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A rule-based image analysis approach for calculating residues and vegetation cover under field conditions

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ABSTRACT

Estimation of soil cover by residues and vegetation is a fundamental issue for many agriculture-related topics, especially topics dealing with mulching practices and soil erosion, because the amount of cover is a basic driver for erosion risk. Soil cover measurement in the field is very time consuming and subjective. Our ambition for this study was to develop a quick and easy-to-handle field method for calculating the amount of different soil cover types, i.e. simultaneously dead and living biomass, in a single-step analysis. We used an object-based image analysis methodology (OBIA) to quantify different cover types. Classification of the images used resulted in the following classes: residues, vegetation, stones, shadow and uncertainty. The shadow and uncertainty classes were used as an image quality parameter.

We compared this method to manual image analysis for the range of between 0 and 50% total cover and different catch crops and winter crops. To increase the accuracy of manual analysis, it was necessary to repeat the assessment five times per image. Degree of agreement between the OBIA method and manual assessment for each of the three different cover types was in the region of 0.8 ($r^2 = 0.78$ for total cover, $r^2 = 0.75$ for residue cover, $r^2 = 0.82$ for vegetation cover). Slopes of the regression intercepts between manual and automated analyses were not different from 1 for total cover and vegetation cover. 95% confidence intervals for the regression lines indicate that confidence limits at total soil cover of 25% (the mean of the investigated range of soil cover) are similar for both the manual evaluation ($CI_{95\%} = 2.8$) and the OBIA method ($CI_{95\%} = 3.1$). The time needed for evaluation was calculated at 115 min per manual image classification and 15 min per automated image classification, which we regard as a major advantage of the OBIA methodology. Finally we suggest that, while similar accuracies of evaluation for both methods have been obtained, the OBIA method allows greater objectivity because of predefined classification algorithms and thus the possibility of back tracing results.

1. Introduction

Estimation of soil cover by residues and/or vegetation is a fundamental issue for many agriculture-related topics, especially topics dealing with mulching practices and soil erosion, because the amount of cover is a basic driver for erosion risk. In addition to the need for parameter values for research purposes, many subsidy programmes for sustainable agriculture support measures for soil cover. These programmes need to ascertain that farmers who receive funds also establish sufficient minimum soil cover, hence there is a need for quick and reliable methods of estimating the mean soil cover rates of a site. Despite the importance of knowing the amount of living as well as dead cover on a soil surface, a surprisingly small number of methods to measure these parameters are available. The main method in common use seems to be manual analysis onsite (Marques et al., 2007; Mohammad and Adam, 2010) or manual image analysis as proposed by Hartwig and Laflen (1978), Corak et al. (1993) or Morrison et al. (1993). One main drawback of manual image analyses is the time needed for evaluation. In addition, these methods may lead to high subjective errors depending on the skills of the evaluating person (Corak et al., 1993). An additional possibility for obtaining soil cover would be use of remote sensing techniques. They however exhibit considerable problems when dealing with a combination of dead and living cover at high spatial resolutions. In addition their use is restricted to flight times and flight conditions furthermore they need to be calibrated against field observations (Arsenault and Bonn, 2005).

With the availability of cheap high-quality digital images, measuring vegetation cover by using automated image analysis is becoming more common (Behrens and Diepenbrock, 2006; Benett et al., 2000; Booth et al., 2005; Campillo et al., 2008; Purcell, 2000; Richardson et al., 2001). One main advantage of image-based methods is that they are faster in processing and can be easily executed (Laliberte et al., 2006).

In these studies the analysis was performed using either handmade programmes together with different existing image software packages (Photoshop, GIMP, IMAGE), or special analysis software like VegMeasure or SigmaScanPro. Most of these studies focussed either on dead (Obade, 2012; Pforte et al., 2012) or living (Behrens and Diepenbrock, 2006;

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Benett et al., 2000; Booth et al., 2005; Campillo et al., 2008; Purcell, 2000) soil cover.

An interesting feature of many applications in photogrammetry and remote sensing is the use of object-based image analysis (OBIA, Blaschke, 2010). OBIA is a photogrammetric method where, in contrast to other methods, not only the single pixel but rather objects resulting from pixels with similar characteristics (=objects) are analysed. Use of object-based approaches for estimating dead and living soil cover out of RGB-layer images is often executed for a small range in soil properties and together with time intensive sampling-based analysis, where the user has to define meaningful samples for each cover type (Laliberte et al., 2010; Luscier et al., 2006; Perez-Cabello et al., 2012).

Our ambition for this study was to develop a quick field method to estimate dead and living soil cover rates at field scale. To account for those ranges of soil cover that are highly important for the parameterization of erosion models and for subsidy purposes, we used total soil covers of 0–50%.

To reduce the time required to carry out evaluation and to avoid the loss of accuracy associated with adapting sample-based classification to different field and plant conditions, we decided to develop an OBIA method based on membership functions. To benchmark results, we compared our method to the manual evaluation described in Hartwig and Laflen (1978).

2. Materials and methods

2.1. Image acquisition

Images were taken between February and May 2012 to obtain low soil covers of residues and vegetation. The image acquisition was done with an ordinary digital camera type: Casio Exilim EX-Z400 12.1 megapixels. Images were taken from approximately 1.4 m height horizontally to the ground. The area for each image was about 1 m^2 (according to Benett et al., 2000; Behrens and Diepenbrock, 2006), and a reference scale was used to obtain similar soil surface areas for the different pictures. All pictures were taken with identical camera settings (best shoot function using flash light, no zoom and constant focus area). Shadow or diffuse sunlight conditions were preferred to avoid getting sharp shadowed areas, according to Pforte et al. (2012).

To obtain a range of potentially different soil and plant conditions, we took the images at different sites in Upper and Lower Austria (the maximum distance between image sites was about 400 km). Care was taken to obtain a similar number of images for different cover crop types (Table 1). The soil colours ranged from 2.5Y (dark brown to olive yellow), 5YR (dark reddish brown to reddish brown), 7.5YR (dark brown to strong brown) and 10YR (very dark brown to brownish yellow) according to the Munsell color scheme (Munsell color company, 1954).

2.2. Manual image analysis

For manual image analysis the photogrammetric grid method similar to Hartwig and Laflen (1978), Corak et al. (1993) and Voßhenrich et al. (2003) was applied. After the image was taken, a regular grid consisting of 391 crossing points (resulting from a regular raster width of 160 × 160 pixels) was digitally inserted in GIMP 2.6 (GNU Image Manipulation Programme). At these crossing points different canopy types were manually analysed. A distinction was made between soil, green (living) vegetation, residues (dead vegetation) and stones. Obtaining accurate estimates of residue cover is often very challenging, because small differences in soil cover cannot easily be distinguished and classified correctly (Obade, 2012). According to Hartwig and Laflen (1978), who repeated image analysis up to twenty times, low accuracy is given between one and three iterations of manual analysis. Above five iterations they observed only a slight improvement, which did not justify the longer time required. We therefore decided to repeat the manual image analysis five times per image.

Table 1
Number of processed samples for different plant species.

Labelling	n	Field crops
Wheat_similar	17	Winter wheat (triticium), winter barley (*Hordeum vulgare*)
Mustard_similar	17	Mustard (*Sinabis arvensis*), phacelia (phacelia)
Bare_&_mulching	16	
Rosette_similar	11	Rapeseed (*Brassica napus*), radish (raphanus)
Total	61	Catch crops and winter crops

2.3. OBIA method

Automated image analysis was done using eCognition 8.7 software (Trimple Germany GmbH), an object-based image analysis programme. eCognition is commonly used for the classification of remote sensing data (Blanchard et al., 2011; Flanders et al., 2003). In eCognition the analysis of images is done in several different steps.

2.3.1. Segmentation

For the splitting up of images in eCognition, several segmentation processes can be used (quadtree, contrast split, multiresolution, spectral difference, multi-threshold and contrast filter segmentation). The multiresolution segmentation algorithm of eCognition is unique and is based on region merging. This operation uses three parameters for dividing the image: scale, shape and compactness. The scale parameter is used for controlling the size of the resulting image objects. The shape parameter defines to which percentage the homogeneity of shape is weighted against the homogeneity of spectral values. The compactness parameter is a sub parameter of shape and is used to optimize image objects with regard to compactness or smoothness (Baatz and Schäpe, 2000; Flanders et al., 2003; Trimple, 2011a,b). The subsequently applied classification scheme depends on these parameter settings (Tzotos et al., 2011).

2.3.2. Classification

The classification process in eCognition can be realized either by using nearest neighbour classification based on samples, or by using membership functions based on fuzzy logic theory combined with user-defined rules (Benz et al., 2004). After testing both of these classification methods, the membership function based on rules was chosen; the nearest neighbour method needed much more processing time and seemed not to be suitable for different soils, residue covers and plant species, also in accordance with Zabala et al. (2012).

2.3.3. Membership function set

Dark areas make any decision in the three RGB layers difficult to handle. To exclude all dark areas, a membership function that classifies them as shadow was applied. Only no shadow parts of the image were considered for the subsequent classification process.

After elimination of dark areas, the living vegetation was detected by use of Degree of Artificiality (DoA) (Sibiryakov, 1996).

$$\mathrm{DoA} = \frac{(\mathrm{G}-\mathrm{R})}{(\mathrm{G}+\mathrm{R})} \tag{1}$$

where G and R are the green and the red layer of the image. When the value of DoA is higher than zero, green vegetation is proven. The use of the DoA alone showed low fitting results. As mentioned in Barnes et al. (2003), sometimes it is useful to use pairs of vegetation indices to discriminate most cover types. To detect all living vegetation, a conversion to the IHS (intensity, hue, saturation) colour space was done and another membership function added. This function was operated in the style described in Laliberte et al. (2006) and Ewing and Horton