Catena 113 (2014) 363–369

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

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

Th. Bauer *, P. Strauss

Institute for Land and Water Management Research, Federal Agency for Water Management, Pollnbergstrasse 1, 3252 Petzenkirchen, Austria

ARTICLE INFO

Article history:
Received 25 September 2012
Received in revised form 19 August 2013
Accepted 20 August 2013

Keywords:
Object-based image analysis
Automated soil cover estimation
Field method
Residue cover estimation
Vegetation cover estimation

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;

* Corresponding author. Tel.: +43 74165108
E-mail address: thomas.bauer@baw.at (T. Bauer).

0341-8162/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.catena.2013.08.022

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

(1999), which showed good results in using IHS for detecting green vegetation.

The remaining part of the image consists of soil, residue and bright stone cover. To separate spectrally similar residues from soil, rules based on the length/width ratio, rectangular fit, number of branches and homogeneity were chosen. The length/width ratio and the rectangular fit reflect the shape of the residues which is completely different to most soil structures. Residues often exhibit rectangular or quadratic shape. Furthermore the number of branches allows a distinction between soil and plant residues, as soil, in contrast to residues, seldom shows sharp edges. The homogeneity rule distinguishes objects with high similarity in their pixel attributes from objects with low homogeneity. Objects which belong to the classification residues are rather homogenous in comparison to soil surfaces. Afterwards, the cover of bright stones was excluded by applying another membership function that considers bright and reflecting objects. To get a range of uncertainty, a membership function was added that uses the ratio to scene parameter (provided by eCognition) for determining if the previous rule set is fulfilled in the best way. The equations for the calculation of brightness, rectangular fit, GLCM homogeneity, number of branches, length/width ratio and ratio of scene are given in the reference handbook for the software used (Trimple, 2011b).

Similarly to other studies, the thresholds of the membership functions were chosen to visually obtain best fits (Blanchard et al., 2011; Flanders et al., 2003; Laliberte et al., 2004, 2007; Lucas et al., 2007; van der Werff and van der Meer, 2008). The resulting classes of the process tree are shadow, vegetation, residues, stones, soil and uncertainty. The soil cover of each individual class is calculated as a percentage of the total explored soil surface.

2.4. Straw reference test

To prove the applicability of the OBIA based method it was tested under artificial laboratory conditions. We used a method similar to Pforte et al. (2012), who spread paper stripes of known area on an artificial surface. Instead of paper stripes we used straw which was placed on a surface area of 1 m^2 of fabric material. The produced surface cover ranged from 0 to 48.8% in steps of 6.2%. Images where taken for every step and analysed with the established membership function set.

2.5. Statistical analysis

Evaluation of the manual image analysis was done according to the following equation:

$$p_i = \frac{\sum n_i}{n} * 100 \tag{2}$$

where p_i is the resulting value in percent for class i, sum of n_i is the sum of all dots classified as i, and n is the number of all dots in the image (391).

After the variables were tested on normal distribution with the Kolmogorov–Smirnov-test, correlation and regression analyses were used to evaluate the relationship between the manual and OBIA method. All statistical analyses were done with SPSS 15.0.1 (SPSS Inc., 1989–2006) and STATISTICA 10 (StatSoft, Inc., 2011). For all tests a significance level p of 0.05 was used.

3. Results and discussion

3.1. Manual image analysis

Table 2 gives basic information for results on manual classifications of the tested images. Standard deviations for repeated manual classification ($n = 5$) of the same pictures reveal that the subjective influence in estimating the total soil cover may be very high. In some cases this was attributed to light conditions, as manual classification was easier for images taken under shadowed or diffuse circumstances, because otherwise huge differences between dark and bright parts of the images arise. The accuracy of manual assessment varied according to the total amount of soil cover (Table 2). In particular, images with soil covers above 10% exhibited high differences between minimum and maximum values. Mean standard deviation for total cover of all images was 2.6.

Table 2
Standard deviation (s_x) of manual image analysis (5 iterations per image) for total cover, green cover and residues.

Cover range (%)	n	Mean	Total cover min	Max	s_x for 5 iterations of manual analysis		
					Total cover	Vegetation	Residues
0 to <10	9	7.2	2.8	10	0.8	0.3	0.7
10 to <20	12	15	9.5	23.3	2.1	0.9	1.5
20 to <30	16	24.1	16.4	33.8	2.9	1.2	2
30 to <40	13	33.6	24.3	44	3.3	0.9	2.7
40 to <50	11	44.1	36.3	52.9	3.2	2.4	2.4
0 to 50	61	25.4	2.8	52.9	2.6	1.2	1.9

Living cover could be evaluated more easily than residues. This is because it is easier to detect green vegetation than to identify brown (dead vegetation) residues against the soil surface background. Approximate labour time needed to perform one analysis (five iterations) was about 2 h, depending on percentage of cover, type of field crop and operator.

3.2. OBIA classification

Before an image can be classified, the segmentation step has to be fulfilled. For this the images were segmented at scale parameter 35, shape/colour parameter 0.7/0.3 and compactness/smoothness at 0.6/0.4. By using these values, meaningful objects (visual inspection) for the given camera settings were produced (Baatz and Schäpe, 2000).

To identify soil cover automatically according to the procedure given in the methods section, we established a schematic process tree (Fig. 1). The degree of compliance was proven visually following Baatz and Schäpe (2000) and Trimple (2011a,b).

The first step of membership function attribution was to eliminate dark areas. The exclusion of dark image parts seems to be a practical way to avoid error in the following functions (see Laliberte et al., 2010). To execute this, a threshold for brightness (<50) was introduced. When using this membership function on black or dark brown soils, soil may be classified as shadow. In this case, the shadow membership function may be skipped.

After removing the shadows, living vegetation was separated. This was performed by using the DoA Index and a conversion into the IHS as described in the Materials and methods section. In contrast to many other papers on image classification of vegetation (Arsenault and Bonn, 2005; Blanchard et al., 2011; Flanders et al., 2003; Guerschman et al., 2009; Laliberte et al., 2010; Pforte et al., 2012), we did not find it necessary to use Near-Infra-Red (NIR) data to achieve good results. However, using a NIR layer it would be possible to split the vegetation cover into different plant species (Lucas et al., 2007; Zhongming et al., 2010).

To separate residues (dead cover) from soil, a set of different thresholds was used to identify bright parts of the images, such as stones. Another rule, based on brightness (>230), was added to avoid errors for bright reflecting cover. In general, this rule could probably also be used for snow cover or other bright shapes such as fertiliser pellets or similar; however, we did not have images with these features to test this assumption.

The remaining part of the unclassified image consisted of soil and an unidentified amount of a mixture of all other classes. If the percentage of this uncertainty, together with the area classified as shadow, reached high values – we arbitrarily defined <5% of total image as still being

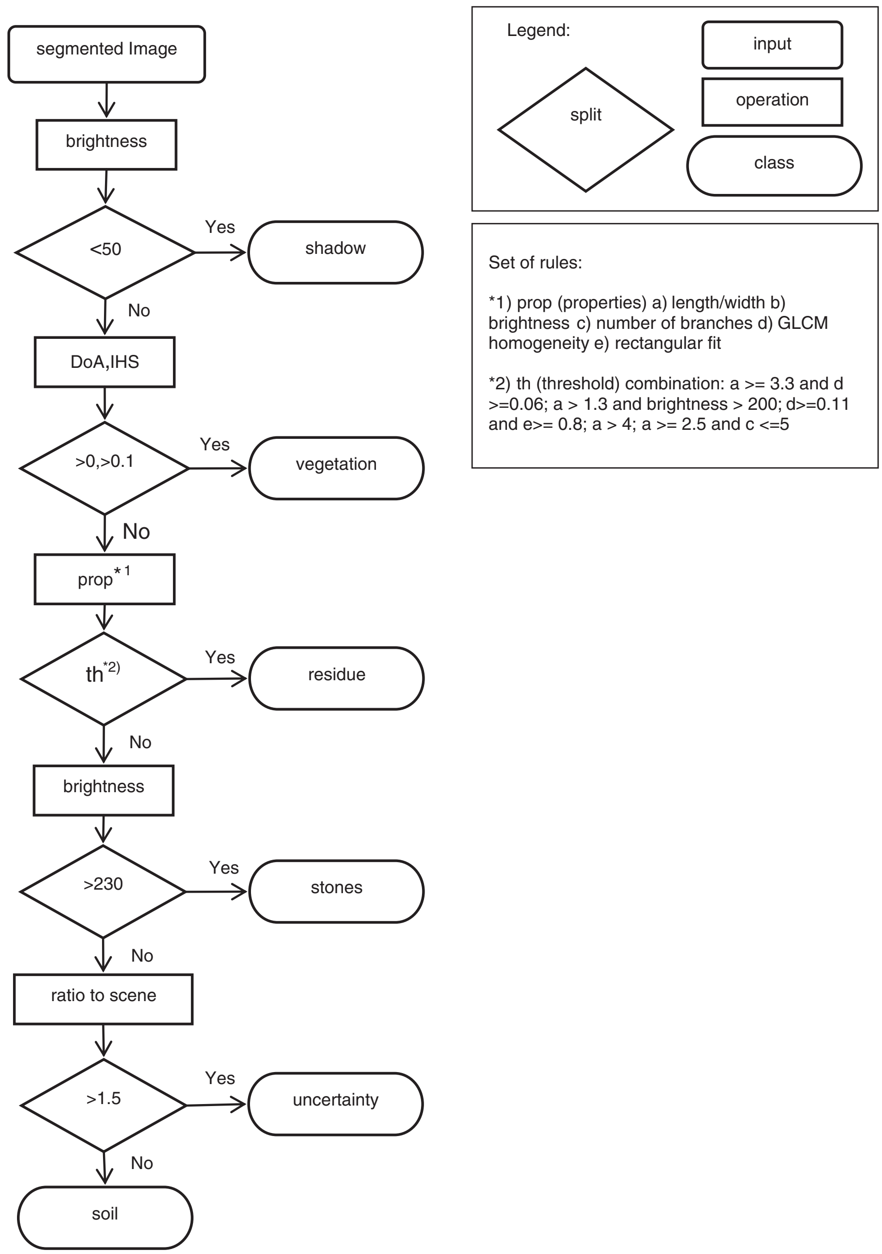

Fig. 1. The process tree of rules for the membership functions and threshold values identified.

an acceptable value – image characteristics were classified as being not suitable for evaluation and image taking was repeated.

According to Fig. 1 and Section 2.3 where a general view of the segmentation and classification process is given, Table 3 offers the detailed classification steps and their parameterisation used. The class 'potential soil' is used temporarily only for processing purposes.

An example for the different processing steps within eCognition is given in Fig. 2. After the image is taken (a), segmentation (b) results in different objects, and these objects are then classified based on the described rules. The result (c) is a mosaic with different soil cover classes.

A comparison of the OBIA based method to the results of the "straw reference test" is given in Fig. 3. The regression analysis shows a slope of 0.97 and an intercept of −0.02 ($R^2 = 0.986$). Thus results of this additional ground truthing test suggest that the OBIA method is able to correctly identify straw cover. However, the general problem of using real ground truth data is yet to be solved (Pforte et al., 2012), because field scale conditions involving living and dead material on a structured soil are quite different from standardized laboratory experiments.

3.3. Technical comparison of methods

Figs. 4 to 6 give the relationship between the manual and the OBIA method for total cover, green cover and residues. The lines of perfect agreement in these figures indicate that total cover and green cover may be calculated without any bias along the tested cover range of 0–50%. This is supported by regression analysis (Table 4) where the slope coefficient for total cover and vegetation is not significantly different from 1.

Fig. 5 reveals that for the estimation of residue cover, a directed error for the OBIA method to over predict low covers and underestimates high residue covers exists — see also regression slope coefficient which is significantly above 1 (Table 4).

The slope constants of the regression analysis given in Table 4 are not different from 1 for total cover and green cover. Confidence limits for the slopes of these regressions and the coefficients of determination also indicate that green cover and total cover are more accurate ($CI_{95\%} = \pm 0.25$) compared to residue cover ($CI_{95\%} = \pm 0.43$).

Table 3
Detailed stepwise application and parameter setting of the rule set in eCogniton.

Step	No.	Input class	Output class		Thresholds
Segmentation	1	RGB image	Unclassified	Multiresolution segmentation of eCognition 8.7	Scale 35/shape 0.7/compactness 0.6
Classification	2	Unclassified	Shadow	Brightness of the objects	<50
Classification	3	Unclassified	Vegetation	DoA-index	>0
Classification	4	Unclassified	Vegetation	HSI colorspace	<=0.4 hue > 0.1
Classification	5	Unclassified	Potential soil	Number of branches of order (1)	<=10
Classification	6	Potential soil	Residues	Length/width ratio of the objects and GLCM homogeneity (all dir.)	>=3.3 and >=0.06
Classification	7	Potential soil	Stones	Brightness	>230
Classification	8	Potential soil	Residues	Length/width ratio of the objects and brightness	>=1.3 and >200
Classification	9	Potential soil	Residues	GLCM homogeneity (all dir.) and rectangular fit	>=0.11 and >=0.8
Classification	10	Potential soil	Residues	Length/width ratio and number of branches of the objects	>=2.5 and <=5
Classification	11	Potential soil	Soil	Unclassified parts of potential soil	All
Classification	12	Unclassified	Soil	Unclassified parts	All
Classification	13	Soil	Residues	Length/width ratio of the objects	>4
Classification	14	Soil	Uncertainty	Ratio to scene	>1.5

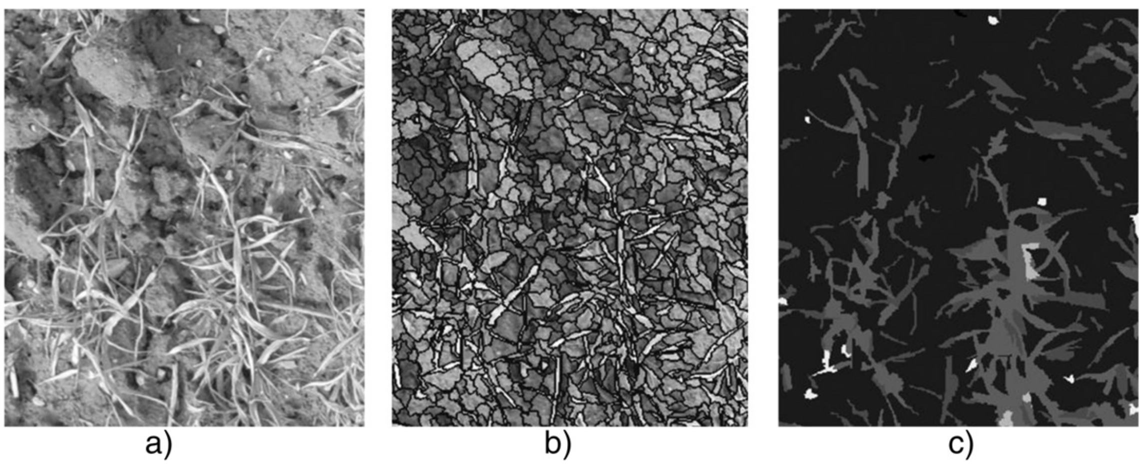

Fig. 2. Stepwise application of eCognition for a partial image (~10 × 10 cm) a) original RGB image b) segmented image c) performed classification with different classes (black — soil, dark grey — living vegetation, bright grey — residues, white — uncertainty).

A comparison of accuracy for both methods shows that for a total cover of 25% (the mean of the investigated range), manual evaluation gives a $CI_{95\%}$ of ± 2.8 for the mean, whereas the OBIA method has a mean $CI_{95\%}$ of ± 3.1.

3.4. Economic comparison of methods

A major reason for favouring OBIA analyses of soil cover may be the shorter time needed for evaluation. For each of the two methods we estimated the time required to carry out the different steps of the procedures (Table 5). Both methods need similar time during the field survey. However, subsequent evaluation steps reveal that, in total, manual analysis needs about 10 times longer for evaluation than the OBIA procedure. The major disadvantage of the OBIA method may be the high costs of software, which may be weighed against the time needed for the manual analysis. Therefore, the automated method seems to be an appropriate alternative only where a large number of estimates are to

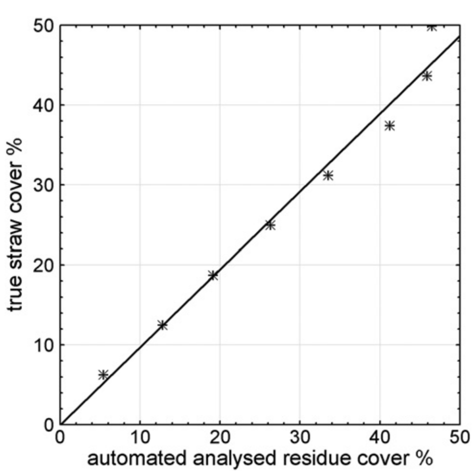

Fig. 3. Comparison between straw reference test and OBIA analysis, range 0–50% soil cover by straw, dots = observation points, continuous line = regression line.

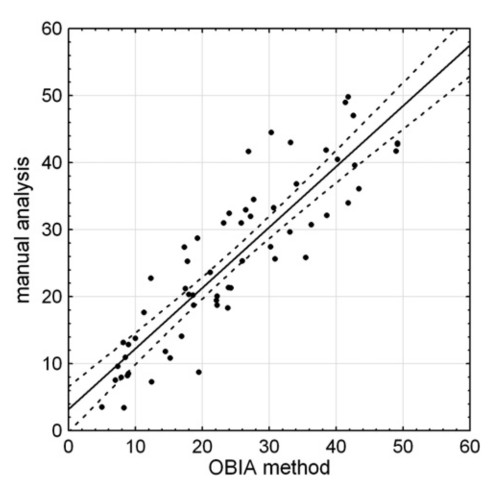

Fig. 4. Comparison between manual analysis and OBIA evaluation using eCognition (n = 61), range 0–50% total soil cover, continuous line = regression line, dashed line = confidence intervals (95%).

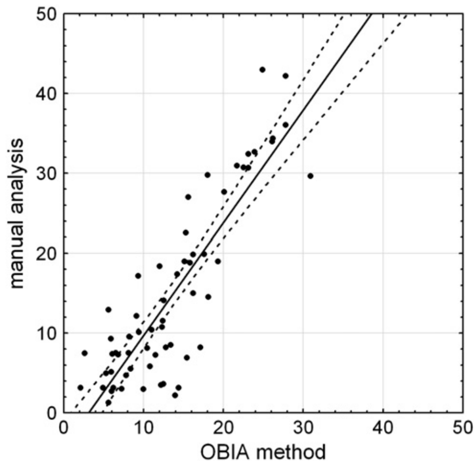

Fig. 5. Comparison between manual analysis and OBIA evaluation using eCognition (n = 61), range 0–50% residue cover, continuous line = regression line, dashed line = confidence intervals (95%).

be done. Assuming for instance hourly labour costs of 20€, the break-even point of equal costs for both methods including software costs is about 260 samples.

4. Conclusion

The purpose of this paper was to introduce a new object-based image analysis method for jointly estimating soil cover by residues and living vegetation, and to provide a comparison with a well-established method.

The OBIA, based on a membership function set, was a successful method of classification. Adjusting thresholds for membership functions and visual inspection of results seemed to be a quick way to get best fitting rules that are appropriate for a broad range of different soil/vegetation conditions.

Against the overall trend of using remote sensing data to estimate soil cover in soil science, we believe that it is highly important to develop and improve methods which could be used for model parameterization at field scale. Using the proposed methodology, it is possible to quickly collect information on plant and residue cover.

A major advantage that we see in the proposed methodology is the higher degree of objectivity that can be reached by the OBIA method, while providing similar uncertainties compared to a method of manual evaluation.

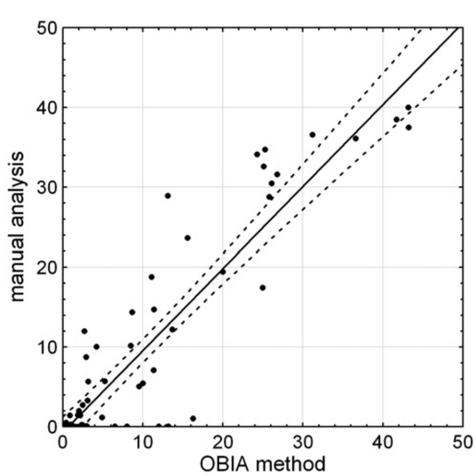

Fig. 6. Comparison between manual analysis and OBIA evaluation using eCognition (n = 61), range 0–50% vegetation cover, continuous line = regression line, dashed line = confidence intervals (95%).

Table 4
Regression analysis of OBIA method compared with manual analysis (n = 61).

Type of cover	Regression	r^2	CI (95%)
Total	$y = 3.20 + 0.91 \pm 0.12\times$	0.78	0.78–1.03
Residue	$y = -4.37 + 1.41 \pm 0.21\times$	0.75	1.20–1.63
Vegetation	$y = -0.74 + 1.02 \pm 0.13\times$	0.82	0.90–1.15

Table 5
Time and effort comparison of manual and automated method.

Time and effort	Manual analysis	OBIA method
Field survey (min)	~5	~5
Time of picture management (min)	~10	~5
Time of image analysis (min)	~20	~5
Iterations	5	1
Total time (min)	115	15
Investment	Low	High (software)
Objectivity	Very low	Medium

A subjective way of finding the best fitting rule thresholds seems to be necessary to obtain suitable results. The process of setting up the right rule set for a wide range of different soils/residues/vegetations requires a degree of knowledge about their characteristics. However, the software used enables the rules and thresholds to be refined and improved at any time in the classification process (see Lucas et al., 2007). A major step in providing more objectivity in the selection process of fitting rules would be a procedure of automated fitting of multiobjective criteria, as already implemented for a wide range of environmental modelling applications (Demarty et al., 2004; Tang et al., 2007; Vrugt et al., 2003).

References

Arsenault, E., Bonn, F., 2005. Evaluation of soil erosion protective cover by crop residues using vegetation indices and spectral mixture analysis of multispectral and hyperspectral data. Catena 62, 157–172.

Baatz, M., Schäpe, A., 2000. Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation. In: Strobl, J., Blaschke, T. (Eds.), Angewandte geographische Informationsverarbeitung, vol. XII. Wichmann, Heidelberg, Germany, pp. 12–23.

Barnes, E.M., Sudduth, K.A., Hummel, J.W., Lesch, S.M., Corwin, D.L., Yang, C., Daughtry, C.S.T., Bausch, W.C., 2003. Remote- and ground-based sensor techniques to map soil properties. J. Photogramm. Remote Sens. 69, 619–630.

Behrens, T., Diepenbrock, W., 2006. Using digital image analysis to describe canopies of winter oilseed rape (*Brassica napus* L.) during vegetative development stages. J. Agron. Crop. Sci. 192, 295–302.

Benett, L.T., Judd, T.S., Adams, M.A., 2000. Close-range vertical photography for measuring changes in perennial grasslands. J. Range Manage. 53, 634–641.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. J. Photogramm. Remote Sens. 58, 239–258.

Blanchard, S.D., Jakubowski, M.K., Kelly, M., 2011. Object-based image analysis of downed logs in disturbed forested landscapes using Lidar. Remote Sens. 3, 2420–2439.

Blaschke, T., 2010. Object based image analysis for remote sensing. J. Photogramm. Remote Sens. 65, 2–16.

Booth, D.T., Cox, S.E., Fifield, C., Phillips, M., Williamson, N., 2005. Image analysis compared with other methods for measuring ground cover. Arid. Land Res. Manage. 19, 91–100.

Campillo, C., Prieto, M.H., Daza, C., Monino, M.J., Garcia, M.I., 2008. Using digital images to characterize canopy coverage and light interception in a processing tomato crop. Hortscience 43, 1780–1786.

Corak, S.J., Kaspar, T.C., Meek, D.W., 1993. Evaluating methods for measuring residue cover. J. Soil Water Conserv. 48, 70–74.

Demarty, J., Ottle, C., Braud, I., Olioso, A., Frangi, J.P., Bastidas, L.A., Gupta, H.V., 2004. Using a multiobjective approach to retrieve information on surface properties used in a SVAT model. J. Hydrol. 287, 214–236.

Ewing, R.P., Horton, R., 1999. Quantitative color image analysis of agronomic images. Agron. J. 91, 148–153.

Flanders, D., Hall-Beyer, M., Pereverzoff, J., 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. Can. J. Remote. Sens. 29, 441–452.

Guerschman, J.P., Hill, M.J., Renzullo, L.J., Barrett, D.J., 2009. Estimating fractional cover of photosynthetic vegetation and bare soil in the Australian tropical savanna region upscaling the EO-1 Hyperion and MODIS sensors. Remote. Sens. Environ. 113, 928–945.

Hartwig, R.O., Laflen, J.M., 1978. A meterstick method for measuring crop residue cover. J. Soil Water Conserv. 33, 90–91.

Laliberte, A.S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., Gonzalez, A.L., 2004. Object-oriented image analysis for mapping shrup encroachment form 1937 to 2003 in southern New Mexico. J. Remote Sens. Environ. 93, 198–210.

Laliberte, A.S., Rango, A., Fredrickson, E.L., 2006. Separating green and senescent vegetation in very high resolution photography using an intensity–hue–saturation transformation and object based classification. ASPRS 2006 Annual Conference, Reno, Nevada.

Laliberte, A.S., Rango, A., Herrick, J.E., Fredrickson, E.L., Bukett, L., 2007. An object image analysis approach for determining fractional cover of senescent and green vegetation with digital plot photography. J. Arid. Environ. 69, 1–14.

Laliberte, A.S., Browning, D.M., Herrick, J.E., Gronemeyer, P., 2010. Hierachival object-based classification of ultra-high-resolution digital mapping camera (DCM) imagery for rangeland mapping and assessment. J. Spat. Sci. 55, 101–115.

Lucas, R., Rowlands, A., Brown, A., Keyworth, S., Bunting, P., 2007. Rule-based classification of multi-temporal satellite imagery for habitat and agricultural land cover mapping. J. Photogramm. Remote Sens. 62, 165–185.

Luscier, J.D., Thompson, W.L., Wilson, J.M., Gorham, B.E., Dragut, L.D., 2006. Using digital photographs and object-based image analysis to estimate percent ground cover in vegetation plots. Front. Ecol. Environ. 4, 408–413.

Marques, M.J., Bienes, R., Jimenez, L., Perez-Rodriguez, R., 2007. Effect of vegetal cover on runoff and soil erosion under light intensity events. Rainfall simulation over USLE plots. Sci. Total. Environ. 378, 161–165.

Mohammad, A.G., Adam, M.A., 2010. The impact of vegetative cover type on runoff and soil erosion under different land uses. Catena 81, 97–103.

Morrison Jr., J.E., Huang, C., Lightle, D.T., Daughtry, C.S.T., 1993. Residue cover measurement techniques. J. Soil Water Conserv. 48, 479–483.

Munsell color company, 1954. Munsell soil color charts, USA.

Obade, V. de P., 2012. Review article: remote sensing, surface residue cover and tillage practice. J. Environ. Prot. 3, 211–217.

Perez-Cabello, F., Cerda, A., de la Riva, J., Echeverria, M.T., Garcia-Martin, A., Ibarra, P., Lasanta, T., Montorio, R., Palacios, V., 2012. Micro-scale post-fire surface changes monitored using high spatial resolution photography in a semiarid environment: a useful tool in the study of post fire soil erosion processes. J. Arid. Environ. 7, 88–96.

Pforte, F., Wilhelm, B., Hensel, O., 2012. Evaluation of an online approach for determination of percentage residue cover. Biosyst. Eng. 112, 121–129.

Purcell, L.C., 2000. Soybean canopy coverage and light interception measurements using digital imagery. Crop. Sci. 40, 834–837.

Richardson, M.D., Karcher, D.E., Purcell, L.C., 2001. Quantifying turfgrass cover using digital image analysis. Crop. Sci. 41, 1884–1888.

Sibiryakov, A., 1996. House detection from aerial color images. Internal Report. Institute of Geodesy and Photogrammetry, Swiss Federal Institute of Technology (ETH), Zürich.

Tang, Y., Reed, P.M., Kollat, J.B., 2007. Parallelization strategies for rapid and robust evolutionary multiobjective optimization in water resources applications. Adv. Water Resour. 30, 335–353.

Trimple, 2011a. eCognition Developer 8.7 Trail, User Guide. Trimple Germany GmbH, Munich, Germany 248.

Trimple, 2011b. eCognition Developer 8.7 Trail, Reference Book. Trimple Germany GmbH, Munich, Germany 416.

Tzotos, A., Karantzalos, K., Argialas, D., 2011. Object-based image analysis through nonlinear scale-space filtering. J. Photogramm. Remote Sens. 66, 2–16.

van der Werff, H.M.A., van der Meer, F.D., 2008. Shape-based classification of spectrally identical objects. J. Photogramm. Remote Sens. 63, 251–258.

Voßhenrich, H.H., Brunotte, J., Ortmeier, B., 2003. Methoden zur Bewertung der Strohverteilung und Einarbeitung. Landtechnik 58, 92–93.

Vrugt, J.A., Gupta, H.V., Bastidas, L.A., Bouten, W., Sorooshian, S., 2003. Effective and efficient algorithm for multiopjective optimization of hydrologic models. Water Resour. Res. 39, 1–19.

Zabala, A., Cea, C., Pons, X., 2012. Segmentation and thematic classification of color orthophotos over non-compressed and JPEG 2000 compressed images. Int. J. Appl. Earth Obs. Geoinf. 15, 92–104.

Zhongming, W., Lees, B.G., Feng, J., Wanning, L., Haijing, S., 2010. Stratified vegetation cover index: a new way to assess vegetation impact on soil erosion. Catena 83, 87–93.