Comparison of visual assessment and digital image analysis for canopy cover estimation

Lucie Büchi[1,*], Marina Wendling[1,2], Pauline Mouly[1], Raphaël Charles[1,2]

[1]Plant Production Systems, Agroscope, Nyon, Switzerland

[2]Research Institute of Organic Agriculture FiBL, Lausanne, Switzerland

*Corresponding author:

L.A.Buchi@greenwich.ac.uk

Present address: Natural Resources Institute, University of Greenwich, United Kingdom

Abstract

Nowadays, in the context of agriculture, cover crops are crops cultivated with the sole aim of providing important ecosystem services such as erosion prevention. Many services offered by these crops are directly linked to the development of their vegetation, and especially of canopy cover. A proper estimation of this cover is thus necessary to evaluate cover crop performance. Many methods to estimate canopy cover exist, but differ in terms of effort and time needed to implement them. In this study, we compared visual assessment of canopy cover in the field with two methods of digital image analysis (Assess and Canopeo), for different cover crop species and vegetation types. Visual estimation was positively correlated with both type of image analysis estimations. However, it showed systematically lower values of canopy cover, especially at intermediate canopy cover values. The type of vegetation influenced the visual and digital image estimations, narrow leaf species being the most difficult to evaluate visually. This study showed that depending on its utilisation, visual canopy cover assessment could be useful, especially when only relative estimation of canopy cover is needed. When absolute canopy cover estimation is needed, the use of digital image analysis should be preferred.

Core ideas

- cover crops provide ecosystem services linked to canopy cover development
- visual assessment of canopy cover is compared with two digital image analysis methods
- visual estimation is well correlated with image estimation but showed lower values
- the choice of the canopy cover estimation method depends on the objective

Introduction

Monitoring of vegetation growth or stand is of crucial importance for many purposes, such as vegetation surveys, forest inventories, grassland and pasture monitoring, field crop and weed development. An extended development of vegetation has been shown to provide important ecosystem services (e.g. reduction of run-off, erosion and nutrient leaching, land stabilisation) and is linked to major ecological properties (e.g. biomass, light interception, evapotranspiration) (Chianucci et al., 2016; Duran and Rodriguez, 2008; Jannoura et al., 2015; Scopel et al., 2013). In the context of agriculture, most of the ecosystem services provided by the vegetation are directly linked to canopy cover, and a threshold of 30% has been often used as a minimal target value for environment protection for pastures and cropland (FAO 2017; Lilley and Moore, 2009). Canopy cover is also closely related to leaf area index (LAI) (Adams and Arkin, 1977; Nielsen et al, 2012) which is key to primary production and the functioning of ecosystems. Canopy cover is generally defined as the proportion of the ground area covered by the vertical projection of the plant canopy (Jennings et al., 1999) and is most often evaluated by modern phenotyping methods by the fraction of green canopy area relative to the total area assessed (fractional green canopy cover, Patrignani and Ochsner, 2015).

Many methods to quantify canopy cover exist (Wilson, 2011), mostly coming from grassland and forest monitoring (Macfarlane and Ogden, 2012). They mainly rely on field measurements or remote sensing methods. Among these methods, the most widespread in agriculture is the visual assessment of cover in the field. Other methods rely on the analysis of digital images either taken in the field with a camera, or taken by satellites or other remote sensing devices, such as light airplanes, multicopters or fixed-wing unmanned aerial vehicle (UAV) (Jannoura et al., 2015; Walter et al., 2015). All these methods bear advantages and drawbacks in terms of accuracy of estimates and time and effort to obtain them. For example, field and natural light conditions are often an obstacle to automated image processing (Yu et al., 2017). Image analysis methods used also to be relatively time consuming compared to a simple visual assessment, which thus continues to be routinely used in vegetation science and field trials. However, with the development of new methods and routine of image acquisition and analysis, and the increased power of portable smartphone applications, image analysis methods are now numerous and easily accessible (Lobet et al., 2013).

Visual assessment of canopy cover has been often discussed and discarded by some scientists because of its potential lack of objectivity and repeatability (Wilson, 2011; Rasmussen et al., 2007). However, several studies have shown agreement between visual assessment and more objective methods (Murphy and Lodge 2002; Vanha-Majamaa et al., 2000; Booth et al., 2006). Now, the efficiency of visual assessment of canopy cover should also be tested against new developed methods. In addition, the efficiency of each method could also depend on the type of vegetation evaluated. Differences between species could be expected, depending on their phenology, shoot architecture, greenness, etc. And thus, the test and calibration of canopy cover evaluation methods should ideally be done on a variety of species.

Cover crops are crops cultivated uniquely to provide ecosystem services such as soil protection against erosion or to compete against weeds, and are not harvested. For these two specific services, canopy cover is particularly important as it is directly linked to the amount of rain or light interception, which will reduce erosion or help to compete against weeds. The rapid development of canopy cover is thus here the main factor insuring that the cover crops could fulfill their mission. It is thus important to monitor canopy cover evolution regularly in the field. However, species differ in the speed and extent of canopy cover development, and some could not be suitable depending on the aim of their cultivation. Canopy cover development is thus a major characteristic of cover crop species.

In this study, we compared three methods of canopy cover estimation for a large array of species used as cover crops, at different developmental stages: 1. visual estimation in the field, 2. analysis of digital images taken in the field with Assess 2.0 (Lamari, 2008), 3.

analysis of digital images taken in the field with Canopeo (Patrignani and Ochsner, 2015). The three methods compared were chosen for their ease of utilisation in the field, without any need of heavy and time consuming implementation. The objectives were to evaluate the results obtained with each method, and the influence of vegetation type on these results. The handling effort and time needed for the implementation of each method was also evaluated.

Materials and Methods

Field experiment

The experiment was carried out in 2013 in Agroscope Changins (46° 24’ N, 06° 14’ E, 430 m) close to Nyon, Switzerland. In this site, the mean temperature is 10.2°C and the average total annual precipitation is 999 mm (30-year averages, 1981-2010).

Canopy cover was estimated in a cover crop experiment described in Wendling et al. (2016). It consisted in twenty cover crop species and two mixtures of species (Table 1) sown at the beginning of August (05.08.2013) in a randomised block design with three replicates. Size of individual plots was 1.5 m x 8 m and row spacing 13.5 cm. Plant density for each species are given in Table S1. The studied species were frost sensitive, and used for short cover crop cultivation before a winter crop (typically seeded mid to end October in this region). All plots were monitored to characterise crop growth dynamics. Main characteristics of the cover crop species in terms of aboveground biomass production and height (measured 49 days after seeding) are given indicatively in Table S1.

Canopy cover estimation methods

The canopy cover provided by the crops was assessed at ten successive dates between the 15.08.2013 and 23.09.2013: at 10, 18, 21, 24, 25, 29, 32, 36, 39 and 49 days after seeding. At that time, most of the species had reached a canopy cover superior to 80%. This gave a total of 614 plot x date observations. Canopy cover was defined as the relative area occupied by the vertical projection of canopy on the soil. For each plot x date, canopy cover was estimated using three different methods, visual assessment in the field, and two digital image analysis variants.

Visual assessment of canopy cover was estimated for each plot by two observers, who discussed together to reach an estimate. The two observers were inexperienced regarding canopy cover estimation before starting this experiment. The area on which the assessment was done varied from date to date according to two different protocols.

For six out of ten dates, canopy cover was estimated globally for the whole plot (1.5 x 8 m), not taking into account weeds. For four out of ten dates, canopy cover was visually assessed in a 0.5 x 0.5 m frame, used for biomass sampling.

Digital image analysis estimations were extracted from pictures taken in the field with a single lens reflex camera (Nikon Coolpix 8400, 6.1 mm = 24 mm lens in 35 mm format equivalent), in natural light conditions. All pictures were taken using the 'automatic' mode of the camera, to ease the process. Pictures had a resolution of 300 x 300 dpi, and were saved in 'jpg' format. For the six dates with global visual estimation, a picture was taken in a section of the plot chosen to be representative of the whole plot, whereas for the dates with biomass sampling, the picture was taken just above the sampling frame. The pictures were taken by one person with outstretched arms, about 1-1.5 m above the vegetation canopy, the most possible parallel to the soil. This represented an approximate field area between 0.9 m^2 and 1.6 m^2 depending on vegetation height. The aim of this method was to get pictures very rapidly without time consuming preparation operations. Pictures were then transferred to a computer and rapidly reframed to avoid too much image distortion on the edges, and to match the sampling frame when appropriate. No correction of exposure or luminosity was done. All pictures were then analysed with two image analysis software, Assess 2.0 (Lamari, 2008) and

Canopeo (Patrignani and Ochsner, 2015). For both softwares, default settings were used in order to test their performance in their most easy and rapid utilisation version.

For the estimations with Assess, we used the automatic canopy cover (called ground cover) estimation option. It uses 'the hue component of HSI colour space to evaluate ground cover' (Lamari, 2008). Thresholding to obtain canopy cover estimation was done automatically by Assess, with no user specific adjustment afterwards. All canopy cover evaluations were checked visually for accuracy in the classification of canopy vs background pixels. Pictures presenting any obvious classification problem were identified visually by comparing the original image with the classification given by Assess.

For the estimation with Canopeo, the application for Android system was used. Canopeo 'is based on color ratios of red to green and blue to green and an excess green index' (Patrignani and Ochsner, 2015). Criteria for the classification of pixels is given in Patrignani and Ochsner (2015). Pictures were analysed automatically with the app, with an adjustment value set to 0.9 (default value).

Both methods were unsupervised and used automatically, without the preliminary use of user supervising.

Data analysis

The canopy cover values obtained from the three evaluation methods were compared with Kendall rank correlation coefficients. Mean signed error (MSE) was computed as the average of the differences between any two methods, whereas mean absolute error (MAE) was computed as the average of the differences between two estimates, taken as absolute values. Correlation coefficients and mean errors were computed globally as well as for each species independently.

All analyses were performed using R 3.3.3 (R Core Team, 2017).

Results and Discussion

Comparison of two methods of digital image analysis

The two methods based on digital image analysis were positively correlated with each other (tau=0.63, $p<0.001$). However, Canopeo showed systematically larger values compared to Assess (MSE = -8.7%, MAE = 9.9%, Table 1, Figure 1).

However, problematic canopy identification by Assess was observed for 28% of the pictures analysed (Figure 1A, white and red dots), while Canopeo presented only 3% of evident problematic identification (but the check of misidentification was less easily done with Canopeo). The main causes of these misidentification were coming, for Assess, from two distinct sources, 1. technical problem, i.e. picture quality (83% of the cases), 2. vegetation status (17% of the cases) (Figure S1).

Concerning picture quality, picture overexposure (pictures taken with intense day light reflecting on the canopy) and shadow (often found together with overexposure problem) were the main problems, as often observed in this type of analysis. These situations conducted to an underestimation of canopy cover by Assess compared to Canopeo. The high number of pictures with exposure problems came from the fact that the pictures were taken in summer (August and September), with no restrictions concerning daytime and sunshine.

Concerning the vegetation, the presence of flowers in the cover crops posed problems for canopy cover estimation, here this concerned particularly white mustard and buckwheat which flowered early compared to the other species. This led to an underestimation of canopy cover. In addition, for very early season pictures, the really small size of seedlings and their often brown-green colour conducted to overestimation by Assess, which wrongly classified background pixels as canopy. The presence of distinct vegetation strata has also been invoked as a potential problem for digital image analysis (Vanha-Majamaa et al., 2000), but this problem was not observed here neither with Assess nor with Canopeo. Indeed, cover crop mixtures, presenting distinct species and thus height and vegetation type, did not show higher canopy cover estimation failure.

Interestingly, Canopeo estimated properly most of the pictures identified as problematic for Assess. In particular, overexposure and shadow did not prevent Canopeo to assess canopy cover properly, in most cases (Figure S1). Similarly, Canopeo had less problems with the small size of seedlings. For example, in the third column of Figure S1, the very small seedlings of the early stage of sorghum emergence were identified correctly by Assess but it misclassified a large part of background as canopy, resulting in an overestimation of canopy cover (17%). In contrast, Canopeo was less confused by the small seedlings and background and estimated the canopy cover at 1%.

The main problem for Canopeo assessment, as for Assess, was cover crop flowers, and especially buckwheat white flowers, which were systematically classified as non canopy. This is illustrated in the last column on the right of Figure S1, where buckwheat is in full bloom, and its white flowers are misclassified by Assess (71%) as well as by Canopeo (71%). Here, with visual assessment, canopy cover was estimated at 95%.

The mean errors in canopy cover estimate between Canopeo and Assess decreased thus to -4% (MSE) and 5% (MAE) when problematic pictures were removed from the computation. Based on these results, Canopeo seemed more reliable than Assess for rapid canopy cover estimation without user intervention, as it was less affected by image quality. It gave however slightly higher values than Assess. In order to know if Canopeo is overestimating canopy cover, or Assess is underestimating it, it would be interesting to compare the performance of these two methods used on artificial images of known cover, as described in Chianucci (2016).

Comparison of visual assessment with digital image analysis methods

The visual assessment method was positively correlated with both methods of digital image analysis (Assess: tau=0.62, $p<0.001$; Canopeo: tau=0.76, $p<0.001$) (Table 1). Lower canopy cover values compared to the digital image analyses were however generally observed (Figure 1), as shown by the negative mean signed errors. The mean absolute error between visual and image estimation was 11%. Tendency to underestimation of cover by human observers has been also shown in other studies (e.g. Murphy and Lodge, 2002; Gallegos Torell and Glimskär, 2009). The relationship between visual and digital image estimations was not linear, as visual assessment errors were higher for intermediate values (Figure 2). Non linear relationships were also observed by Murphy and Lodge (2002) and Gallegos Torell and Glimskär (2009). This could be explained by the fact that high or low canopy cover values are easier to identify visually, as 0% and 100% canopy cover are evident universal benchmarks. Then as the effective canopy cover values move away from these extremes, the difficulty to estimate it visually increases. This effect could probably be reduced by using canopy cover scales to provide additional objective benchmarks to the observer and help assess canopy cover (Figure S2). Indeed, previous studies have shown that a calibration training of the observers with information on 'true' canopy cover, prior to visual assessment, could improve the accuracy of this method (e.g. Gallegos Torell and Glimskär, 2009). However, it has been shown that observer could generally not distinguish differences in canopy cover smaller than 10% (Hahn and Scheuring, 2003). In contrast, experienced and inexperienced observers performed similarly in most studies (Dethier et al., 1993; Murphy and Lodge 2002; Bergstedt et al., 2009).

The results of the visual and digital image canopy cover estimation were also influenced by the cover crop species evaluated (Table 1, Figure 3). The five highest mean absolute errors (mean of visual vs Assess and mean vs Canopeo errors) were observed for hemp, black oat, sorghum, buckwheat and foxtail millet with values higher than 14%, while the values for the other species ranged between 7% and 14%. For the three poaceae species and hemp, visual assessment underestimated drastically the effective canopy cover compared to digital image analysis methods (Figure 3B). The difficulty to assess canopy cover visually for these species was due to their characteristic foliage, showing a multitude of long narrow leaves (or leaflets for hemp), and their rather high height. In field conditions, plants were also generally slightly moving due to wind, which further increased the difficulty of visual assessment for this type of vegetation. In contrast, cover crop species with large and big leaves, such as mustards and chia, showed the lowest mean absolute errors, once removed identified problematic image analysis. Alternatively, canopy cover by small leaves species but with creeping behaviour, such as vetch and lentils, were easier to assess than poaceae and hemp, as they tended to form a dense mass on the soil. This agreed with the results from Gallegos Torell and Glimskär (2009) who also showed a stronger underestimation of canopy cover for narrow leaves compared to broad leaves, and from Kennedy and Addison (1987) who observed high errors for certain types of leaves.

As mentioned above, an inaccurate estimation of canopy cover of mixtures showing different vegetation strata by digital image analysis could have been expected, and so a better result of visual assessment, which can take into account these multilayers more easily, could have been postulated. This was however not the case here.

However, the human eye proved to be more efficient than digital image analysis in the problematic situations listed in the preceding section. In particular, this was evident in the presence of flowers, which could be easily classified as canopy by the eye, contrary to analysis softwares (Figure 3C). In addition, with visual assessment it was also possible, to a certain extent, to distinguish cover crop from weeds, which is not easily done with image analysis softwares. Technical problems such as overexposure and shadows were also generally avoided in visual assessment (Figure 3D). Automated phenotyping methods are in contrast particularly sensitive to natural light conditions and solutions to this problem are not yet easily implemented (Yu et al., 2017). In contrast, the difficulty to assess canopy cover for small seedlings was often also a problem for visual assessment. In particular, the brownish seedlings of phacelia presented a challenge for visual assessment as well as for image analysis.

Visual assessment of canopy cover was done following two variants, the first one as an overall assessment of the whole cover crop plot (57% of all estimates), and the second one as a specific assessment on a quadrat used for biomass sampling (43% of all estimates). For the second variant, the pictures for digital image analysis were taken on the same quadrat as for visual assessment. An improvement in the concordance between visual and digital estimation done on the same quadrats was thus expected. This was however not the case here. The mean absolute error did not change with the use of biomass sampling quadrat compared to overall visual assessment (Table 1) whereas the correlations coefficients even decreased (Assess: from 0.70 to 0.44; Canopeo: from 0.72 to 0.48). However, as these two variants were not applied at the same dates, a confounding effect of estimation dates and vegetation status could play a role here.

Aside from estimation errors, differences between visual assessment and digital image analysis could also reflect representativeness issues. The pictures for digital image analysis were taken at a specific position in the plot. A 'representative' place was always chosen to record the pictures, but it remained necessarily limited to a subsample of the whole plot. Here the human eye is probably more able to take into account and aggregate the spatial variability of canopy cover. In this respect, Canopeo proposes a tool that could not be tested here but could turn to be useful when spatial variability is present, that is the possibility to analyse videos instead of pictures. They showed that, depending on the standing variability, between 6 to 45 images, extracted from a video, would be needed to obtain an accurate canopy cover estimation on 40 m transects (Patrignani and Ochsner, 2015). Alternatively, several pictures of each plot could have been taken manually in the field, and an average value of canopy cover computed. However, Hill et al. (2011) have shown that in vineyard canopy analysis, close-up images gave cover estimation highly correlated to that obtained by whole canopy images.

Handling and analysis time

The three methods presented in this study differed also by the time needed to implement them. For visual assessment, about 43 minutes were necessary in the field to evaluate 100 cover crop plots by two observers rating all plots together to obtain a consensus.

For the digital image analysis with Assess, about 30 minutes were necessary to take 100 pictures in the field, with no check of the picture quality, and then 10 minutes to analyse them using a macro, allowing to automating the process. Together, this would be faster than for the visual assessment. However, before analysing the images, the pictures needed to be reframed to remove image distortion on the edges (and sometimes the photographer's feet) and potential shadow due to the photographer. This problem could however be avoided by a more careful positioning when taking the pictures in the field. This step was time consuming compared to the other two, about 38 minutes for 100 pictures. In total, with this method, 78 minutes were needed to obtain a canopy cover estimation for 100 pictures, without any visual check of the accuracy of the analysis. Here, spending a bit more time in the field to take better pictures could surely decrease efficiently the time needed then to reframe the pictures on the computer and to avoid later problems with the automatic image analysis. In addition, following a more specific protocol to take the pictures, such as avoiding full sunlight, or using a shadowing device would probably improve the image analysis. However, it would greatly increase the time needed to take the pictures, rendering this method clearly not competitive for a frequent monitoring of a high number of plots.

Concerning Canopeo, we did not use here the app for direct canopy cover estimation in the field, which would be the more effective way of using it. We could estimate that, using it in the field, would necessitate an amount of time between the visual assessment and the recording of the pictures, so around 30-45 minutes, with a rapid check of the quality of the picture and of the canopy identification.

Conclusions

This study showed that visual assessment of canopy cover in cover crop stands is highly correlated with values obtained from so called objective methods such as digital image analysis. However, a systematic underestimation of canopy cover was observed for visual assessment compared to digital image analysis, especially for intermediate cover values and for narrow leaf species. The choice of the method depends thus strongly on the goal of the evaluation. Indeed, if the aim of canopy cover evaluation is, for example, to compare treatments or to regularly monitor a vast number of plots, the visual assessment of relative canopy cover values is reliable enough and can be used efficiently to obtain rapidly valuable results. Visual estimates could also be improved by prior calibration with real canopy cover scales. Such a calibration should take into account the specificities of the evaluated species, as the visual impression of a plant stand is strongly influenced by the type of vegetation. Visual assessment is also more powerful than simple field pictures to take into account spatial variability in canopy cover. In addition, the rapidity and universal potential application of visual canopy cover assessment renders it still useful, even in front of the growing field of highly complex phenotyping techniques. However, when absolute values of canopy cover are needed, for example to estimate associated yield, to compare results from different experiments, or to avoid operational bias, digital image analysis should be preferred. The use of an application like Canopeo appears to be a good compromise between rapid visual assessment and complex phenotyping methods to be used as a routine method in large field trials.

Acknowledgments

The authors thank Cindy Bally and Nicolas Widmer for the field experiment management. This study was partly funded by the Swiss National Science Foundation in the framework of the National Research Program NRP 68 'Sustainable Use of Soil as a Resource' [grant 406840-143063].

References

Adams, J., and Arkin, G., 1977. A light interception method for measuring row crop ground cover. Soil Sci. Soc. Am. J. 41:789–792.

Bergstedt, J., Westerberg, L., and Milberg, P., 2009. In the eye of the beholder: bias and stochastic variation in cover estimates. Plant Ecol. 204:271-283.

Booth, D.T., Cox, S.E., Meikle, T.W., and Fitzgerald, C., 2006. The accuracy of ground-cover measurements. Rangeland Ecol. Manag. 59:179-188.

Chianucci, F., 2016. A note on estimating canopy cover from digital cover and hemispherical photography. Silva Fenn. 50, doi: 10.14214/sf.1518

Chianucci, F., Disperati, L., Guzzi, D., Bianchini, D., Nardino, V., Lastri, C., and Corona, P., 2016. Estimation of canopy attributes in beech forests using true colour digital images from a small fixed-wing UAV. Int. J. Appl. Earth Obs. 47:60-68.

Dethier, M.N., Graham, E.S., Cohen, S., and Tear, L.M., 1993. Visual versus random-point percent cover estimations: objective is not always better. Mar. Ecol. Prog. Ser. 96:93-100.

Duran, Z.V.H., and Rodriguez, P.C.R., 2008. Soil-erosion and runoff prevention by plant covers. A review. Agron. Sustain. Dev. 28:65–86.

FAO, 2017. Food and Agriculture Organization of the United Nations: Conservation Agriculture [online]. Available at: http://www.fao.org/ag/ca (accessed 05.07.17.).

Gallegos Torell, A., and Glimskär, A., 2009. Computer-aided calibration for visual estimation of vegetation cover. J. Veg. Sci. 20:973-983.

Hahn, I., and Scheuring, I., 2003. The effect of measurement scales on estimating vegetation cover: a computer assisted experiment. Community Ecol. 4:29–33.

Hill, G.N., Beresford, R.M., Wood, P.N., Kim, K.S., and Wright, P.J., 2011. Image-assisted gap estimation, a simple method for measuring grapevine leaf canopy density. Crop Sci. 51:2801-2808.

Jannoura, R., Brinkmann, K., Uteau, D., Bruns, C., and Joergensen, R.G., 2015. Monitoring of crop biomass using true colour aerial photographs taken from a remote controlled hexacopter. Biosyst. Eng. 129:341-351.

Jennings, S. B., Brown, N. D., and Sheil, D., 1999. Assessing forest canopies and understorey illumination: canopy closure, canopy cover and other measures. Forestry 72:59-74.

Kennedy, K.A., and Addison, P.A., 1987. Some considerations for the use of visual estimates of plant cover in biomonitoring. J. Ecol. 75:151–157.

Lamari, L., 2008. Assess 2.0. Image Analysis Software for Plant Disease Quantification. The American Phytopathological Society. ISBN 978-0-89054-369-6

Lilley, J.M., and Moore, A.D., 2009. Trade-offs between productivity and ground cover in mixed farming systems in the Murrumbidgee catchment of New South Wales. Anim. Prod. Sci. 49:837–851.

Lobet, G., Draye, X., and Périlleux, C., 2013. An online database for plant image analysis software tools. Plant Methods 9:38.

Macfarlane, C., and Ogden, G. N., 2012. Automated estimation of foliage cover in forest understorey from digital nadir images. Methods Ecol.Evol. 3:405-415.

Murphy, S.R., and Lodge, G.M., 2002. Ground cover in temperate native perennial grass pastures. I. A comparison of four estimation methods. Rangel. J. 24:288-300.

Nielsen, D., Miceli-Garcia, J.J., and Lyon, D.J., 2012. Canopy cover and leaf area index relationships for wheat, triticale, and corn. Agron. J. 104:1569-1573.

Patrignani, A., and Ochsner, T.E., 2015. Canopeo: a powerful new tool for measuring fractional green canopy cover. Agron. J. 107:2312-2320.

Rasmussen, J., Norremark, M., and Bibby, B.M., 2007. Assessment of leaf cover and crop soil cover in weed harrowing research using digital images. Weed Res. 47:299-310.

R Core Team, 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, http://www.R-project.org

Scopel, E., Triomphe, B., Affholder, F., Da Silva, F.A.M., Corbeels, M., Xavier, J.H.V., Lahmar, R., Recous, S., Bernoux, M., Blanchart, E., de Carvalho Mendes, I., and DeTourdonnet, S., 2013. Conservation agriculture cropping systems in temperate and tropical conditions, performances and impacts. A review. Agron. Sustain.Dev. 33:113–130.

Vanha-Majamaa, I., Salemaa, M., Tuominen, S., and Mikkola, K., 2000. Digitized photographs in vegetation analysis – a comparison of cover estimates. Appl. Veg. Sci. 3:89-94.

Walter, A., Liebisch, F., and Hund, A., 2015. Plant phenotyping: from bean weighing to image analysis. Plant Methods 11:14.

Wendling, M., Büchi, L., Amossé, C., Sinaj, S., Walter, A., and Charles, R., 2016. Influence of root and leaf traits on the uptake of nutrients in cover crops. Plant Soil 409, 419-434.

Wilson, J.B., 2011. Cover plus: ways of measuring plant canopies and the terms used for them. J. Veg. Sci. 22:197-206.

Yu, K., Kirchgessner, N., Grieder, C., Walter, A., and Hund, A., 2017. An image analysis pipeline for automated classification of imaging light conditions and for quantification of wheat canopy cover time series in field phenotyping. Plant Methods 13:15.

Table and Figure legends

Table 1 Correlation coefficients, mean signed and absolute errors for the overall dataset and for each species independently. Non significant correlations coefficient are indicated in italics. The column 'Prob' indicates the number of problematic image analysis identified for each case. 'N' gives the total number of canopy cover values used for each case.

Figure 1 Relationship between canopy cover estimation methods. A. digital image analysis with Assess vs Canopeo, B. visual assessment vs digital image analysis with Assess, C. visual assessment vs digital image analysis with Canopeo. The red dots represent problematic analysis due to the presence of flowers, white dots represent problematic image analysis due to other factors (e.g. overexposure). The dashed line is the line 1:1.

Figure 2 Mean absolute error of canopy cover visual assessment compared to mean canopy cover obtained with the two methods of digital image analysis, Assess (grey dots and line), and Canopeo (white dots and dashed line). The lines are trend lines fitted using a locally-weighted polynomial regression as smoothing algorithm.

Figure 3 Relationship between canopy cover estimation with visual assessment vs digital image analysis with Assess, for four individual species. A. Niger, B. Sorghum, C. Buckwheat, D. Indian mustard. The red dots represent problematic analysis due to the presence of flowers, white dots represent problematic image analysis due to other factors (e.g. overexposure). The dashed lines are the lines 1:1, the plain lines the linear regression of visual assessment on digital image analysis.

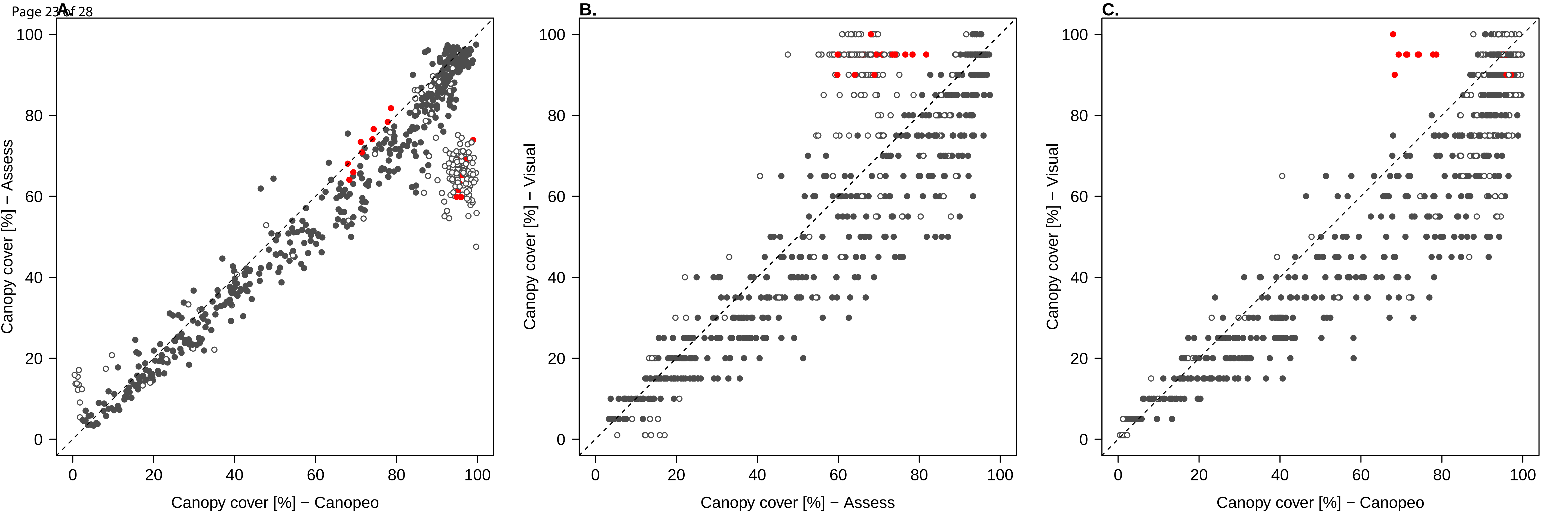
Table S1 List of the evaluated species, with cultivar, targeted plant density [plant/m^2] and vegetation characteristics. Aboveground biomass [t/ha] and height [cm] were measured at the last canopy cover estimation date (23.09, 49 days after seeding).

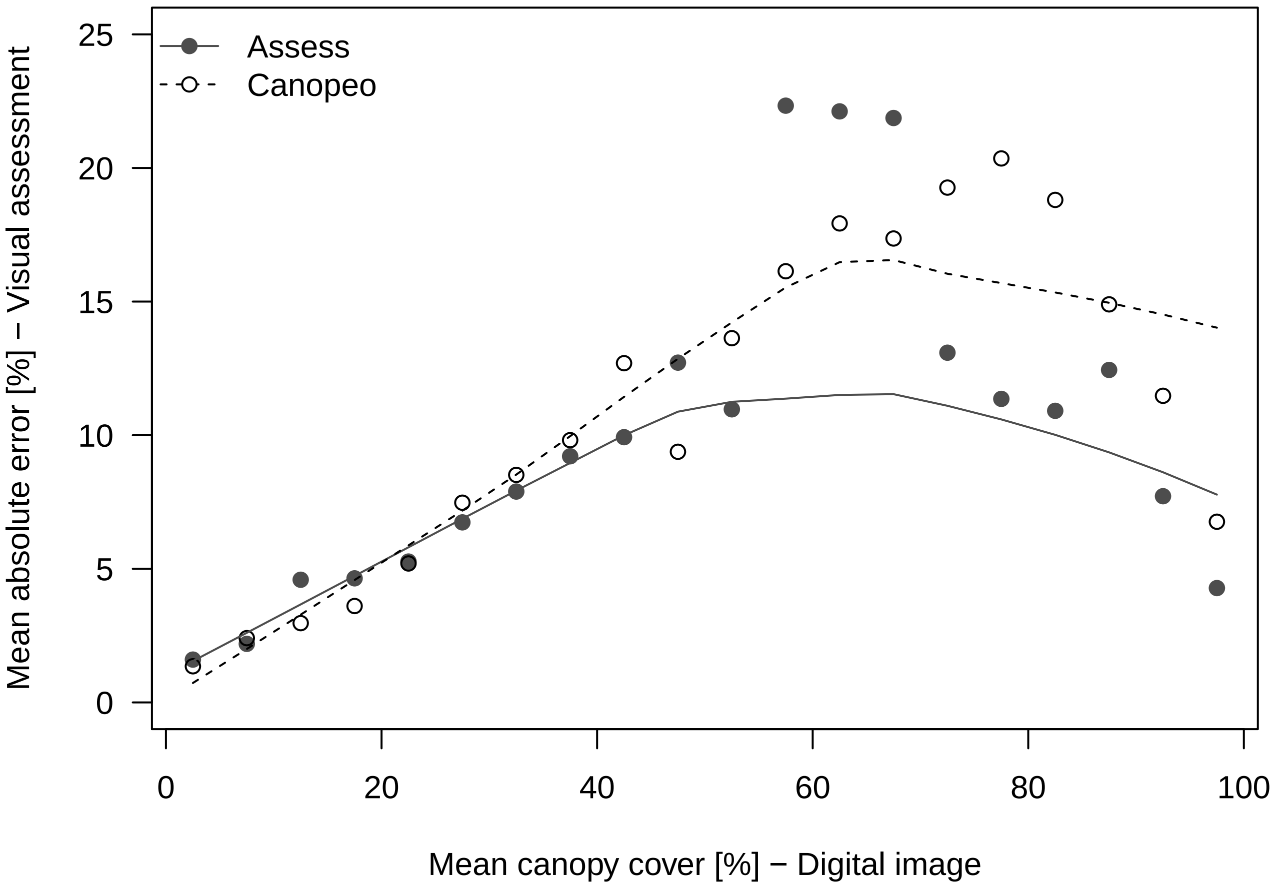
Figure S1 Examples of problematic digital image analysis by Assess and Canopeo. For Assess, areas in purple represent the areas counted as vegetation, and thus taken into account for canopy cover estimation; for Canopeo these areas are shown in white. In the first column on the left, the original digital image of sunflower is good and the analysis by the two softwares is correct. In the second column, the original image is overexposed and some yellow mustard flowers are present. In the third column, this picture of the early stage of sorghum emergence shows very small seedlings. In the last column on the right, buckwheat is in full bloom.

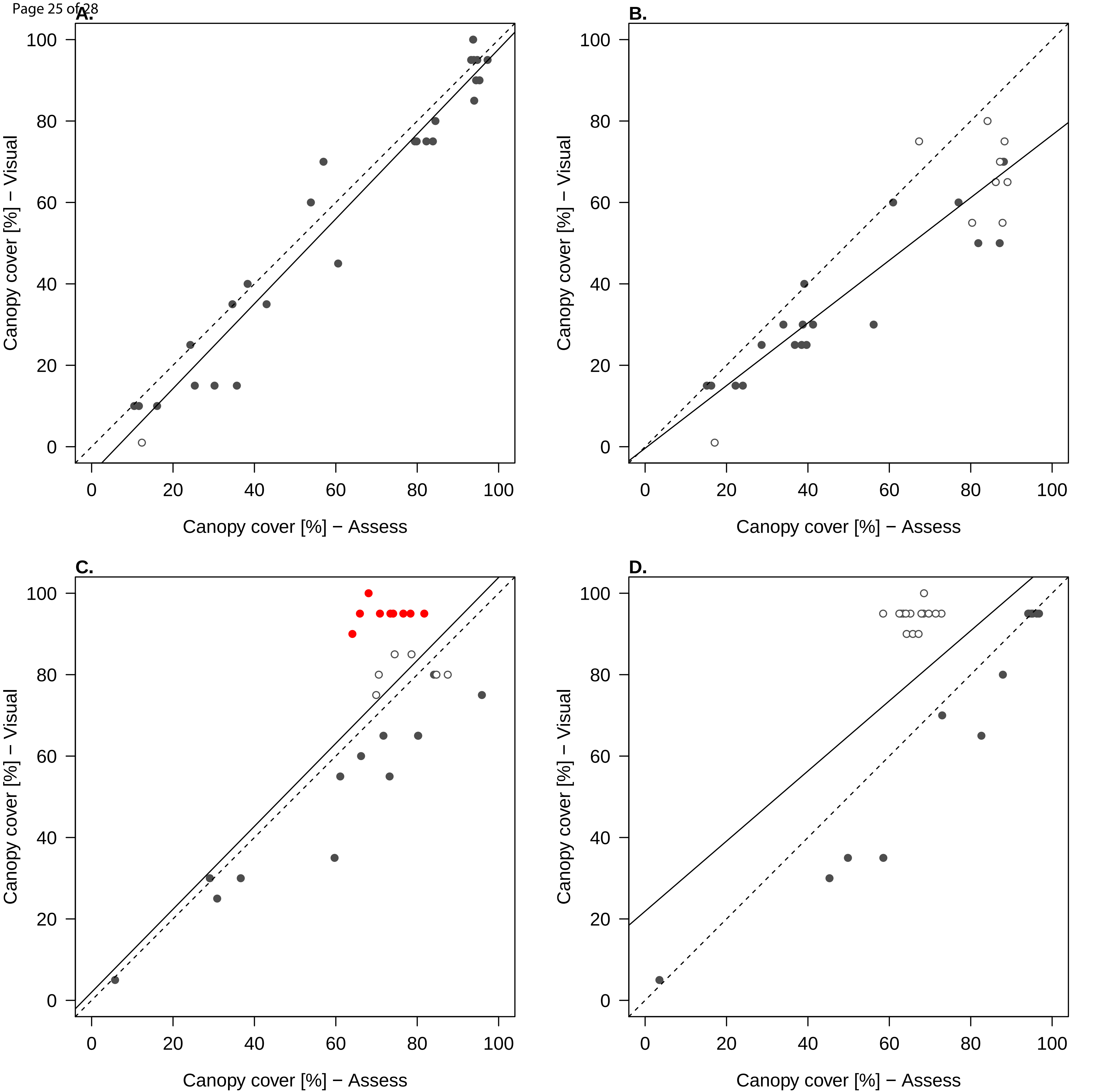
Figure S2 Example of an 'objective' canopy cover scale (here for faba bean) that can be used to calibrate visual assessment. The pictures were taken in the field and then analysed by Canopeo to obtain 'real' canopy cover values.

Table 1

	Assess vs Canopeo			Visual vs Assess			Visual vs Canopeo			Prob	N
	corr	MSE	MAE	corr	MSE	MAE	corr	MSE	MAE		
Overall	0.63	-8.7	9.9	0.62	-0.2	11.9	0.76	-8.9	10.8	174	616
Without quadrat	0.72	-7.7	9.3	0.70	-2.3	11.5	0.81	-10.1	11.3	95	352
Within quadrat	0.48	-9.9	10.6	0.44	2.7	12.4	0.65	-7.2	10.1	79	264
White mustard	*0.15*	-18.8	19.7	*-0.04*	11.3	19.8	0.46	-7.6	7.7	14	28
Indian mustard	*0.03*	-17.7	18.1	0.31	12.2	18.3	0.49	-5.5	6.4	15	28
Turnip rape	0.68	-10.7	11.1	0.56	0.2	11.9	0.69	-10.5	10.9	8	28
Daikon radish	0.60	-6.7	7.7	0.69	-1.6	7.9	0.63	-8.4	10.0	5	28
Forage radish	*0.20*	-10.5	11.2	0.36	2.6	12.0	0.56	-7.8	8.7	8	28
Faba bean	0.81	-1.5	5.8	0.86	-5.4	8.4	0.81	-6.9	9.2	8	28
Lentil	0.80	-6.0	6.7	0.80	3.3	8.0	0.90	-2.7	6.8	6	28
Field pea	0.60	-10.3	10.4	0.59	1.3	11.9	0.73	-9.0	11.0	8	28
Berseem clover	0.88	-3.7	5.0	0.86	-3.5	8.6	0.87	-7.2	9.6	3	28
Common vetch	0.72	-10.3	14.0	0.73	6.6	13.1	0.83	-3.7	5.9	12	28
Black oat	0.57	-11.1	12.0	0.57	-9.2	13.7	0.73	-20.2	20.3	6	28
Foxtail millet	0.86	-4.6	5.8	0.83	-11.7	12.5	0.87	-16.3	16.5	4	27
Sorghum	0.75	-5.6	6.8	0.72	-13.6	14.2	0.66	-19.2	19.2	9	28
Sunflower	0.69	-6.8	7.9	0.71	-3.5	9.8	0.68	-10.3	12.4	5	28
Niger	0.82	-3.8	5.0	0.84	-4.0	6.4	0.80	-7.8	8.7	1	27
Phacelia	0.34	-16.5	21.6	0.47	15.6	21.7	0.72	-0.9	5.3	21	28
Buckwheat	0.68	-4.6	5.6	0.32	3.3	13.5	*0.18*	-1.3	15.8	15	28
Flax	0.94	-4.9	5.0	0.78	-5.8	8.1	0.81	-10.7	10.9	0	28
Hemp	0.73	-10.0	10.1	0.65	-10.5	13.4	0.78	-20.5	20.7	4	28
Chia	0.78	-7.9	8.8	0.74	1.1	8.4	0.86	-6.8	7.1	5	28
4-species mix	0.31	-11.6	12.0	0.40	6.4	11.8	0.60	-5.2	6.8	9	28
11-species mix	0.63	-6.6	7.2	0.69	0.0	8.1	0.75	-6.6	8.5	8	28


A.
Canopy cover [%] − Assess
Canopy cover [%] − Canopeo
0
20
40
60
80
100
B.
Canopy cover [%] − Visual
Canopy cover [%] − Assess
C.
Canopy cover [%] − Visual
Canopy cover [%] − Canopeo


Assess
Canopeo
Mean absolute error [%] − Visual assessment
Mean canopy cover [%] − Digital image
0
5
10
15
20
25
0
20
40
60
80
100



A.
B.
C.
D.
Canopy cover [%] − Visual
Canopy cover [%] − Assess
0
20
40
60
80
100

Table S1 List of the evaluated species, with cultivar, targeted plant density [plant/m^2] and vegetation characteristics. Aboveground biomass [t/ha] and height [cm] were measured at the last canopy cover estimation date (23.09, 49 days after seeding).

Latin name	**Common name**	**Cultivar**	**Plant density** pl/m2	**Aboveground biomass** t/ha	**Height** cm
Brassicaceae					
Sinapis alba	White mustard	Albatros	300	4.5	117
Brassica juncea	Indian mustard	Vitasso	500	3.8	59
Brassica rapa campestris	Turnip rape	Nokonova	500	3.9	45
Raphanus sativus longipinnatus	Daikon radish	Structurator	80	4.8	38
Raphanus sativus oleiformis	Forage radish	Pegletta	200	4.0	49
Fabaceae					
Vicia faba	Faba bean	Fuego	80	3.3	62
Lens nigricans	Lentil	Lenti-fix	200	1.6	21
Pisum sativum	Field pea	Arkta	150	2.8	34
Trifolium alexandrinum	Berseem clover	Tabor	500	2.7	55
Vicia sativa	Common vetch	Candy	200	3.0	32
Poaceae					
Avena strigosa	Black oat	Pratex	400	3.9	65
Setaria italica	Foxtail millet	Extenso	400	2.2	46
Sorghum sudanense	Sorghum	Hay-king	200	3.4	84
Asteraceae					
Helianthus annuus	Sunflower	Iregi	80	6.4	109
Guizotia abyssinica	Niger	Azofix	300	3.6	68
Other families					
Phacelia tanacetifolia	Phacelia	Balo	500	3.4	50
Fagopyrum esculentum	Buckwheat	Lilea	200	4.9	72
Linum usitatissimum	Flax	Princess	500	2.7	51
Cannabis sativa	Hemp	Fedora	200	4.0	84
Salvia hispanica	Chia	Unknown	500	2.7	61
Mixtures					
4-species mix				5.5	63
11-species mix				4.2	80

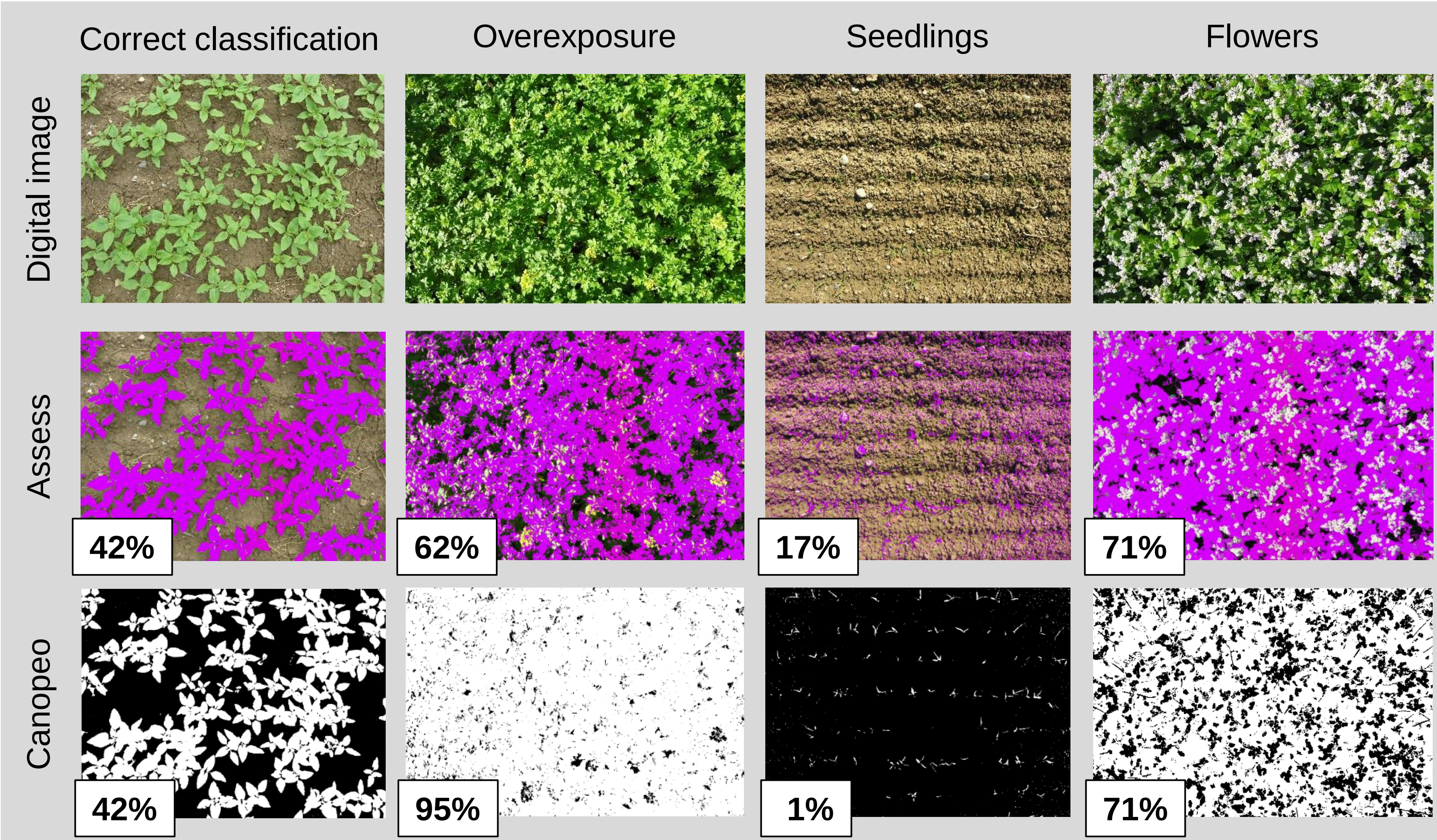


Figure S1 Examples of problematic digital image analysis by Assess and Canopeo. For Assess, areas in purple represent the areas counted as vegetation, and thus taken into account for canopy cover estimation; for Canopeo these areas are shown in white. In the first column on the left, the original digital image of sunflower is good and the analysis by the two softwares is correct. In the second column, the original image is overexposed and some yellow mustard flowers are present. In the third column, this picture of the early stage of sorghum emergence shows very small seedlings. In the last column on the right, buckwheat is in full bloom.

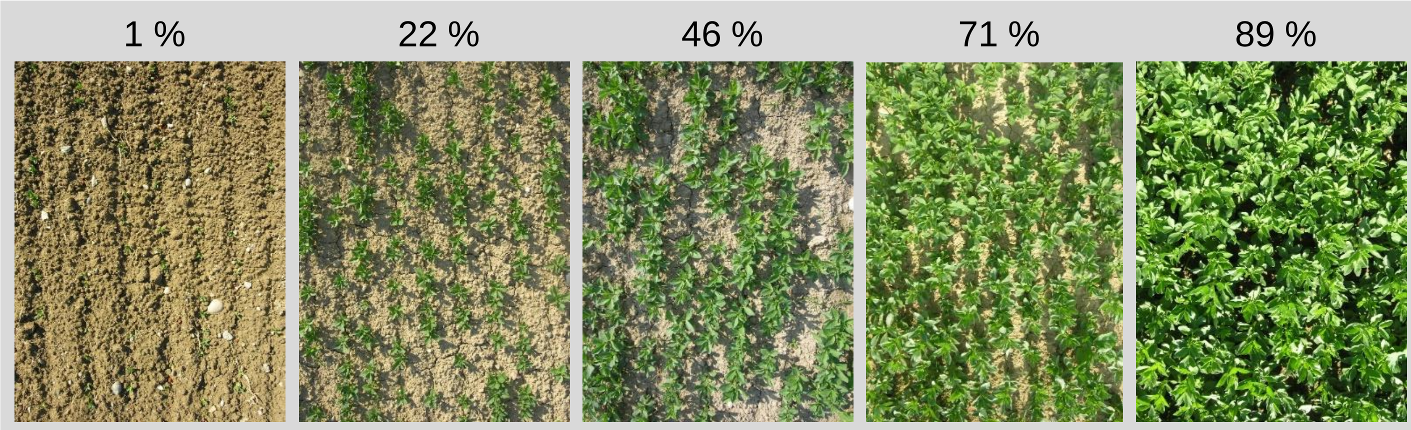


Figure S2 Example of an 'objective' canopy cover scale (here for faba bean) that can be used to calibrate visual assessment. The pictures were taken in the field and then analysed by Canopeo to obtain 'real' canopy cover values.