physical, chemical and biological properties of the soil (Descroix et al., 2001; Elwell and Stocking, 1976). Grassland is the dominant land use type in the Alps above 1500 m a.s.l. (BFS, 2005). Usually, vegetation cover is regionalized by assigning uniform values from literature or field measured data to a classified land-cover map (Folly et al., 1996; Morgan, 1995; Wischmeier and Smith, 1978). The latter method results in constant values for alpine grasslands, and does not account for spatial variation in fractional vegetation cover.

Remote sensing allows a survey of erosion features such as gullies, landslides or vegetation disturbance to collect input data for soil erosion models even in remote areas (De Jong, 1994; Vrieling, 2006). Most commonly used techniques to assist erosion assessment are image classification, spectral indices and spectral unmixing. Spectral indices and especially spectral unmixing are useful to derive vegetation abundances (Vrieling, 2006). Spectral indices such as the Normalized Difference Vegetation Index (NDVI) have been used for the direct mapping of vegetation cover (Liu et al., 2004; Thiam, 2003) or to improve the mapping of C factor, which represents the effects of all interrelated cover and management variables in the Universal Soil Loss Equation, by establishing regression analysis (De Jong, 1994; De Jong et al., 1999). For some regions vegetation indices were found to have low correlation with the C factor (De Jong, 1994; Tweddales et al., 2000) due to the sensitivity of the NDVI to vitality of vegetation (De Jong, 1994). The problem was overcome by using linear spectral unmixing (LSU). Asner and Heidebrecht (2000) could successfully map non-photosynthetic vegetation using the LSU technique. Linear spectral unmixing also proved to be superior to NDVI for mapping the C factor by regression analysis (De Asis and Omasa, 2007; De Asis et al., 2008). So far, LSU has been used with satellite systems with a medium spatial resolution and medium to high spectral resolution due to the higher number of spectral bands. The alpine environment exhibits a spatially complex and heterogeneous biogeochemical structure, where abundances of bare soil, vegetation, and rock vary at small scales making it difficult to map these key parameters for soil erosion assessments. A possible solution to account for the problem of spatial heterogeneity might be the usage of very high resolution satellite imagery as high resolution vegetation cover data is
crucial for soil erosion modelling (Meusburger et al., submitted for publication).

The objective of this study is to test the suitability of high resolution QuickBird imagery in estimating vegetation cover abundances in an alpine catchment. In many regions, vegetation cover is characterised by strong temporal dynamics that needs to be considered for erosion assessment (Vrieling, 2006). In alpine areas temporal dynamics are less important because disturbances in vegetation cover due to trampling, overgrazing, cutting, snow transport and landslides recover slowly and do not follow a seasonal dynamic as on arable land, where ploughing and harvesting is applied. The QuickBird image was taken in autumn, because we assume that fractional vegetation cover mapped in autumn is a decisive parameter for soil erosion risk. Bare soil areas that have not recovered during the growing season are persistent and are prone for winter damages and subsequent snowmelt, when highest erosion rates can be expected (Konz et al., 2009). In our study site, sheet erosion and landslides are dominant. Rill erosion is scarce, which might be mostly due to the high content of skeleton in the soil. Fractional vegetation cover (FVC) in the field is defined here as the percentage of an area covered by grass. The inverse of FVC equals to the fraction of bare soil. We aim to map FVC for grassland areas by NDVI, linear spectral unmixing (LSU) and mixture tuned matched filtering (MTMF) and relate this to ground truth measurements. Prior to the unmixing analysis a supervised land-cover classification of the image is done to allow for stratified evaluation of the image.

2. Materials and methods

2.1. Site description

The study site is located in the Urseren Valley, Central Swiss Alps (46.36°N, −8.32°E) and covers approximately 67 km². Elevation of the U-shaped valley ranges from 1400 m to 3200 m a.s.l. The valley has heterogeneous geologic formations which correspond to a geological fault line with NW-SE extension (Fig. 1). The climate is alpine with a mean air temperature of 3.1 °C and a mean annual rainfall of about 1400 mm per year measured at the climate station in Andermatt (1901–1961; 1442 m a.s.l.; data from MeteoSwiss). The valley is snow covered for 5–6 months (from November to April) with the maximum snow height in March and drained by the river Reuss. Its nivo-glacial runoff regime is replenished by summer and early autumn floods with peak runoff in June (BAFU, 2009). The main land-cover types of the 67 km² study site in 2000 were 64% alpine grasslands and dwarf-shrubs, 26% scree and bare rock mainly at higher elevations, and 5% shrubs. The remaining 5% are covered by glacier, forest or settlement (Swisstopo, 2006). For a more detailed description of the study site, see Meusburger and Alewell (2008).

2.2. Pre-processing of the QuickBird image

QuickBird standard imagery was acquired on October 17, 2006 (10:51 UTC), under clear sky conditions. The sun elevation at the time of capture was 34.1° with a nadir view angle of 16.1°. The imagery was geo-corrected by the satellite data providers with a published spatial accuracy of 14 m root mean square error (RMSE). The imagery contains four multispectral bands with a 2.4 m spatial resolution: the wavelength of the respective bands is 0.45–0.52 μm (blue); 0.52–0.60 μm (green); 0.63–0.69 μm (red); 0.76–0.90 μm (near infrared). The QuickBird panchromatic band (0.45–0.90 μm) has a 0.6 m spatial resolution. Standard QuickBird imagery is already radiometrically corrected. The correction accounts for instrument specific errors only, consequently further image correction is necessary.

The image correction procedure requires three steps (Edwards et al., 1999): conversion of the digital number (DN) recorded at the sensor to satellite radiance; conversion of satellite radiance to satellite reflectance at the sensor, and finally the conversion to ground reflectance by removal of topographic- and atmospheric (absorption and scattering) effects. The conversion from DN values to radiances was performed according to the technical note from Digital Globe (Krause, 2003). For the conversion of satellite radiance to apparent reflectance $\rho$ (−) the following equation was used

![Fig. 1. Geographic location of the QuickBird image (false colour). The white lines separate different geologic formations. The white dots show the locations of ground truth measurements of fractional vegetation cover.](image-url)
\[ \rho = \frac{\pi \times L \times d^2}{\text{ESUN} \times \cos(\theta s)} \]  
\[ d = (1 - 0.01674 \times \cos(0.9856 \times (\text{JD} - 4))) \]

where JD is the Julian Day of the image acquisition.

The image was corrected for topographic effects only, due to a high visibility (>50 km) during image acquisition and lacking additional information on atmospheric conditions. The topographic correction was done with a DEM (25 m grid; ±3 m vertical accuracy in the Alps; Swisstopo, 2006) and the TOPOCOR module of the Atcor3 software package (Richter, 2005). The correction factor is:

\[ f = 1 - \left(1 - \cos{\beta} \cos{\delta} \right) \times w, \quad \text{if } \lambda < 1.1 \text{ m} \mu \]

\( \beta \) is the local zenith angle and \( w \) a wavelength (\( \lambda \)) depending weighting coefficient. For \( \lambda \geq 1.1 \text{ m} \mu \) \( w \) becomes 1 (Richter, 2005). Furthermore, the factor \( f \) includes a bound to prevent overcorrection.

2.3. Field measurements

2.3.1. Ground truth measurements

The FVC for 43 plots along two elevation gradients (ranging from 1450 m to 2150 m a.s.l.) and along the valley transect (Fig. 1) was measured two weeks after the image was taken. Sites showing impact of sheet erosion, trampling overgrazing or cutting were chosen for ground truth sites with low FVC. A mesh with 10 × 10 cells (cell size 100 cm²) was put on the earth surface to measure FVC. For each cell, the FVC was visually estimated and averaged over the total mesh area. The geographic position of each ground truth site was determined using Garmin eTrex Summit GPS (3 m accuracy; Garmin International Inc., Olathe, KS, USA). Because of the geolocational uncertainty of the QuickBird image and the effects of surrounding pixel radiance, ground truth plots with a homogenous surface characteristic for at least 5 m × 5 m were chosen. The single coordinates of the ground truth sites were measured together with the coordinates of characteristic identifiable features in the image (e.g., boulders, crossroads etc.) to allow better localisation using the pan-sharpened image. The ground truth values did not show a normal distribution, because of a limited availability of ground truth sites with low FVC especially at higher elevation with lower land use intensity.

2.4. Image land-cover classification

All image analysis was performed using ENVI 4.3 software (Research Systems Inc., Boulder, CO). We used supervised classification with a maximum likelihood classifier for land-cover mapping. Land-cover was classified into the following nine categories: forest, shrub, dwarf-shrub, grassland, non-photosynthetic vegetation, snow, water, bare soil, and rock. The artificial category shadow was introduced because of the distinct topography of the study area. For each land-cover class the maximum likelihood classifier was trained on three locations in the valley with 144–1876 pixels per training class. For the land-cover type grassland a higher probability threshold (of 0.75) was used in order to include grassland with reduced FVC. To measure the accuracy of the classification, the kappa coefficient (\( \kappa \)) and overall accuracy were calculated. In total, 3217 independent pixels with five ground truth locations per class were used to assess the classification accuracy.

Fig. 2. Sub-image of the QuickBird scene showing (left) the resulting land-cover map compared to land-cover information of the Swisstopo 1:25,000 Vector dataset and (right) normalized abundances of vegetation, bare soil and RMSE for the linear spectral unmixing model. The lighter the colour, the higher the proportion of an endmember (and error) within the pixel.
2.5. Mapping of fractional vegetation cover

We compared the performance of the Normalized Difference Vegetation Index (NDVI) with that of two spectral unmixing approaches. The NDVI is the most widespread spectral ratio of near infrared and red bands and is used for monitoring global vegetation cover (Tucker, 1979).

The spectral unmixing assumes that the reflectance of each pixel is a combination of spectral endmembers (Adams et al., 1995). Most rural land endmember combinations are green vegetation, non-photosynthetic vegetation, bare soil, rock, and shadow (Adams et al., 1995; Roberts et al., 1993; Theseira et al., 2003). A crucial step in spectral unmixing analysis is the determination of spectral endmembers that are pure elements located at the corners of the spectral space. Endmember spectra combine to produce all of the spectra in the image.

The Pixel Purity Index (PPI) algorithm is a common method to find the most “spectrally pure” (extreme) pixels in multispectral images (Boardman and Kruse, 1994). It is computed by repeatedly projecting n-dimensional scatter plots onto a random unit vector. The ones falling at the extremes of each vector line are recorded. After many repeated projections, the total number of times each pixel is marked as extreme is noted. The pixels that count above a certain cut-off threshold are declared “pure” and are the potential endmember spectra. We used 5000 iterations with a threshold of 2.5. Before the PPI is applied, a “noisewhitenning” dimensionality reduction step is performed by using a Minimum Noise Fraction (MNF) transformation (Green et al., 1988). Previous studies have shown that the use of the MNF transform can improve the quality of fraction images through decorrelation (Van der Meer and De Jong, 2000). The MNF transformation is in principle a two-phase principal component analysis that segregates the noise from the data resulting in a reduced number of bands containing the most meaningful information. A dark shadow part of the image behind the main mountain ridge was used to steer the MNF algorithm. The dimensionality of the QuickBird image was not reduced by the procedure. We selected the pixels with the highest PPI values as candidate endmembers. The final endmembers were then selected by referring to the QuickBird image and the field survey (e.g. vegetation with homogenous canopy and without boulders). Average reflectance of selected representative pixels (average of 2–81 pixels) with high PPI values that correspond to selected endmembers were used in the subsequent unmixing analysis. Five endmembers were identified for the study site: snow, vegetation, rock, bare soil, and water/shadow. We used two spectral unmixing approaches: linear spectral unmixing (LSU) and mixture tuned matched filtering (MTMF). The LSU method is limited by the assumption that pixel composition is made up of a limited number of elements, because of mathematical reasons, the number of elements cannot exceed the number of spectral bands plus one (Adams et al., 1995). Considering the correlations between the visible bands of the QuickBird imagery, the approach is limited to three endmembers. In order to bypass this limitation the results of the land-cover classification were used to stratify the image in advance. The following categories were masked prior to the LSU analysis: forest, shrub, dwarf-shrub, snow, water and rock. Grassland, bare soil and shadow were used as endmembers. An advantage of LSU is the supply of a residual error for each pixel in the image. The residual error is the difference between the measured and modelled spectrum in each band. Averaged residuals over all bands give an RMSE, which is useful to check for the validity of selected endmembers. The unmixing was constrained to fix the fraction of any endmember between 0 and 1, and the sum of fractions for each pixel equal to 1. In regions with steep topography, shadowed areas are present in the image. However, because shadow is not a physical component, it was removed by normalization (Adams et al., 1995; Hill and Foody, 1994; Smith et al., 1992).

MTMF is another type of spectral unmixing that performs a ‘partial’ spectral unmixing by identifying only a single endmember at a time without knowing the other background endmember signatures (Boardman, 1998). From spectral mixture modelling, it takes over the leverage arising from the mixed pixel model, the constraints on feasibility including the unit-sum and positivity requirements. The response of the endmember of interest is maximized and the unknown background is suppressed (Harsanyi and Chang, 1994). The MTMF and LSU score indicate how well the image pixel compares to the reference spectrum and measures how spectrally abundant a material is in the image pixel. Provided that spectra of the single components mix linearly, spectral abundance in an image pixel corresponds to physical abundance in the same location on the ground.

The advantage of the MTMF compared to LSU is that it is unnecessary to identify all endmembers in a scene (Glenn et al., 2005; Harris and Asner, 2003; Mundt et al., 2005; Parker Williams and Hunt, 2002). Consequently the number of endmembers is independent from the number of spectral bands (Boardman, 1998). For our study area, the sum of the MTMF scores at each pixel was usually less than unity probably due to unidentified background material within the pixel. Because MTMF routine projects the mean of the background data to zero negative MTMF scores or MTMF scores greater than 1 (for at least one of the four endmembers) were present on many pixels for our study site. These values are physically meaningless and were re-scored as 0 or 1 (Robichaud et al., 2007). For the MTMF approach, two ground truth sites were excluded due to high infeasibility values. In contrast to the LSU that was performed using the masked image, the MTMF analysis was applied for the entire image. Finally, all mapped abundances were multiplied by 100 to express as % parallel to the percentage ground data.

3. Results and discussion

3.1. Mapping of land-cover by image classification

At higher elevations the problem aroused that spectral signature of bare soils and non-photosynthetic vegetation are very similar because siliceous geology with podsolic soils is predominant. The rusty colour of the podsolic soils is similar to the colour of non-photosynthetic vegetation. With the available training data either classifying landslide areas in low elevations as non-photosynthetic vegetation or non-photosynthetic vegetation at higher elevations as bare soil was possible. At higher elevation NDVI of non-photosynthetic vegetation training areas was above 0.2 while bare soil areas were below. Thus, subsequent to the supervised classification all pixels classified as bare soil above 2000 m a.s.l. with a NDVI greater than 0.2 were changed to non-photosynthetic vegetation. The elevation above 2000 m a.s.l. was chosen because it produced best classification results compared to the ground truth data. The problem of the discrimination between non-photosynthetic vegetation and soil might be solved by using multi-temporal QuickBird imagery. In the summer season (July, August) the elevated non-photosynthetic vegetation is green vegetation.

The achieved overall accuracy of land-cover classification using the independent pixel dataset is 93.3% (3000/3217 Pixels) and the k=0.92. In total, 0.81% of the dataset remained unclassified. The land-cover classes of bare soil (after correction), grassland, rock, snow, water, forest, and shadow have high classification accuracies (82–100%), while classes of dwarf-shrub, shrub, and non-photosynthetic vegetation have lower classification accura-
Table 1
Confusion matrix for the supervised land-cover classification (npv = non-photosynthetic vegetation).

<table>
<thead>
<tr>
<th>Class</th>
<th>Bare soil</th>
<th>Grassland</th>
<th>Dwarf-shrubs</th>
<th>Shrubs</th>
<th>Rock</th>
<th>Snow</th>
<th>Water</th>
<th>Forest</th>
<th>npv</th>
<th>Shadow</th>
<th>Total</th>
<th>Produces accuracy (%)</th>
<th>User accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unclassified</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>26</td>
<td>0</td>
<td>26</td>
</tr>
<tr>
<td>Bare soil</td>
<td>214</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>26</td>
<td>223</td>
<td>97.27</td>
</tr>
<tr>
<td>Grassland</td>
<td>0</td>
<td>232</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>339</td>
<td>92.22</td>
</tr>
<tr>
<td>Dwarf-shrubs</td>
<td>0</td>
<td>0</td>
<td>160</td>
<td>14</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>0</td>
<td>204</td>
<td>204</td>
<td>74.77</td>
</tr>
<tr>
<td>Shrubs</td>
<td>0</td>
<td>28</td>
<td>54</td>
<td>217</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>320</td>
<td>320</td>
<td>91.18</td>
</tr>
<tr>
<td>Rock</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>411</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>423</td>
<td>423</td>
<td>99.04</td>
</tr>
<tr>
<td>Snow</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>235</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>235</td>
<td>235</td>
<td>99.58</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>216</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>216</td>
<td>216</td>
<td>83.72</td>
</tr>
<tr>
<td>Forest</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>248</td>
<td>0</td>
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<td>0</td>
<td>1</td>
<td>255</td>
<td>255</td>
<td>90.51</td>
</tr>
<tr>
<td>npv</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>122</td>
<td>0</td>
<td>122</td>
<td>122</td>
<td>78.21</td>
</tr>
<tr>
<td>Shadow</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>845</td>
<td>95.54</td>
</tr>
<tr>
<td>Total</td>
<td>220</td>
<td>360</td>
<td>214</td>
<td>238</td>
<td>415</td>
<td>236</td>
<td>258</td>
<td>274</td>
<td>153</td>
<td>846</td>
<td>3217</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The disadvantage of mapping FVC by NDVI is its dependency on the vitality of the vegetation (De Jong, 1994). Spectral indices enhance the spectral contribution of green vegetation in images while minimizing contributions from bare soil, atmosphere and illumination angle. Although spectral indices produce reliable estimates of green vegetation cover, the accuracy of non-photosynthetic vegetation is less satisfactory (De Jong, 1994). Moreover, quantification of low FVC using NDVI is weakened by the increasing influence of the variability of background bare soil albedo (Harris and Asner, 2003). The chosen ground truth sites showed minor influence of non-photosynthetic vegetation. Larger errors might be expected for grassland with a higher proportion of non-photosynthetic vegetation. While NDVI utilizes only the visible and near infrared band, the unmixing approach makes use of the entire spectral reflectance (De Asis and Omasa, 2007).

Scatter plots between ground truth FVC and percentage bare soil and abundances determined with LSU and MTMF are given in Fig. 4. Using linear regression between ground truth data and the satellite derived abundances could be described with a coefficient of determination of \( r^2 = 0.85 \) for LSU and 0.71 for MTMF. Low, but still significant (at a 0.01 level) regression was obtained between bare soil abundance and ground truth bare soil fractions with \( r^2 = 0.28 \) for LSU and \( r^2 = 0.39 \) for MTMF. The abundances of vegetation and bare soil do not sum up to 100% because of the high RMSE of the unmixed images caused by the confusion between bare soil and shadow. Only residues of the regression between FVC and LSU- derived vegetation abundance have no significant (at a 0.05 level) difference to a normal distribution. The LSU- and MTMF-derived abundances represent a physical percentage of a material on the ground-surface and should lie on a 1:1 line with the values measured on the ground. The measured ground truth values were generally higher than the corresponding LSU- and MTMF-derived abundances. For the FVC this can be explained by the choice of the grassland endmember that was located on a golf course situated in the study site.

3.2. Mapping of bare soil and vegetation abundance relative to ground truth measurements

The abundance images derived using LSU for vegetation, bare soil and RMSE are shown in Fig. 2 (right). The figures show high spatial variability that represents the different cover conditions in the study area. Vegetation abundance is highest close to the valley bottom. The evident bare soil areas correspond to landslides, overgrazed areas, road- and river-banks and areas affected by sheet erosion. The RMSE image shows no recognizable pattern for the grassland areas indicating that the chosen endmembers are valid. High RMSE values are evident for areas covered with rock, landslides with rock outcrops and shrubs. These land-cover types were subsequently masked. The mean RMSE value for the masked image is 0.52.

The scatter plot between the ground truth FVC and the NDVI (Fig. 3) has difficulties discerning different levels of ground truth FVC for high abundances (40–100%). The low abundances (0–5%) are overestimated by NDVI. Linear regression yielded an overall coefficient of determination of \( r^2 = 0.64 \).

The disadvantage of mapping FVC by NDVI is its dependence on the vitality of the vegetation (De Jong, 1994). Spectral indices enhance the spectral contribution of green vegetation in images while minimizing contributions from bare soil, atmosphere and illumination angle. Although spectral indices produce

Fig. 3. Scatter plot of NDVI versus the ground truth fractional vegetation cover.
ground truth data and RMSE was worse. The better performance of the golf course endmember might be due to the absence of non-photosynthetic vegetation. In October (time of image capture) the chlorophyll content in natural grassland already decreased compared to the irrigated golf course. The unmixing might work also with a generic grassland endmember, which would spare the procedure for the local image selection. Still a direct application (without the correction for the deviation from the 1:1 line) in soil erosion models would not be feasible due to the underestimation of the physical percentage. Using the regression equation established between the vegetation abundance maps and the ground truth data it is possible to convert the vegetation abundance map to the FVC map.

For the MTMF-derived abundances, we observe even stronger deviations, which might be due to the partial unmixing algorithm, where the abundances were not constrained to sum to unity. If an endmember is not found in the pixel, the pixel is classified as background material (Boardman, 1995). In our case not every endmember is found in every pixel, which caused zeros on the scatter plots, especially for the bare soil abundance (Fig. 4).

The high coefficient of determination yielded for the mapping of vegetation abundances may be due to the very distinct reflectance curves of vegetation if they are compared with reflectance of bare soil, rock and water. The less distinct spectral signature of bare soil is probably the main reason for the worse estimates of bare soil abundances. Another explanation is the higher spectral variability of the soil depending on its genesis and erosion status. Regarding the abundance of bare soil, we believe the obtained results are not precise enough for further application.

In general, QuickBird is not the 'optimal' sensor for unmixing approaches due to the small number of spectral bands. For the mapping of bare soil abundances the systems seems to reach its limits. This is mainly due to the lack of short wave infrared channels that are important for mineral and rock discrimination since minerals have numerous absorption bands in this wavelength range. This problem might be solved by using images of the WorldView-2 satellite (launched in October 2009) that provides 8 spectral bands at 1.8 m resolution at nadir. Nonetheless, the results from the linear regression show that the ground measured FVC and the abundances mapped by LSU and MTMF had a significant correlation. Especially the LSU-derived linear regression equation between vegetation abundance and ground truth FVC may be used to quantitatively predict ground FVC. The FVC map allows for a first allocation of potential soil erosion risk areas and improves estimates of soil erosion models (Meusburger et al., submitted for publication).

4. Conclusion

The supervised classification identified the typical land-cover types of alpine regions successfully with an overall accuracy of 93.3%. Relative abundance of vegetation cover could be mapped for grassland areas using NDVI, linear spectral unmixing and mixture tuned matched filtering with coefficients of determination between ground truth and derived FVC of \( r^2 = 0.64 \) for NDVI, \( r^2 = 0.85 \) for LSU, and \( r^2 = 0.71 \) for MTMF. The spectral unmixing approaches (LSU, MTMF) failed to map bare soil abundance, which might be due to the low spectral resolution of the QuickBird imagery and the high variability of the spectral signature of bare soil. The small scale heterogeneity and extreme topography make high demands for the remote sensing of an alpine environment. High spatial resolutions are needed that only few satellite systems such as IKONOS and QuickBird offer. The disadvantage of these systems is the small spectral resolution that causes difficulties in separating bare soil areas from non-photosynthetic vegetation and rock. Sufficient ground truth data is required to handle these difficul-
ties. The produced abundance maps of vegetation are preferable to only parameterising thematic land-cover classes because it retains spatial and distributional information.

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References


