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METHODS

Potential uses of small unmanned aircraft systems (UAS) in weed research

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Summary

Small unmanned aerial systems (UAS) with cameras have not been adopted in weed research, but offer low-cost sensing with high flexibility in terms of spatial resolution. A small rotary-wing UAS was tested as part of a search for an inexpensive, user-friendly and reliable aircraft for practical applications in UAS imagery weed research. In two experiments with post-emergence weed harrowing in barley, the crop resistance parameter, which reflects the crop response to harrowing, was unaffected by image capture altitude in the range from 1 to 50 m. This corresponded to image spatial resolution in the range from 0.3 to 17.1 mm per pixel. This finding is important because spatial resolution is inversely related to sensing capacity. We captured 20 plots comprising a total of about 0.2 ha in one image at 50 m altitude without losing information about the cultivation impacts on vegetation compared with ground truth data. UAS imagery also gave excellent results in logarithmic sprayer experiments in oilseed rape, where we captured 37 m long plots in each image from an altitude of 35 m. Furthermore, perennial weeds could be mapped from UAS images. These first experiences with a small rotary-wing UAS show that it is relatively easy to integrate as a tool in weed research and offers great potential for site-specific weed management.

Keywords: site-specific weed management, sampling, precision agriculture, perennial weed, patch spraying, non-chemical weed control, mapping.

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Introduction

Drones have a lengthy military history, but recent technological progress has made them popular for civil remote sensing applications (Hardin & Jensen, 2011; Watts *et al.*, 2012). In the scientific literature, drones are usually called unmanned aircraft systems (UAS). There are two main categories of UAS: fixed-wing and rotary-wing. Fixed-wing aircraft are capable of flight because they have wings that generate lift due to the forward airspeed and wing shape. Rotary-wing aircraft use lift generated by rotor blades mounted on a spinning shaft. Rotary-wing aircraft may have one or several rotors. Rotary-wing aircraft have vertical take-off and landing and can perform stationary flight and operate safely at low altitudes, which makes them useful in high spatial resolution remote sensing. Fixed-wing aircraft have to fly relatively fast because they

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need to create enough lift to sustain their weight. The ability of rotary-wing aircraft to fly at slow speeds minimises the problem of forward image motion and makes it easier to collect overlapping images at regular distance intervals along a flight path, which is important for stitching and mapping procedures.

Small rotary-wing aircraft weighing a few kilograms and having a flight-time of less than one hour have been developed into flexible, user-friendly and cost-effective camera and sensor platforms with promising abilities for agricultural remote sensing data collection (Zhang & Kovacs, 2012). These small rotary-wing devices have been developed and assembled by research groups (Primicerio *et al.*, 2012) and by industries (Lim *et al.*, 2012), and the variety of models available on the market makes it possible to find a suitable UAS for a range of technical and economic conditions. López-Granados (2011) concluded that UAS have great potential in weed management. However, only two practical applications were reviewed: one involving a large UAS flying at high altitude (6400 m) giving coarse spatial image resolution (0.5 m per pixel) (Herwitz *et al.*, 2004) and another a relatively large and advanced industrial helicopter (rotor diameter = 2 m) used for aquatic weed surveillance (Göktoğan *et al.*, 2010). Christensen *et al.* (2009) concluded that aerial-based remote sensing is a possibility when dense and uniform patches larger than 1 m by 1 m are present, but emphasised that aerial-based remote sensing is of little practical use because it can be difficult to acquire the data when needed. Those authors obviously had satellites and piloted aircrafts in mind, not small UAS. Until now, small UAS have not seriously been considered as a tool by the weed research community.

Previous studies on small UAS have mainly concentrated on technical aspects (Xiang & Tian, 2011; Lim *et al.*, 2012; Mahony *et al.*, 2012), and they have been presented as a promising tool in agriculture (Schmale *et al.*, 2008; Zhang & Kovacs, 2012; Garcia-Ruiz *et al.*, 2013). The objectives of the present work were to present results based on images of crops and weeds obtained using a small-scale, off-the-shelf rotary-wing UAS, so as to encourage weed scientists to consider UAS as a camera and sensor platform in future research. Due to the limited information about the practical use of UAS in weed research, two cases are presented to illustrate potential applications.

UAS and camera

In autumn 2011, we searched the market for a rotary-wing UAS that costs less than 3000 Euros and was easy to operate and maintain. We chose a hexacopter with six rotors (Hexa XL) (HiSystems GmbH, Moormerland, Germany) and with the capacity to automatically hold its position at up to 13 m s^{-1} wind speed and to fly to GPS positions by itself (waypoints) (Fig. 1). Navigation between up to a maximum of 30 waypoints is possible using the current firmware. Take-off and landing are manually controlled using a remote control unit. The weight is about 2200 g with a camera mount in place and a 6600 mAh lithium ion polymer battery to power the motors and the control system. Flight time is about 15–20 min with a payload of 400 g, which corresponds to a high-quality compact digital camera. Sensors for flight stability and waypoint navigation include gyroscope, accelerometer, compass, GPS unit and altitude sensor. Altitude operation is from 2 to 100 m. National aviation regulations do not allow altitudes above 100 m.

A standard RGB camera (PowerShot G12, Canon Inc., Tokyo, Japan) with a 10 megapixel CCD sensor (3648 × 2736 pixels) was used as an image sensor. Focal length can be varied from 28 to 140 mm (35 mm film equivalent), and for aerial imaging, the camera can run an intervalometer script taking a photo every 5 s. Imagery is acquired with maximum wide-angle, auto focus, auto exposure, auto white balance, image stabilisation, aperture f-number 2.8 and ISO 200. The relationship between altitude, image resolution and area covered by one image is given in Table 1.

Image analysis

Digital image analysis estimates leaf cover and the excess green index (ExG), a colour index that quantifies green vegetation reflectance (Woebbecke *et al.*, 1995). Leaf cover was estimated by Imaging Crop Response Analyser software (http://imaging-crops.dk/), which calculates the percentage of pixels in the image determined to be green. The software is based on an

Fig. 1 Hexacopter with camera.

Table 1 Relationship between altitude, image resolution and area covered by a single image acquired with a Canon G12 (maximum wide-angle)

Altitude (m)	Image resolution (mm per pixel)	Image area (m^2)
1	0.3	1.16
5	1.7	29.1
15	5.1	262
25	8.5	728
50	17.1	2911

automated procedure for thresholding the breakpoint between pixels containing green and pixels containing other colours (Rasmussen *et al.*, 2007).

The Excess Green Index (ExG) is calculated according to the following:

$$\mathrm{ExG}_{x,y} = 2 \cdot G_{x,y} - R_{x,y} - B_{x,y} \quad (1)$$

where $\mathrm{ExG}_{x,y}$ is the excessive green index and $G_{x,y}$, $R_{x,y}$ and $B_{x,y}$ are the green, red and blue intensities (0–255), respectively, for each pixel co-ordinate (x, y). MATLAB (2011a, MathWorks Inc., MA, USA) was used for the ExG calculation.

Case 1 Crop resistance to weed harrowing

Crop resistance is a parameter used in weed harrowing to calculate crop-weed selectivity and crop recovery (Rasmussen *et al.*, 2008, 2009). Crop resistance is a regression parameter that describes the decline in leaf cover as a result of harrowing. In 2007, digital image analysis was introduced to make objective estimations of leaf cover impacts (Rasmussen *et al.*, 2007). The standard procedure is that four images, each covering about 1 m^2 (vertical projection), are captured in each experimental plot immediately after harrowing.

Case 1 investigated the prospects of using UAS imagery to assess post-emergence weed harrowing impacts on crops. Two experiments with post-emergence weed harrowing in barley (*Hordeum vulgare* L.) were carried out to investigate how image acquisition altitude, which is inversely related to image resolution (mm per pixel), influences the estimation of crop resistance. The first experiment was carried out in spring barley in May 2012 and the second in winter barley in October 2012. In both experiments, a range from 0 to 4 consecutive passes was made with a flex tine harrow in a completely randomised block design with four replicate blocks (20 plots). Barley had 2–3 leaves, and plots were 3 m by 12 m.

As a general rule, leaf cover declines exponentially with increasing number of passes (Rasmussen *et al.*, 2007, 2009):

$$L = L_0 \cdot \exp(-b \cdot N) \quad (2)$$

where L is leaf cover in cultivated plots, L_0 is a regression parameter that gives the leaf cover in untreated plots, b is the resistance parameter (decline rate) and N is the number of passes.

In winter barley, however, leaf cover declines linearly with number of passes:

$$L = L_0 - b \cdot N \quad (3)$$

where b is the slope parameter that describes the additive effect of harrowing. Leaf cover was substituted with ExG for the analysis of ExG response to harrowing.

Image acquisition

In spring barley, four ground truth pictures, each covering about 1 m^2 (vertical projection), were captured in each plot immediately after harrowing. Aerial pictures were captured from the hexacopter at four different altitudes (5, 15, 25 and 45 m). Whole plots were cropped from images except at 5 m, where pictures only covered about one-third of a plot. In winter barley, there were no ground truth pictures, and the altitudes used for image capture varied from 9 to 50 m (Table 2). In each plot, a sub-plot (1.6 m by 1.6 m) was marked and these subplots were cropped from images before image analysis.

In spring barley, the hexacopter was navigated manually using the remote control unit, while in winter barley, waypoint navigation was used, which also included altitude data capture. In spring barley, it was not possible to monitor altitude while flying, because the hexacopter was not equipped with telemetry (wireless data transmission from the hexacopter). Therefore, the hexacopter slowly increased its altitude while images were captured every 5 s. After landing, we selected images for the predetermined altitudes by combining camera time information and log file information, including time, altitude, GPS position and other flight information.

Statistical analysis

Linear regression was used to estimate and test whether altitude influenced the crop resistance parameter (slope) and the intercept (where the regression line crosses the x-axis) Eqns (2) and (3), as outlined in Rasmussen *et al.* (2008, 2009).

Results

The crop resistance parameter (b) and the estimated leaf cover in untreated plots (L_0) were both unaffected

Table 2 Parameter estimates according to Eqns (2) and (3) relative to the altitude of image capture. L_0 is vegetation in untreated plots (leaf cover or ExG) and b is the resistance parameter (decline in vegetation relative to harrowing passes)

		Response variable			
		Leaf cover		ExG	
Time	Altitude (m)	L_0	B	L_0	B
Spring 2012	1	28% (22–35%)	0.230 (0.136–0.324)*	39.3 (34.5–45.6)	0.213 (0.156–0.271)*
	5	29% (25–34%)	0.263 (0.197–0.329)*	38.5 (32.8–44.6)	0.222 (0.164–0.279)*
	15	35% (20–41%)	0.330 (0.264–0.397)*	42.5 (36.6–48.9)	0.236 (0.182–0.291)*
	25	–	–	43.8 (38.1–50.4)	0.216 (0.162–0.271)*
	45	–	–	39.6 (34.1–46.1)	0.183 (0.122–0.244)*
Autumn 2012	9	14% (12–17%)	1.47 (0.32–2.61)†	22.8 (20.7–24.9)	4.38 (3.58–5.17)†
	15	15% (12–18%)	1.50 (0.36–2.64)†	23.6 (21.5–25.8)	4.40 (3.61–5.20)†
	20	15% (12–18%)	1.68 (0.54–2.82)†	24.2 (22.1–26.4)	4.60 (3.80–5.39)†
	25	–	–	24.2 (22.0–26.3)	4.63 (3.83–5.42)†
	30	–	–	24.8 (22.6–26.9)	4.73 (3.93–5.52)†
	35	–	–	24.6 (22.4–26.7)	4.69 (3.89–5.48)†
	40	–	–	24.3 (22.2–26.4)	4.44 (3.64–5.23)†
	50	–	–	22.6 (20.5–24.8)	4.51 (3.72–5.31)†

*In Eqn. (2).
†In Eqn. (3).

by altitude ($P > 0.05$) (Table 2). Therefore, intensity–response curves were unaffected by image resolution (Fig. 2). Leaf cover was only possible to estimate up to 15 m (5.1 mm per pixel). Above 15 m, discrimination between vegetation and soil became unreliable, because pixels contained mixed spectra from vegetation and non-vegetation background and thereby lost their spectral purity. Pixels with mixed colours did not affect the ExG calculations. When crop resistance was assessed as ExG impacts, there was no altitude limit for parameter estimation.

In spring barley, calculations based on leaf cover and ExG resulted in identical resistance parameters, but in winter barley, the absolute and relative vegetation decline was lower when estimated from leaf cover than with ExG (Table 2). In autumn 2012, the light intensity was low and the soil colour was affected by cultivation. Further studies are needed to reveal if these factors affect the relationship between leaf cover and ExG decline rates.

Case 2 Logarithmic sprayer experiments

Logarithmic sprayers are used to screen for herbicide selectivity with a comprehensive range of doses (Tind *et al.*, 2009). Logarithmic sprayers exponentially decrease initial maximum dose in a response to travel time that can be converted into dose. One key challenge in logarithmic sprayer experiments is the assessment of plant responses. Tind *et al.* (2009) visually assessed the responses at 5–8 different distances in the plot. Case 2 investigated the prospects of using UAS imagery to estimate dose–response relationships in logarithmic sprayer

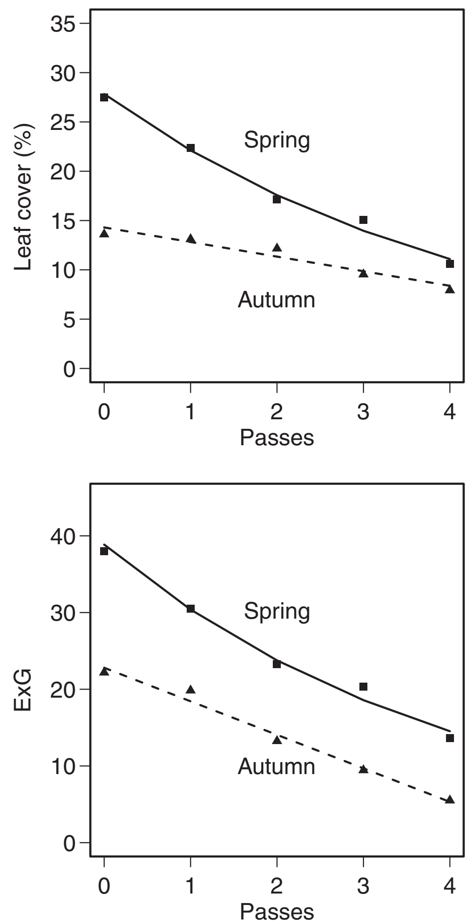

Fig. 2 Intensity–response curves for post-emergence weed harrowing in the barley experiments (spring and autumn) based on-ground truth images in spring and images captured at 9 m in autumn.

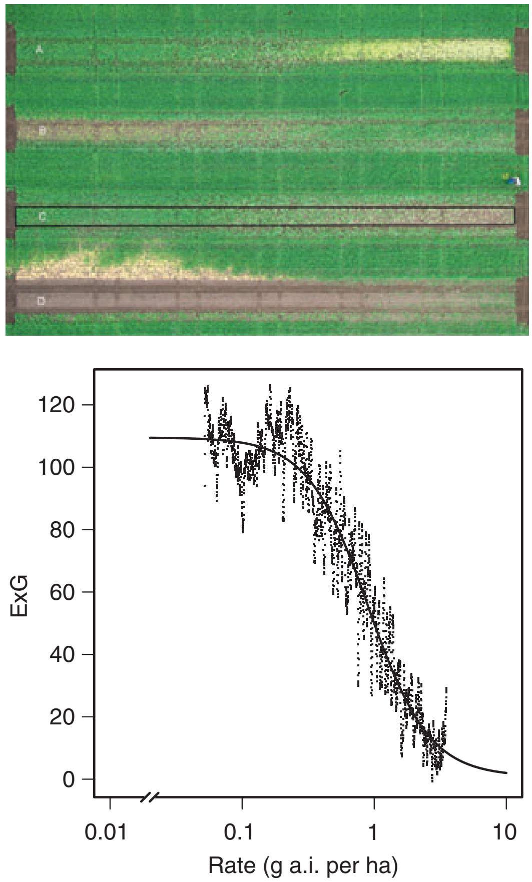

Fig. 3 Image of four 37 m long plots with four different herbicides in a logarithmic sprayer experiment (upper) and the dose–response fit in plot C (lower). The parameters were d = 109 (0.4), c = 6.6 (0.91), b = 2.0 (0.04) and ED50 = 0.85 (0.01) according to Eqn (4).

experiments. Four logarithmic sprayer plots (A, B, C and D) separated by untreated strips were treated with four different herbicides (Fig. 3), but only the analysis of plot c with diquat is shown (Fig. 3). The net size of plots was 37 m × 1.5 m (shown for plot c in Fig. 3a). To capture the whole length of plots, images were taken at an altitude of 35 m. The crop was spring oilseed rape (*Brassica napus* L. subsp. *napus*), and the dose was halved every 6 m along the plot. The maximum diquat dose was 2.7 kg ha^{-1}, and the spray volume was 150 l ha^{-1}.

To analyse the crop response, the average ExG was calculated for each 1.5 m column height of pixels, giving 128 observations each representing a plot length of 11.7 mm. The total number of columns was 3150. A log-logistic dose–response model was fitted to the data (Ritz & Streibig, 2005):

$$ExG = c + \frac{d - c}{1 + \exp[b \cdot (\log(x) - \log(\mathrm{ED}_{50}))]} \qquad (4)$$

where c and d are the lower and upper limit, respectively, and b denotes the relative slope at ED_{50}, which is the dose (x) necessary to reduce the ExG values half-way between c and d (Fig. 3). Parameters were precisely estimated, even though there was divergence from the log-logistic upper limit; this was due to the rather numerous observations.

Discussion and conclusions

Case 1 showed that crop resistance parameters in weed harrowing may be estimated on the basis of images captured at 50 m or higher when calculations are based on ExG. Images covering up to 3000 m^2 with a resolution of 17 mm per pixel were just as good as images captured at the ground (0.3 mm per pixel). This means that assessment of the variability of field vegetation may be based on images captured at high altitudes (50 m and above), because there was no information loss within the altitude range 1–50 m. Whether this is dependent on the causes creating vegetation variability (e.g. crop density and drought stress) is still too early to evaluate.

Leaf cover is easier comprehended than is ExG because it is a measure that we can relate to directly. However, image resolutions coarser than 5 mm per pixel were unsuitable for leaf cover assessment, because it was not possible to estimate reliable threshold values for the separation of vegetation and background. If leaf cover is required as a vegetation measure, the relationship between ExG and leaf cover has to be estimated from high-resolution images (<5 mm per pixel) to translate high-altitude ExG estimations to leaf cover.

Case 2 showed that dose–response curves from logarithmic sprayer experiments can be estimated on the

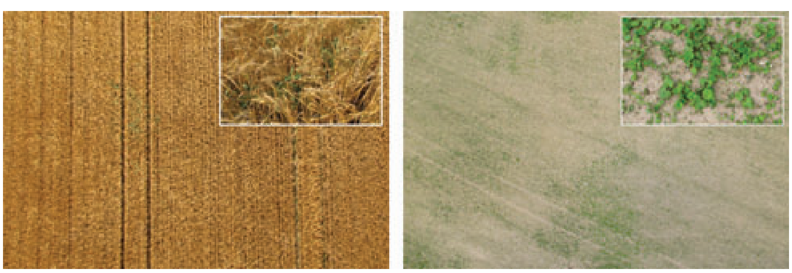

Fig. 4 *Cirsium arvense* (L.) Scop. in mature barley (left) and *Tussilago farfara* (L.) in newly emerged barley (right).

basis of images covering 37 m long plots (11.7 mm per pixel). Furthermore, UAS imagery gives an excellent visual overview of experiments, which may be helpful in interpretation of data (Fig. 3).

Proximal (on-ground) and remote sensing of crops and weeds are a critical component for the adoption of site-specific weed management, because weed seedling distributions are spatially heterogeneous within agricultural fields (Gerhards, 2010). Procedures for automation of weed seedling detection already exist with on-ground image sensors and automated algorithms that discriminate crop and weeds (Weis & Sökefeld, 2010). It will hardly be possible to discriminate between crop and weeds at early growth stages of cereals on the basis on aerial images, but Rydberg *et al.* (2007) showed that patches of weed seedlings in cereals can be identified due to a distinct bright green colour in coarse resolution aerial images (70 mm per pixel). In row crops, weed cover between crop rows can be scouted by UAS born sensors, if crop rows can be identified. Row identification should be possible by image analysis or by GPS triangulation. The value of weed cover assessment of inter-row weeds with ground-based vegetation sensors mounted on sprayers has been demonstrated by Longchamps *et al.* (2012).

Advantages of using UAS born sensors instead of ground-based sensors on sprayers are that UAS can cover large areas in a short time and weeds can be mapped before weed control is carried out. Real-time assessment of weeds based on sensors mounted on sprayers or tractors offers no possibility of *a priori* planning of the weed control. For example, choice of herbicide(s) and choice of field spray volume have to be carried out before the actual spraying takes place. Therefore, *a priori* maps based on UAS imagery may provide advantages for practical weed management. Some weeds may be mapped from aerial images due to clear differences in colour or size (Fig. 4). However, the distinction and quantification of weeds from UAS imagery are still a challenge. Our main emphasis is on perennial weeds, because they are relatively easy to identify from UAS images. The difference in leaf orientation between crop and weeds can enhance their separation when viewed from above (Fig. 4). Mapping of easily distinguishable weeds from UAS imagery should have higher capacity (ha h^{-1}) than with ground-based sensors and possibly higher precision too. It is still too early to evaluate the capacity, but it is expected that one hectare can be mapped within a few minutes with UAS imagery. Higher precision is expected because UAS imagery is independent of extrapolation procedures, which contribute to mapping errors (Rew *et al.*, 2001). As opposed to ground-based sensing, UAS sensing covers the entire field surface.

There are almost no reports of small rotary-wing imagery being used in weed research, and very few weed scientists seem to be aware of the potential of UAS imagery. Therefore, it is important to emphasise that UAS are relatively easy to adopt as a camera or sensor platform. The main challenge seems not to be image acquisition, but automated analysis and interpretation of the data. The major challenge with UAS is to ensure that the aircraft will actually fly as wished, so weed scientists only need to concentrate on the data collection rather than the chore of flying safely. This may seem trivial, but if the UAS cannot stay aloft and positioned, then even small software, hardware or pilot errors may develop into destructive accidents within a split second. Low-cost UAS require manual take-off and landing with a remote control unit, which requires training, and even if the UAS can fly in an automatic mode by waypoint navigation, the operator should be able to fly the aircraft in manual control mode too. Knowledge about applications of UAS in agriculture is scattered in Europe and there is a need to bring together existing expertise with UAS to facilitate knowledge sharing. In conclusion, our first experiences with UAS imagery show that it is relatively easy to integrate as a tool in weed research. However, we acknowledge that there are a number of key issues that need to be solved, for example, georeferencing, mosaicking and information extraction workflow. Knowledge sharing and collaboration are needed to further develop UAS applications in weed research and management.

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