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Sensor technology for precision weeding in cereals

Evaluation of a novel convolutional neural network to estimate weed cover, crop cover and soil cover in near-ground red-green-blue images

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SUMMARY:

Precision weeding or site-specific weed management (SSWM) take into account the spatial distribution of weeds within fields to avoid unnecessary herbicide use or intensive soil disturbance (and hence energy consumption).

The objective of this study was to evaluate a novel machine vision algorithm, called the ‘AI algorithm’ (referring to Artificial Intelligence), intended for post-emergence SSWM in cereals.

Our conclusion is that the AI algorithm should be suitable for patch spraying with selective herbicides in small-grain cereals at early growth stages (about two leaves to early tillering). If the intended use is precision weed harrowing, in which also post-harrow images can be used to control the weed harrow intensity, the AI algorithm should be improved by including such images in the training data. Another future goal is to make the algorithm able to distinguish weed species of special interest, for example cleavers (Galium aparine L.).

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Summary

Precision weeding or site-specific weed management (SSWM) take into account the spatial distribution of weeds within fields to avoid unnecessary herbicide use or intensive soil disturbance (and hence energy consumption).

Objective of this study was to evaluate a novel machine vision algorithm intended for post-emergence SSWM in cereals. The algorithm is called the 'AI algorithm' (referring to Artificial Intelligence). Primary use of the *AI algorithm* is patch spraying (on/off) of selective herbicides after crop emergence, but precision weed harrowing (after crop emergence) may also be an application. The evaluated algorithm cannot differentiate between weed species. The algorithm uses deep learning techniques to predict the following three classes in digital RGB (red-green-blue) images (field-of-view about 0.06 m^2): weed, crop (cereal) and soil (background).

To evaluate the *AI algorithm*, an independent dataset of images in five spring barley (*Hordeum vulgare* L.) fields was used. None of the images in this dataset were used in the training of the algorithm. Algorithm outputs were calculated into weed cover, crop cover and soil cover, i.e. the percentage of image covered by weeds, cereal plants and soil, respectively. Algorithm predictions were compared with ground truth data, i.e. images manually annotated (at pixel-level), using linear regression and the predicted R^2 statistic (R^2_{pred}).

For precision weed harrowing, it is of value that the *AI algorithm* handle images before and after weed harrowing. Hence, the dataset was divided into two categories. For pre-weeding images, very good R^2_{pred} values resulted: 95.9% (weed cover), 98.6% (crop cover) and 99.02% (soil cover). For post-harrow images, R^2_{pred} was similar for crop cover (97.7%) and soil cover (98.8%), but considerably lower for weed cover (88.4%). This was not unexpected since the *AI algorithm* had not been trained with post-harrow images (but various cereal species). Assessed with two relevant threshold models, the *AI algorithm* predicted the percentage correct weeding decision (per image) - 'weeding necessary' and 'weeding unnecessary'- very well, about 94-95%. Compared to our previous classical machine vision algorithm ('CMV algorithm'), the novel *AI algorithm* had significantly better prediction capability.

Our conclusion is that the *AI algorithm* should be suitable for patch spraying with selective herbicides in small-grain cereals at early growth stages (about two leaves to early tillering). If the intended use is precision weed harrowing, in which also post-harrow images can be used to control the weed harrow intensity, the *AI algorithm* should be improved by including such images in the training data. Another future goal is to make the algorithm able to distinguish weed species of special interest, for example cleavers (*Galium aparine* L.).

Sammendrag (Summary in Norwegian)

Presisjonstiltak mot ugras eller stedsspesifikk ugrasbekjempelse tar hensyn til ugrasets faktiske utbredelse i åkeren for å unngå unødvendig bruk av ugrasmidler (herbicider) eller intensiv jordarbeiding (og dermed energibruk). Formålet med denne studien var å evaluere en ny maskinsynsalgoritme utviklet for presisjonstiltak mot ugras etter kornets oppkomst. Algoritmen er kalt 'AI-algoritmen' (med henvisning til Artificial Intelligence (kunstig intelligens)).

Primær bruk av *AI-algoritmen* er automatisk flekksprøyting (på/av) av selektive ugrasmidler etter kornets oppkomst. Stedsspesifikk ugrasharving (etter kornets oppkomst) er også svært relevant. Algoritmen kan ikke skille mellom ugrasarter. Algoritmen bruker dyplæringsteknikker (convolutional neural network) for å estimere følgende tre klasser i bakkenære digitalbilder (RGB-bilder) (dekker ca. 0.06 m^2): Ugras, nytteplante (korn) og jord (bakgrunn).

For å evaluere *AI-algoritmen* ble et uavhengig datasett bestående av bilder fra fem åkre med vårbygg (*Hordeum vulgare* L.) brukt. Ingen av bildene i dette datasettet hadde vært brukt til trening (kalibrering) av algoritmen. Algoritmens utdata ble omregnet til prosent dekning av ugras, korn og jord per bilde. Algoritmens prediksjoner for de tre klassene ble sammenlignet med sanne verdier, dvs. bilder manuelt annotert (på piksel-nivå), ved bruk av linear regresjon og indikatoren predikert R^2 (R^2_{pred}).

For stedsspesifikk ugrasharving, er det en fordel at AI-algoritmen også fungerer godt på bilder tatt rett etter ugrasharvingen. Datasettet ble derfor delt i to kategorier (før ugrasharving, etter ugrasharving). For bildene tatt før ugrasharving ble R^2_{pred} verdier høye: 95.9% (ugras), 98.6% (korn) and 99.02% (jord). For bildene tatt etter ugrasharving var verdiene i samme område for korn (97.7%) og jord (98.8%), men betydelig lavere for ugras (88.4%). Dette var ikke uventet fordi *AI-algoritmen* bare hadde vært trent (kalibrert) med bilder før ugrasharving (og på mange ulike kornarter). Vurdert med to relevante skadeterskelmodeller, var AI-algoritmen svært god til å predikere korrekt tiltaksbeslutning (per bilde), dvs. 'ugrastiltak nødvendig' og 'ugrastiltak unødvendig': ca. 94-95%. Sammenlignet med vår tidligere algoritme basert på klassisk bildeanalyse ('CMV algoritmen') hadde den nye AI algoritmen vesentlig bedre prediksjonsevne.

Konklusjonen er at *AI-algoritmen* burde være velegnet til automatisk flekksprøyting med selektive ugrasmidler i korn på tidlige vekststadier (ca. to varige blad til tidlig busking). Hvis tiltenkt bruk er sensor-styrt ugrasharving, hvor også bilder rett etter harving kan regulere harveintensiteten, bør *AI-algoritmen* forbedres ved å inkludere slike bilder i treningsdatasettet. Et annet framtidig mål er å gjøre algoritmen i stand til å identifisere spesielt viktige ugras, f. eks. klengemaure (*Galium aparine* L.).

Content

1 Introduction

Weeds compete with crop plants for resources and space, and without adequate management, weeds will reduce crop yields significantly. For example, the global average potential loss in wheat is estimated to 46% (Oerke 2006). With the herbicides' arrival in the 1970'ies, weed control became effective. However, herbicides may spread to nature and cause unwanted side-effects on non-target organisms including humans (van Bruggen et al. 2018). Furthermore, overreliance on herbicides may cause weeds to develop herbicide resistance meaning that weeds will be unaffected by normal herbicide doses. In September 2022, 267 herbicide resistant weed species have been reported globally (Heap 2022).

To prevent negative impacts of pesticides, most European countries have implemented the principles of integrated pest management (IPM), in EU known as Framework Directive 2009/128/EC. These days (autumn 2022) this Directive is under revision and is suggested to be a regulation indicating an even stronger emphasis on IPM and the reduced use of traditional chemical pesticides (https://food.ec.europa.eu/system/files/2022-06/pesticides_sud_eval_2022_reg_2022-305_en.pdf). Hence, farmers should use prevention measures before herbicide-free methods. If herbicides are needed, a site-specific adjustment to the actual weediness should be used, which fits well with the phenomenon that weeds generally occur in patches within arable fields (e.g. Wallinga et al. 1998; Heijting et al. 2007; Nordmeyer 2009; Metcalfe et al. 2018). Hence, the required weed control efficacy varies within fields. With the development of computer- and machine vision technologies, the old idea and concept of weed economic thresholds to determine the need of direct weed control (e.g. Gerowitt & Heitefuss 1990) has been re-vitalized for use at the sub-field scale (Berge et al. 2008b; Ritter et al. 2008; Keller et al. 2014; Ali et al. 2015; San Martin et al. 2016). Precision weeding, site-specific weed management (SSWM), patch spraying and variable rate application are terms used for weed management approaches that takes into account the spatial intra-field variation in weediness (e.g. Christensen et al. 2003; Nordmeyer 2006; Wiles 2009; Table 1 in Lati et al. 2021). The spatial resolution of precision weeding can vary from targeting individual weeds (a few cm^2) in the close-to-crop area of e.g. sugar beets to large patches (several m^2) of weeds in cereals (cf. Fig. 1 in Christensen et al. 2009). Precision weed harrowing (Rueda-Ayala et al. 2015, Spaeth et al. 2021) and patch spraying of herbicides (Gutjahr et al. 2012; Hamouz et al. 2014; Gonzalez de Soto et al. 2016) are examples which are applicable to e.g. small-grain cereals and maize. These approaches can realize IPM by using herbicide-free methods and "partial applications". Gerhards et al. (2022) recently reviewed advances in SSWM in agriculture.

To implement precision weeding, sensor technologies capable in estimating within-field variation in weediness automatically is a prerequisite (Fernandez-Quintanilla et al. 2018). Many studies for the goal of precision weeding have dealt with automatic classification of weeds and crop plants in close-range RGB images based on classical hand-crafted feature-based methods (e.g. Midtiby et al. 2011; Swain et al. 2011; Berge et al. 2012; Laursen et al. 2016; Dyrmann et al. 2018). For precision weed harrowing in cereals, several (Rasmussen et al. 2008; Rueda-Ayala et al. 2011) have suggested automatic analysis of RGB images as a method to optimise the harrowing intensity at the sub-field scale. Their algorithms did not discriminate between crop and weed plants. Later, Rueda-Ayala et al. (2013) discriminated weeds from crop plants using bi-spectral cameras with near-infrared and red bands for precision weed harrowing. Wang et al. (2019) and Machleb et al. (2020) gave reviews on ground-based weed detection techniques and sensor-based mechanical weed control, respectively.

Deep learning (DL) is a modern adaptive technique for image and data analysis with a series of advantages (Chavan & Nandedkar 2018). DL has been successfully applied in various topics and has entered the agricultural sector as well. Recognising weeds in images with DL is relatively popular (Kamilaris & Prenafeta-Boldu 2018; Wang et al. 2019). RGB imagery, both via UAV (unmanned aerial vehicle) (e.g. Sørensen et al. 2017; Huang et al. 2018a and 2018b; Valente et al. 2019) and at ground (e.g. Dyrmann et al. 2016; Knoll et al. 2019; Sharpe et al. 2019), are explored. Sørensen et al. (2017) used convolutional neural networks (CNN) to detect patches of the perennial weed *Cirsium arvense* in cereals from UAV RGB imagery acquired near crop harvest. The average accuracies across flight altitude were 95% (spring barley) and 97.5% (winter wheat). Dyrmann et al. (2016) used CNN to identify 18 weed species (or weed species groups) and four crop species (wheat, barley, maize and sugar beet) at the early growth stages in near-ground RGB images. Mean classification accuracy was 86%, with 98% as the best (sugar beet). For real-time precision weeding in sugar beet, Milioto et al. (2018) suggested a CNN-model that made use of existing knowledge (14 channels and vegetation indices) and required relatively few RGB images to re-train it for new fields. Chavan & Nandedkar (2018) proposed a CNN-model, which was a hybrid of two neural network architectures to classify three crop species (wheat, maize, sugar beet) and nine weed species at early growth stages (up to four true leaves) in near-ground RGB images. Compared to the two input architectures, the hybrid performed better, with mean accuracy 98% versus 95% (AlexNet) and 93% (VGGNET). To quantify the number of weeds in winter wheat with heavy leaf occlusions, Dyrmann et al. (2017) suggested a CNN-model (based on DetectNet and GoogLeNet) also for near-ground nadir-view RGB images. Evaluated with images showing the heaviest occlusion, only about 50% of the weeds were detected. The weeds missed were either very small, heavily occluded or grass species. Authors explained the relatively low recall rate with the quality of the training data. Karimi et al. (2018) proposed a CNN-model to estimate the position and number of cereal stem emerging points, and hence the number of crop plants, at the early growth stage. The method resulted in a coefficient of determination of about 87% between predicted and true values in the range zero to appr. 200 plants per image (proximate nadir RGB images). Huang et al. (2018a; 2018b) used fully convolutional networks (FCN) for pixel-level classification of low altitude UAV RGB imagery in rice into three classes, i.e. weeds, crop and soil (incl. other non-plant surfaces). Their best algorithms gave overall accuracies of 93.5% (FCN-8s) and 91.96% (FCN-4s). In close-range RGB imagery in paddy fields, Ma et al (2019) achieved an average accuracy rate of 92.7% with FCN (SegNet) when segmenting the classes crop (rice), weeds and background. In close-range RGB imagery, Knoll et al. (2019) achieved accuracy rates of 93.6 and 96.8% for their two CNNs for classification of pixels into crop (carrot) and weeds. Motivated by the successful results above, last years' increase in computing power and decrease in run time, we utilized DL techniques to make a novel algorithm expected to be more precise and robust than our previous algorithm for patch spraying of selective herbicides in small-grain cereals (Berge et al. 2008a; Berge et al. 2012).

1.1 Objective of study

The aim of current study was to evaluate the performance of a novel machine vision algorithm based on deep learning techniques (a fully convolutional neural network), hereafter the 'AI algorithm'. The intended use is precision weeding in cereals at the early crop growth stage (i.e. from about two leaves to early tillering). The primary use of the *AI algorithm* is herbicide patch spraying, but precision weed harrowing is also relevant. The evaluated *AI algorithm* classifies all pixels in near-ground, nadir RGB images into either weed, crop (cereals) or soil (background). The relative weed cover (RWC) defined as weed cover/(weed cover+crop cover), was also assessed, since it has shown high potential in predicting the crop yield-loss (e.g. Lemieux et al 2003). For precision weed harrowing, the AI algorithm should handle both pre-harrowing and post-harrow images. In post-harrow images, crop and weed plants will be partly covered by soil. To evaluate the *AI algorithm*, a completely independent dataset of images acquired either immediately before or after weed harrowing (one pass) in five spring barley fields was used. The true values of weed cover, crop cover and soil cover per image in this dataset were achieved through manual annotation of all the weed and crop pixels in each image. Remaining pixels were defined as soil background. None of these five barley fields were used in the training of the *AI algorithm*. The performance of the *AI algorithm* was compared with the performance of our older algorithm based on classical machine vision (Berge et al. 2008a; Berge et al. 2012), hereafter the 'CMV algorithm'. To make use of the *AI algorithm* in future precision weeding research and developments, the regression model parameters to predict the true value of weed cover, crop cover and soil cover from the raw output values from the *AI algorithm* were estimated.

2 Materials and Methods

The three predefined classes in the current version of the *AI algorithm* were weeds, crop (cereals) and soil (background). The three classes sum up to 100% in each image. Algorithm was a convolutional neural network (CNN) programmed in Python, with use of the PyTorch library (https://pytorch.org). The training data of the algorithm originated from many farmers' fields in both spring - and winter cereals (barley (*Hordeum vulgare* L.), wheat (*Triticum aestivum* L.), oats (*Avena sativa* L.) and rye (*Secale cereale* L.)) collected during the period 2009-2018 in several countries in Europe (Norway, Denmark, Germany and Spain). Images used as training data were acquired at the time for early post-emergence weed management in autumn (winter cereals) or spring (spring- and winter cereals), i.e. crop about two leaves to early tillering. The crop row distance varied from 125 mm (Norway, Denmark) to 150 mm (Germany, Spain). No images were from fields already sprayed with herbicides or subject to mechanical weeding. All images in the training data were acquired with RGB camera with an embedded custom-built flash which in principle "neutralize" variations in ambient illumination conditions. This setup was identical to the camera setup used to collect the evaluation dataset.

A custom-made program with class labelling and annotation abilities was used to create ground truth data to train the CNN. To compensate for the limited size of the training dataset (n=231 images), transfer learning and data augmentation were implemented. Parameters and weights from networks trained on large image databases such as ImageNet and CIFAR-10 had been used to initialize parts of the network. To increase the size of the dataset, random cropping, scaling and RGB variation were implemented.

Images for independent evaluation of the AI algorithm were collected (see examples in **Figure 1**a-d) in five trials in spring barley, *H. vulgare* (cultivars Helium, Fairytale and Salome), with crop row spacing 125 mm with naturally occurring weeds during four years (2015-2018), see **Table 1**. Fields were in SE Norway (59°19'-59°40', 10°45'-11°02'). Images were captured at a forward speed of 4 km h^{-1} from a 'Troll frame' (Underhaug Fabrikker AS, Nærbø, Norway) mounted at the rear side of the tractor (**Figure 2**).

Table 1. Overview of the main weed species and number of images in the independent evaluation dataset acquired in five spring barley (*H. vulgare*, cultivars Helium, Fairytale and Salome) trials during the years 2015-2018 in SE Norway.

Trial ID (cultivar)	Main weed species	Pre-harrowing	Post-harrowing	Total
150604 (Helium)	*Chenopodium album, Erodium cicutarium, Gnaphalium uliginosum, Lamium purpureum, Tripleurospermum inodorum, Poa annua, Fallopia convolvulus, Spergula arvensis, Stellaria media, Viola arvensis*	23	31	54
160602 (Helium)	*Chenopodium album, Erodium cicutarium, Fumaria officinalis, Lamium purpureum, Tripleurospermum inodorum, Poa annua, Viola arvensis*	10	14	24
160607 (Helium)	*Fumaria officinalis, Galeopsis sp., Poa annua, Viola arvensis*	21	15	36
170601 (Fairytale)	*Chenopodium album, Galeopsis sp., Lamium purpureum, Polygonum aviculare, Fallopia convolvulus, Viola arvensis*	8	12	20
180531 (Salome)	*Chenopodium album, Erodium cicutarium, Lamium purpureum, Poa annua, Viola arvensis*, volunteer Brassica*	10	12	22
Total		72	84	156

** volunteer Brassica rapa ssp. oleifera and/or Brassica napus ssp. oleifera*

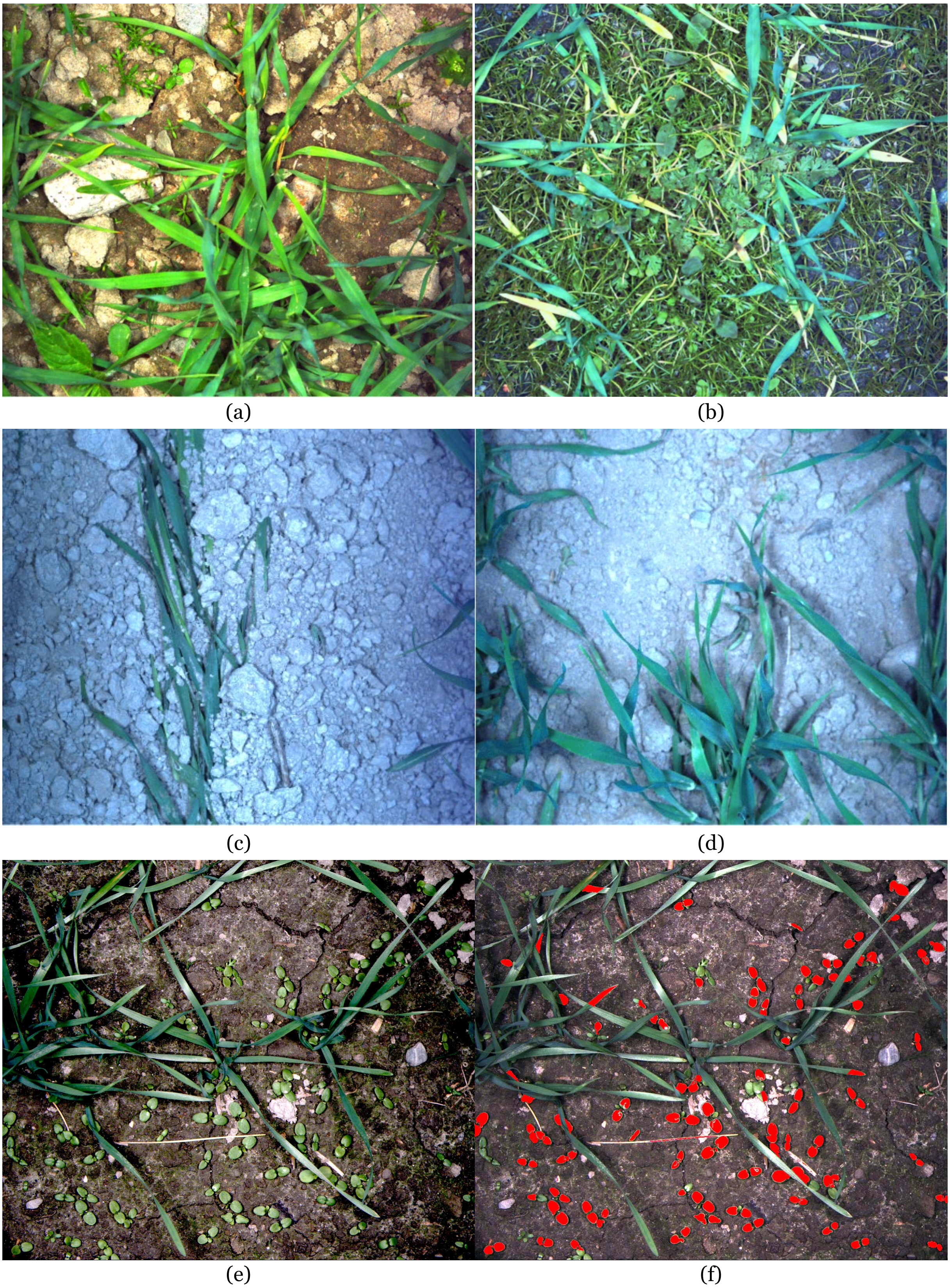


Figure 1. Examples of images in the independent evaluation dataset (a-d), as well an example of an original image (e) classified with the old 'CMV algorithm' (f; pixels in red classified as weeds). Images were acquired immediately before post-emergence weeding (a and b) or immediately after weed harrowing once (c and d) with RGB camera mounted at rear side of tractor while driving at 4 km h^{-1} (cf. Figure 2). Distance between lens and ground was about 0.7 m, providing a field of view of about 0.27 m × 0.22 m. Upper right image (b) is the one marked with asterisk (*) in Figure 3. Photos: Adigo AS.

(a)

(b)

Figure 2. a: Platform used to collect the independent evaluation dataset of RGB images (about 0.27 m × 0.22 m). The black (and grey) box mounted to a bendable arm is the RGB camera with embedded flash. Distance from lens to ground was about 0.7 m. b: Weed harrow used before and after imaging. Photos: T. W. Berge, NIBIO.

The camera setup constituted of a 5MP mega pixel RGB camera (FLIR, chameleon3) equipped with a 25 mm lens (Computar) and a custom-built flash to ensure optimum illumination and neutralization of variation in ambient sunlight conditions. The platform was based on a Linux-based computer that sampled one frame every 0.5 second and positions with a RTK-GNSS receiver (Septentrio, PolaRX) with an antenna mounted at the top of the tractor cab. The position of the camera ensured that the impact of the wheels on the plants were not captured in the images. The image resolution was 2448 pixels × 2048 pixels. Distance between lens and ground was about 0.7 m, providing a field of view of about 0.27 m × 0.22 m. Images were acquired when the spring barley crop and weeds were at the early growth stage, i.e. crop at BBCH 13-23. Images were acquired immediately before and after (same day) weed harrowing (one pass) at various harrowing intensity levels (imposed by varying the tine angle of the harrow at driving speed 8 km h^{-1}).

We have previously developed a classical algorithm based on shape features to estimate the weed cover and crop cover in proximate nadir view RGB images (see an example of output in **Figure 1**f) with the purpose of patch spraying of herbicide against annual weeds in cereals. For further details, see Berge et al. 2008a and 2012. In current study, this old algorithm - the 'CMV algorithm'- was included for comparison (benchmarking).

In total, several thousand images were acquired in the five spring barley fields. From this large dataset, a subset was selected semi-randomly. First, all images were analysed by the old *CMV algorithm* with default parameter values. Then, outputs were grouped into five groups according to predicted value of weed cover and crop cover. Thereafter, a random sample was selected from each group ensuring a wide range in weed and crop cover values, which constituted the final independent evaluation dataset of 156 images (**Table 1**). The same labelling - and annotation program used for training was used to create the true values of weed cover, crop cover and soil cover in the evaluation dataset.

Linear regression models with two parameters (intercept and slope) were fitted to the evaluation dataset with the ground truth values of weed cover, crop cover, soil cover and RWC (relative weed cover = weed cover/weed cover+crop cover) as response variables, and the corresponding outputs of the machine vision algorithms as independent variables. Minitab® Statistical Software (version 18.1, www.minitab.com) was used. The statistic predicted R^2 (coefficient of determination) was used to assess the machine vision algorithms' performance. Minitab calculates predicted R^2 (R^2_{pred}) by systematically removing each observation from the dataset, estimating the regression equation, and determining how well the model predicts the removed observation. This statistic was considered adequate and efficient for these algorithms because we were not interested in estimating the exact position of weed pixels in the images, but only to know the total weed cover per image.

To make use of the *AI algorithm* in future precision weeding applications, the regression model parameters to predict the true value of weed cover, crop cover, soil cover and RWC from the raw output values from the *AI algorithm* were estimated. Separate models were fitted to the pre-weeding images and post-harrow images for weed cover, crop cover, soil cover and RWC. With reasonable results for the post-harrow images, it would mean that the novel *AI algorithm* - which was only trained with pre-weeding images -, could have a wider area of application than originally (i.e. herbicide patch spraying), e.g. post-emergence precision weed harrowing. We also fitted regression models irrespective of whether image was acquired before or after the weed harrowing. Besides R^2_{pred}, visual inspection of the classified images was used to judge the performance of the *AI algorithm*.

The biological weed threshold corresponds to the weediness level wherein a significant negative impact on crop yield is expected. In the case of patch spraying, i.e. spraying only sub-field areas above a certain weediness level, the *AI algorithm* needs to be good at predicting whether a sub-field area is above or below the threshold. We tested the performance of the *AI algorithm* and the old *CMV algorithm* in this respect using two different biological threshold models on the individual images in the full evaluation dataset (n = 156 images): RWC > 0.042 and Weed cover > 2.09%. These models were chosen due to own previous (Berge et al. 2012) and recent results (Berge et al. 2022), respectively.

3 Results

For the pre-harrowing images in the evaluation dataset, the *AI algorithm* was better than the *CMV algorithm*, especially for weed cover with R^2_{pred} = 95.9% versus 75.5% (**Figure 3**b) and RWC with R^2_{pred} = 94.5% versus 69.95% (**Figure 3**d). The *CMV algorithm* performed better for barley cover and soil cover than for weed cover and RWC. The values of R^2_{pred} were 91.2% (barley cover) and 97.8% (soil cover) (**Figures 3**a and 3c). However, this was still not as good as the *AI algorithm* with values of R^2_{pred} being 98.6% (barley cover) and 99.02% (soil cover). The estimated parameter values of the four linear regression models for the *AI algorithm* are given in **Table 2**.

For the post-harrowing dataset, the *AI algorithm* was better than the *CMV algorithm*, especially for RWC with R^2_{pred} = 85.9% versus only 10.6% (**Figure 4**d). But also for weed cover and barley cover the *AI algorithm* outperformed the old algorithm, the R^2_{pred} values for weed cover and barley cover were 88.4% versus 56.2% (**Figure 4**b) and 97.7% versus 83.9% (**Figure 4**a), respectively. For soil cover, however, the *AI algorithm* was only slightly better than the *CMV algorithm* with R^2_{pred} = 98.8% versus 95.4% (Figure 4c). The estimated parameter values of the four linear regression models for the *AI algorithm* are given in **Table 3**.

For the full dataset, irrespective of image was taken before or after weed harrowing, the values of R^2_{pred} for the four regression models for the *AI algorithm* were all high and above 90% (**Figure 5**). Soil cover had the highest R^2_{pred} (98.9%), followed by barley cover (98.1%), weed cover (92.9%) and RWC (90.8%). The estimated parameter values of the four regression models for the *AI algorithm* are given in **Table 4**.

Assessed for its ability to predict the correct weed management decision, the *AI algorithm* performed better than the *CMV algorithm*, especially for the threshold model based on RWC (**Table 5**). The percentage correct decisions with the *CMV algorithm* based on the two tested threshold models, Weed cover > 2.09% and RWC > 0.042, were 91% and about 79%, respectively, whereas the *AI algorithm* achieved about 94-95% for both threshold models.

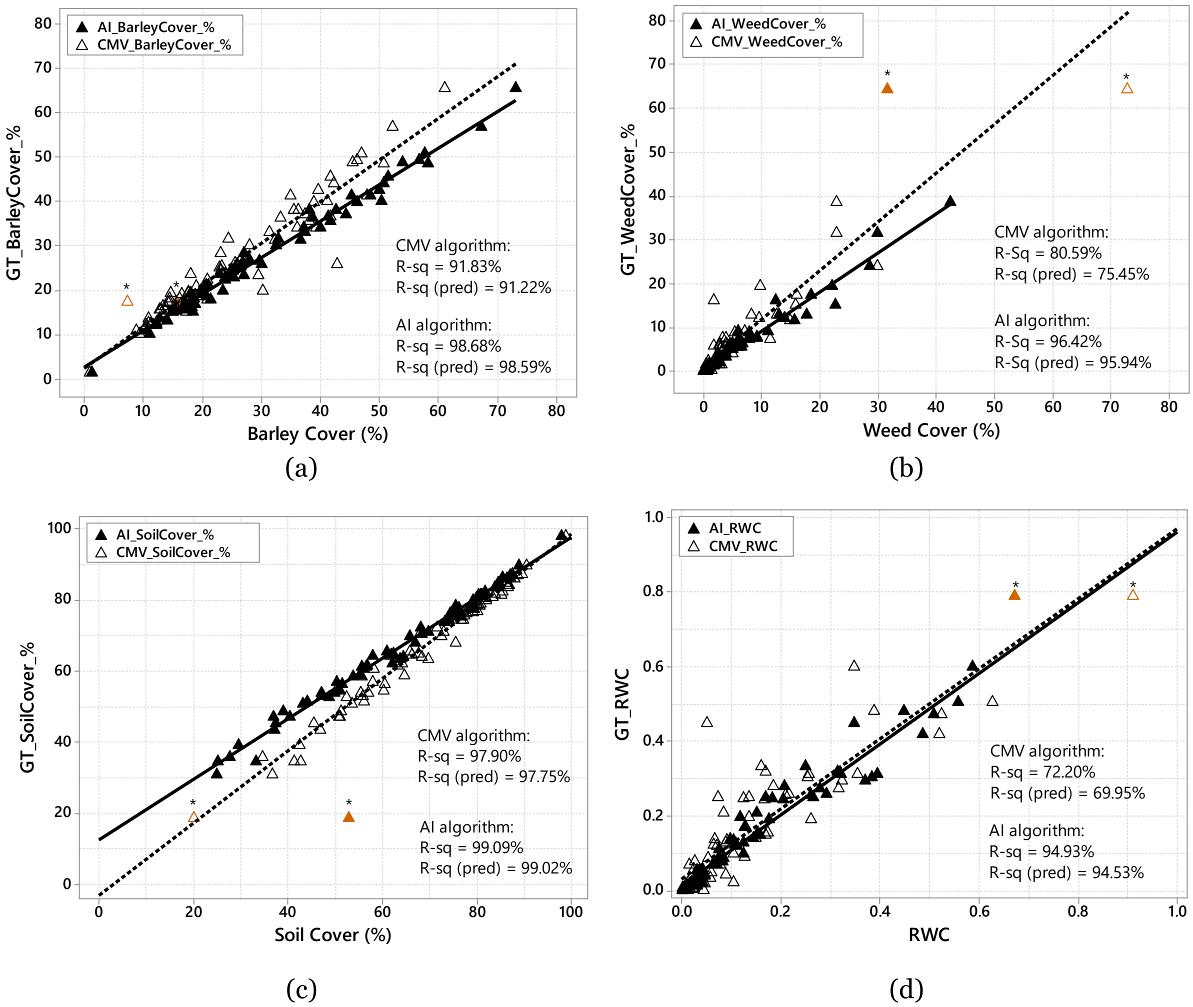
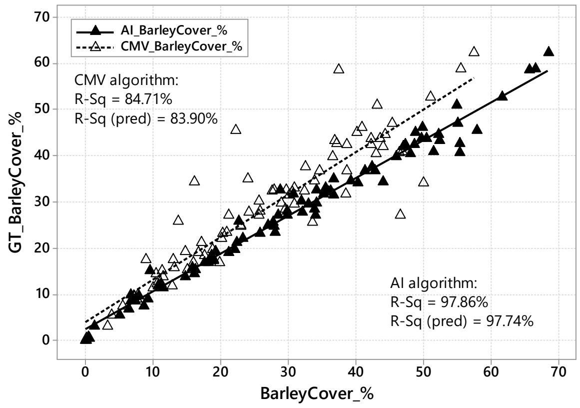


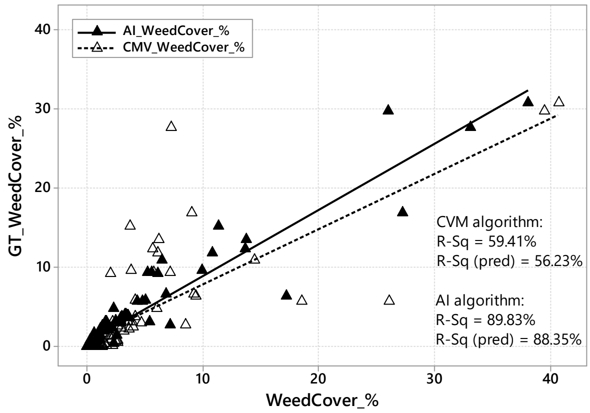
Figure 3. Evaluation dataset of images acquired *pre*-harrowing (n=72 images) with fitted linear regression models (n=71 images) of the true values (y-axis) versus the predicted values (x-axis) by the novel *AI algorithm* (filled symbol, continuous line) and the old *CMV algorithm* (open symbol, dotted line). (a) Crop (barley) cover; (b) weed cover; (c) soil cover; (d) RWC (relative weed cover = weed cover/weed cover+crop cover). The estimated parameter values of the regression models for the AI algorithm are given in Table 2. The dots annotated in red colour/with an asterisk (*) is the data point omitted in the regressions, i.e. the image in Figure 1b.

Table 2. Estimated parameter values of the linear regression models predicting the true values of pre-harrowing weed cover, crop (barley) cover, soil cover and RWC (relative weed cover = weed cover/weed cover+crop cover) per image from the corresponding raw outputs estimated by the novel *AI algorithm* (cf. Figure 3). Number of observations in the evaluation dataset = 71 images. SE = Standard error, S = standard deviation of distance between data values and the linear model.

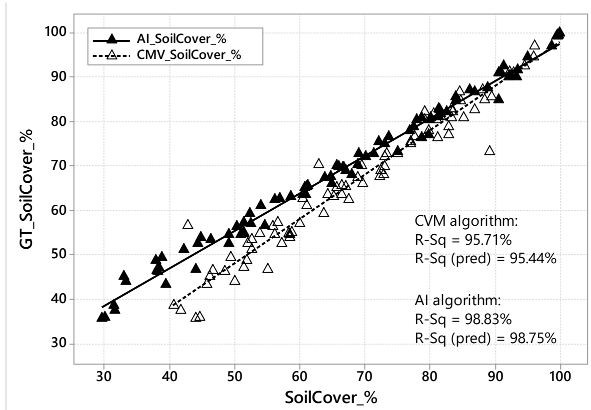
	a (slope)		b (intercept)		S	R^2	R^2_{pred}
	Parameter	SE	Parameter	SE			
Weed cover	0.88781	0.02061	0.42895	0.20154	1.39874	96.42	95.94
Barley cover	0.82620	0.01149	2.563288	0.37703	1.46549	98.68	98.59
Soil cover	0.85124	0.00979	12.41054	0.66438	1.50474	99.09	99.02
RWC	0.94854	0.02638	0.01382	0.00533	0.03333	94.93	94.53



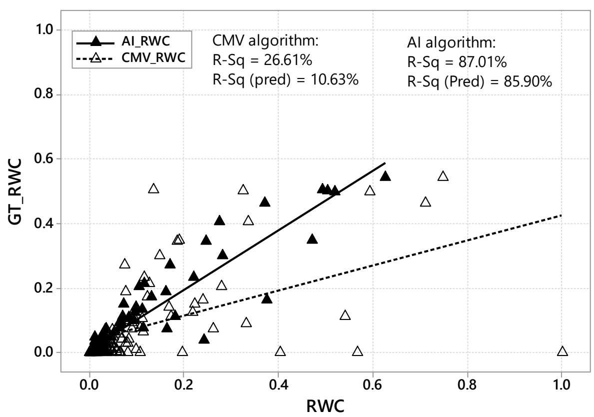
(a)



(b)



(c)

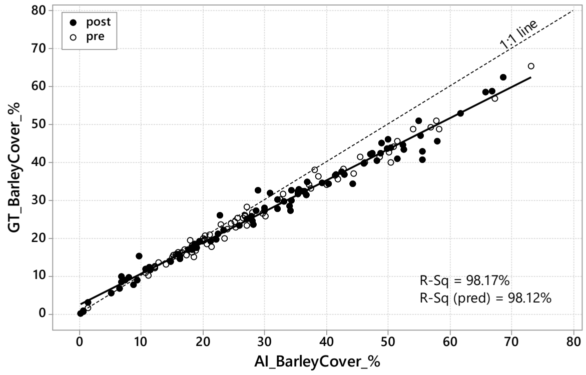


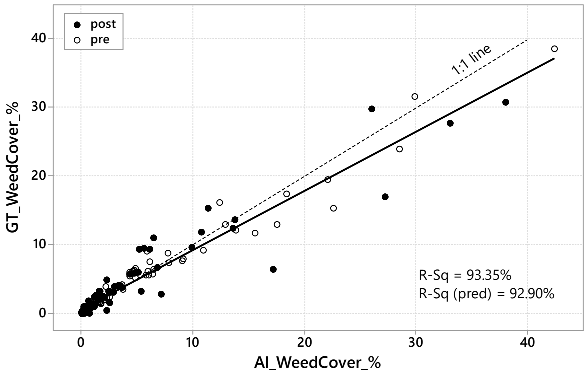
(d)

Figure 4. Evaluation dataset of images acquired *post*-harrowing (n=84) with fitted linear regression models of the true values (y-axis) versus predicted values (x-axis) by the novel *AI algorithm* (filled symbol, continuous line) and old CMV algorithm (open symbol, dotted line). (a) Crop (barley) cover; (b) weed cover; (c) soil cover; (d) RWC (relative weed cover = weed cover/weed cover+crop cover). The estimated parameter values of the regression models for the *AI algorithm* are given in Table 3.

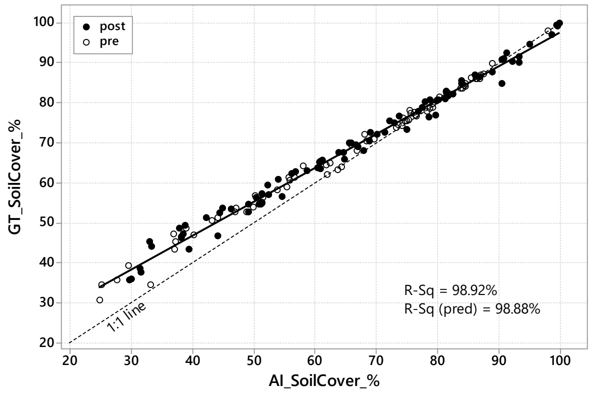
Table 3. Estimated parameter values of the linear regression models predicting the true values of post-harrowing weed cover, crop (barley) cover, soil cover and RWC (relative weed cover = weed cover/weed cover+crop cover) per image from the corresponding raw outputs estimated by the novel *AI algorithm* (cf. Figure 4). Number of observations in the evaluation dataset = 84 images. SE = Standard error, S = standard deviation of distance between data values and the linear model.

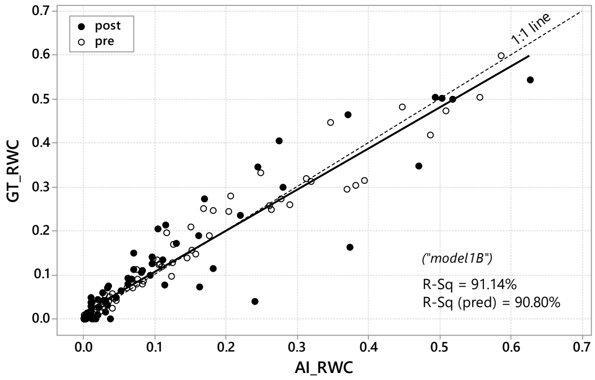
	a (slope)		b (intercept)		S	R^2	R^2_{pred}
	Parameter	SE	Parameter	SE			
Weed cover	0.83513	0.03104	0.57942	0.24887	2.02796	89.83	88.35
Barley cover	0.81795	0.01335	2.52290	0.47064	2.12811	97.86	97.74
Soil cover	0.84253	0.01014	13.42559	0.69450	1.81473	98.83	98.75
RWC	0.91904	0.03922	0.01260	0.00639	0.04975	87.01	85.90





(a) (b)





(c) (d)

Figure 5. True values (y-axis) predicted by the novel *AI algorithm* for the pre-harrowing images (open symbols, n=71) and the post-harrow images (filled symbols, n=84), and the corresponding fitted linear regression models (solid lines) and 1:1 lines (dotted lines). (a) Crop (barley) cover; (b) weed cover; (c) soil cover; (d) RWC (relative weed cover = weed cover/weed cover+crop cover). The estimated parameter values of the regression models for the novel *AI algorithm* are given in Table 4.

Table 4. Estimated parameter values of the linear regression models predicting the true values of weed cover, crop (barley) cover, soil cover and RWC (relative weed cover = weed cover/weed cover+crop cover) per image from the corresponding raw outputs estimated by the novel *AI algorithm* (cf. Figure 5). Number of observations in the independent evaluation dataset = 155 images (71 pre-harrowing + 84 post-harrowing). SE = Standard error, S = standard deviation of distance between data values and the linear model.

	a (slope)		b (intercept)		S	R^2	R^2_{pred}
	Parameter	SE	Parameter	SE			
Weed cover	0.86320	0.01863	0.51719	0.16525	1.76881	93.35	92.90
Barley cover	0.82076	0.00905	2.56705	0.30910	1.84948	98.17	98.12
Soil cover	0.84632	0.00715	12.97285	0.48742	1.68601	98.92	98.88
RWC	0.93631	0.02360	0.01311	0.00429	0.04286	91.14	90.80

Table 5. Percentages of correct (in bold) and false weed control decisions predicted by the novel *AI algorithm* and the old *CMV algorithm* tested for two different threshold models (weed cover > 2.09%, RWC > 0.042). Calculations are based on raw outputs of the two algorithms versus the corresponding ground truth irrespective of images acquired pre- or post-harrowing (n= 156 images).

		Weed cover > 2.09%				RWC > 0.042			
		AI algorithm		*CMV algorithm*		*AI algorithm*		*CMV algorithm*	
		Above	Below	Above	Below	Above	Below	Above	Below
Ground Truth	**Above**	42.3	3.8	42.9	3.2	48.7	5.1	49.4	4.5
	Below	1.3	52.6	5.8	48.1	0.6	45.5	16.7	29.5

4 Discussion

The finding that the *AI algorithm* based on deep learning techniques performed better than our old *CMV algorithm* based on classical image analysis techniques was in agreement with Sørensen et al. (2017). They found that a CNN-based algorithm performed better than their previous classical algorithm for the detection of creeping thistle (*Cirsium arvense* (L.) Scop.) in cereals shortly before crop harvest.

The better performance of our *AI algorithm* was demonstrated in terms of both the R^2_{pred} values between the estimated and true values of the target classes (i.e. total weed cover, crop cover, soil cover (cf. **Figure 3** and **4**)) and the percentage correct weed control decisions (i.e. 'weeding necessary' or 'weeding not necessary') based on the two biological threshold models tested (cf. **Table 5**). For soil cover, the *AI algorithm* performed only slightly better than the old *CMV algorithm* for both pre-weeding and post-harrow images. This was expected since it is generally much less demanding to distinguish soil from green plants - irrespective of plants being subject to disturbance like weed harrowing or not - than to distinguish specific plants (crop) from other plants (weeds).

In the post-harrowing situation, the appearance of the plants can be quite different from undisturbed plants and generally show a disturbed "combed" looking (cf. **Figure 1**c). Neither of the algorithms were trained with images acquired after weed harrowing. This explained the generally lower R^2_{pred} values for the post-harrowing images compared to the pre-harrowing images (cf. **Figure 3** versus **Figure 4**). The difference in performance between the new *AI algorithm* and the old *CMV algorithm* was generally largest for the post-harrow images. For the post-harrow images, the *AI algorithm* performed about 57% (weed cover), 17% (crop cover), 4% (soil cover) and more than 700% (RWC) better than the old *CMV algorithm*. The corresponding figures for the pre-harrowing images were 27% (weed cover), 8% (crop cover), 1% (soil cover) and 35% (RWC). Hence, for practical precision weeding, the *AI algorithm* is clearly the recommended alternative.

Interestingly, the *AI algorithm* could not predict the weed cover very well in one extremely weedy pre-harrow image. In this particular image - in which the weeds made up a green "carpet" beneath the crop plants (cf. **Figure 1**b) - the prediction by the *AI algorithm* (32% weed cover) represented a much larger deviation from the ground truth (64% weed cover) than the prediction by the old *CMV algorithm* (73% weed cover). In this specific image, the *AI algorithm* seemed to confuse true weedy pixels with soil. A possible reason for this incapability, was the lack of such extreme high weed cover values in the training data. Dyrmann et al. (2016) used CNN to discriminate weed classes in proximate RGB images, and the class with the smallest training dataset achieved the poorest accuracy. If the practical use of the *AI algorithm* is to decide whether to weed or not weed a management cell based on weediness thresholds, the inaccuracy revealed in estimating extreme values like discussed above will have no influence as long as the actual threshold value is relatively small (cf. **Table 5**).

We only included images in spring barley (of three cultivars) in the evaluation dataset. We have no reason to believe that the *AI algorithm* would perform significantly differently with other small grain cereal species like wheat, oat and rye at the same growth stages. These species have leaves which are very similar in shape and size, and the training data we used included a range of cereal species – and cultivars, acquired both in autumn and spring.

The usual crop row distance in conventional cereal production in N Europe is 125 mm. The *AI algorithm* is expected to be suited for cereals with other distances as well since it was trained with images acquired in other European countries where row spacing was 150 mm. Only RGB images acquired near-ground at nadir view have been included in the training of the *AI algorithm*. Hence, other types of images, for example perspective view (at near ground) or high-altitude imagery from UAVs would not be suitable at this point.

The version of the *AI algorithm* evaluated in the current study is not expected to be valid for growth stages deviating substantially from the growth stages included in the training data (i.e. about two leaves to moderate tillering of the crop), like for example glyphosate application close to crop maturity or in stubble fields. By inclusion of a set of images from new situations in the training data, however, deep learning algorithms such as the *AI algorithm*, can easily adapt and extend its domain.

The images used for independent evaluation were acquired at driving speed 4 km h^{-1}. In operational on-the-go precision weeding in cereals, however, driving speeds in the range about 7 to 12 km h^{-1} are faced. Own previous field tests have shown that the image quality remained unchanged at speeds up to 12 km h^{-1} and that the *AI algorithm* could conduct on-the-go patch spraying at 8 km h^{-1} with cameras mounted at the sprayer boom.

The *AI algorithm* should be applicable to both on-the-go (real-time, online) and offline (map-based) precision weeding in cereals, as well as other image-based assessments wherein values of weed cover, cereal cover or soil cover are of interest. These can be research purposes in weed science, but also for estimation of the total plant cover in models for predicting soil erosion or fate of pesticides. A possible crop protection application might be variable rate applications of fungicides (cf. Dammer et al. 2009; Tackenberg et al. 2018).

5 Conclusions

Precision weeding or site-specific weed management (SSWM) in cereals at the early growth stages requires sensor-based weed monitoring techniques and valid decision models to translate the sensor measurements into sound site-specific weed management decisions.

In the current study, a novel machine vision algorithm (based on the deep learning technique convolutional neural network) which classifies pixels in near-ground RGB images into the three classes, - weed, crop (cereals) and soil (background) -, was evaluated. The version of the algorithm evaluated cannot differentiate between weed species.

Compared to a previous classical machine vision algorithm ('CMV algorithm'), the novel *AI algorithm* had significantly better prediction capabilities. This was true in terms of the coefficient of determination (R^2_{pred}) between the ground truth and algorithm predictions of total weed cover, crop cover and soil cover per image, as well as binary weed management decisions - 'weeding necessary' and 'weeding not necessary' - as assessed with two relevant weed threshold models for post-emergence SSWM in cereals.

Our conclusion is that the evaluated *AI algorithm* should be suitable for patch spraying with selective herbicides in small-grain cereals at early growth stages, i.e. about two leaves to early tillering. Both map-based (offline) and on-the-go (real-time, online) SSWM is applicable. If the intended use is precision weed harrowing, in which also post-harrow images will be used to control the harrow intensity, the *AI algorithm* should be improved by including such images in the training data. Another goal of future work is to make the algorithm be able to distinguish weed species of special interest, e.g. cleavers (*Galium aparine* L.).

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Adigo AS built the RGB camera system and developed the machine vision algorithms for a customer (Dimensions Agri Technologies AS).

NIBIO
NORWEGIAN INSTITUTE OF
BIOECONOMY RESEARCH

NIBIO - Norwegian Institute of Bioeconomy Research was established July 1 2015 as a merger between the Norwegian Institute for Agricultural and Environmental Research, the Norwegian Agricultural Economics Research Institute and Norwegian Forest and Landscape Institute.

The basis of bioeconomics is the utilisation and management of fresh photosynthesis, rather than a fossile economy based on preserved photosynthesis (oil). NIBIO is to become the leading national centre for development of knowledge in bioeconomics. The goal of the Institute is to contribute to food security, sustainable resource management, innovation and value creation through research and knowledge production within food, forestry and other biobased industries. The Institute will deliver research, managerial support and knowledge for use in national preparedness, as well as for businesses and the society at large.

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