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ORIGINAL RESEARCH

Capturing hedgerow structure and flowering abundance with UAV remote sensing

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Abstract

Hedgerows are an abundant and ecologically important feature of many rural areas. Their biodiversity value depends on composition, structure and availability of food resources, which can be significantly impacted by poor management. However, information about hedgerow condition is very limited due to field surveys being costly and labour-intensive. Unmanned aerial vehicles (UAVs) equipped with miniaturized cameras could prove a more cost-effective and time-efficient hedgerow surveying solution while preserving a high level of detail unattainable with airborne or satellite sensors. This study explored whether UAV remote sensing is a viable alternative for performing hedgerow condition surveys at local scale, focusing on hedgerow structure and flowering abundance. We acquired UAV Red, Green and Blue (RGB) and multispectral nadir and oblique imagery of structurally different hedgerows and used them to generate 3D point clouds and models with SfM workflow. Height thresholding allowed extraction of hedgerow extents, with root-mean-square error (RMSE) of height and width ranging from 0.11 to 0.23 m. RGB flower classification showed poor relationship with ground measurements (R^2 = 0.31–0.42) due to confusion with woody material of hedgerows. Inclusion of a near-infrared channel in multispectral imagery significantly improved the relationship (R^2 = 0.68–0.75, RMSE = 10%). Our study shows UAV remote sensing has high potential for performing detailed surveys of hedgerows, providing better characterization of structural variations and distribution of flowers than traditional ground surveys due to larger coverage. More comprehensive understanding of hedgerow, or other vegetated buffer strips, conditions offered by UAV surveys can enable better informed decisions on habitat management and biodiversity conservation in rural areas. Acquisitions over larger areas, potentially integrated with satellite remote sensing, can allow assessment of hedgerow connectivity over farm to landscape scales, contributing to better understanding of the hedgerow network and its role as a wildlife corridor.

Introduction

Expansion and intensification of agricultural practices has had a negative impact on biodiversity levels in rural areas due to habitat fragmentation, with remnant patches of natural and seminatural land cover being the only safe havens for wildlife. Among these are hedgerows, which consist of lines of trees, shrubs, and associated herbaceous understory vegetation. Although hedgerows are predominant in temperate Western Europe where they form a contiguous network across the farmed landscapes, similar features can also be found elsewhere, for example, the Mediterranean, North America and Australia. In the British context, hedgerows are typically low, continuous lines of shrubby vegetation, maintained this way through regular trimming. They support flora and provide critical habitat to a wide variety of bird, small mammal, reptile, amphibian and invertebrate species, which depend on them for food and shelter (Denton & Beebee, 1994; Fuller et al., 2001; Gelling et al., 2007; Maudsley, 2000), and were found to contain a greater diversity of organisms than other habitats within agricultural landscapes (Burel, 1996).

The value of a hedgerow for biodiversity conservation can be related to the availability of berry and floral resources, and to its structural condition with a range of characteristics, such as height, width, woody biomass, gappiness and structural complexity, commonly identified as indicators (Graham et al., 2018). Increased hedgerow connectivity facilitates both local foraging activity and larger-scale movement (Hinsley & Bellamy, 2019), whereas wider, denser and more structurally complex hedgerows typically provide better shelter and increase foraging area, offering a greater variety and quantity of resources (Graham et al., 2018). Hedgerows with abundant food resources provide important forage to wildlife; flowers are crucial sources of nectar for pollinating insects, which trigger production of berries that resident and overwintering birds feed on. Furthermore, flowering hedgerows can counter the loss of pollinators in agricultural landscapes that depend on their services by providing alternative sources of nectar and pollen when crops are not in bloom (Kremen et al., 2019). Beyond the benefits to biodiversity, hedgerows offer great potential for carbon sequestration, water and soil conservation, as well as for reducing pollutant run-off from fields (Baudry et al., 2000; Falloon et al., 2004), acting as windbreaks and providing livestock barriers.

Continuous management of hedgerows is imperative for ensuring they do not develop into scrub or lines of trees, as well as for preventing encroachment to adjacent agricultural land. The frequency, timing and technique of cutting impact the structural condition and value of hedgerows for biodiversity conservation (Barr et al., 2005). As previous season's growth is necessary for berry production, overly frequent cutting can significantly reduce the number of flowers and berries, which are crucial resources for pollinating insects and birds (Staley et al., 2012); it also leads to lower woody biomass and less complex branch structure (Facey et al., 2014; Maudsley, 2000). Likewise, the timing of hedge cutting is of importance: spring and early summer coincide with bird nesting, whereas autumn is important for the production of berry resources, which birds and small mammals then forage over winter (Barr et al., 2005).

Despite the prevalence of hedgerows in rural areas and their ecological importance, information about their composition, structure and condition is very limited as field surveys are labour-intensive and require an appropriate level of knowledge, which makes them suitable only for a limited number of sites and coverage of small areas. As an alternative to extensive field campaigns, remote sensing is commonly used for habitat monitoring. Applications of remote sensing for hedgerow monitoring have so far focused on mapping and characterization of hedgerow networks at a landscape scale using radar (Betbeder et al., 2014), LiDAR (Vannier & Hubert-Moy, 2014) and high spatial resolution satellite and aerial imagery (Sheeren et al., 2009; Vannier & Hubert-Moy, 2014). Although such inventories increase our understanding of the spatial organization and evolution of hedgerow networks, they cannot provide sufficient information on habitat quality of individual hedgerows due to the required level of detail. Very high spatial resolution data are necessary to capture fine structural variations and to detect flower clusters on hedgerows. Unmanned aerial vehicles (UAVs) equipped with miniaturized sensors can potentially fill this niche. However, although there is an increasing number of publications that demonstrate the potential of UAV remote sensing for vegetation surveys (Eugenio et al., 2020; Radoglou-Grammatikis et al., 2020; Smigaj et al., 2019), such studies have yet to be performed on hedgerows. Therefore, this study aims to investigate whether UAV remote sensing can be used effectively for performing hedgerow condition surveys, focusing on capturing hedgerow structure and flowering abundance.

Materials and Methods

Study area

The study site was located at Nafferton Farm in the Tyne Valley, northeast England (54°59'09"N 1°54'03"W, Fig. 1). The farm is managed by Newcastle University and covers an area of 498 hectares. Borders of agricultural fields in the area are marked by woodland patches, stonewalls and hedgerow networks with the two dominant species being hawthorn *Crataegus monogyna* Jacq. and blackthorn *Prunus spinose* L., which are managed by rotational cutting with flail or circular saw. For this study, hedgerows surrounding Back Field, left fallow in 2019, were chosen due to structural variability, that is, recently trimmed (2–3 years prior) to the south, untrimmed to the west and tall and overgrown to the north (Fig. 1). At the time of data collection, herbaceous vegetation in hedgerow margins varied in height from 0.2 to 1.3 m, approximately.

Unmanned aerial vehicle data acquisition

UAV survey took place on 22 May 2019 during hawthorn's flowering onset. Two systems, a Phantom 4 Pro with DJI FC6310 camera and a DJI Matrice 600 equipped with Micasense RedEdge-M multispectral camera (spectral bands: blue – 475 nm, green – 560 nm, red – 668 nm, red edge – 717 nm, near-infrared – 880 nm) were used to

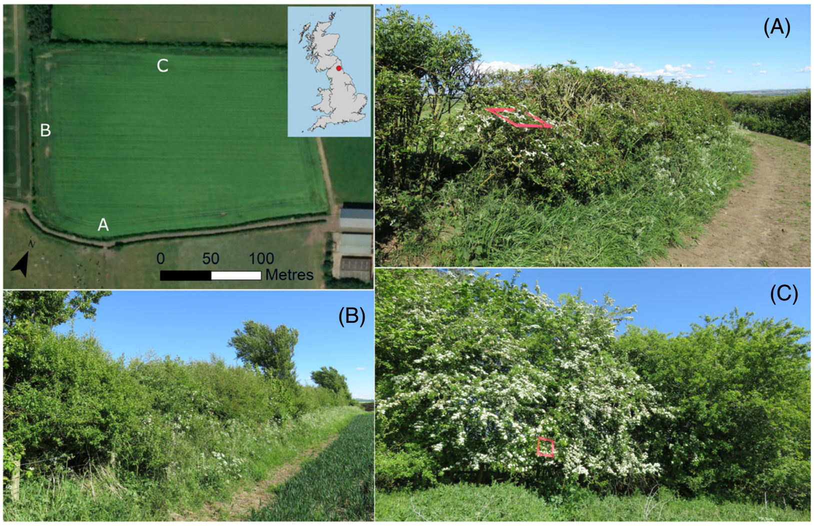

Figure 1. Study area in Nafferton Farm, northeast England (54°59′09"N 1°54′03"W, top left). In May 2019, following hedgerows surrounding the field were surveyed: (A) recently trimmed, (B) untrimmed and (C) tall and overgrown. Background image data: © Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, AeroGRID, IGN and the GIS User Community.

obtain nadir-looking imagery from an altitude of 50 m and oblique imagery capturing hedgerow sides from an altitude of 30 m (at 30 degrees). Multispectral imagery was acquired within 1 h of the solar noon, followed by RGB image collection. Immediately before and after each multispectral flight, a calibration panel was imaged to facilitate reflectance calibration. In total, 640 m of the field border was captured with Phantom 4 (2 flights, 1054 images) and 450 m with MicaSense RedEdge-M (2 flights, 780 images). Ten ground control points were established in the area for orientation and scaling of the photogrammetric image block using real-time kinematic (RTK) GNSS mode.

Ground measurements

Ground structural measurement of hedgerows A and B (see Fig. 1 for reference) were performed approximately every 10 m. Height and width at 1.5 m were measured with the aid of a levelling staff. To measure flowering abundance across the study area, 75 quadrats (30 × 30 cm) were established and deployed on hedgerows A, B and C (see Fig. 1 for reference); the number of flowers within a depth of 10 cm was then counted. (Fig. 1). Additionally, each quadrat was photographed from a distance of approximately 1 m using an off-the-shelf RGB camera to calculate flower fraction (%); flower area was extracted with Random Forest unsupervised classification (Fig. 2). Exact locations of the structural and flower abundance measurements were recorded using RTK GNSS to aid validation.

Unmanned aerial vehicle data preprocessing

The acquired datasets were processed separately using Agisoft Metashape Professional software, which implements the SfM-MVS pipeline, to generate point clouds, 3D textured models and orthomosaics. To ensure accurate reflectance calibration was applied, the two multispectral flights were processed separately. The resultant point density was 974.76 pts/m^2 for the RGB and 123.89 pts/m^2 for the multispectral dataset, yielding orthomosaic's ground resolution of 1.09 cm and 2.55–3.15 cm correspondingly.

Digital elevation models (DEMs) of the study area with a spatial resolution of 50 cm were generated for each dataset using bare earth points that were extracted with LASTools 'lasground' filtering algorithm (Isenburg, 2014). The DEMs were then used to normalize the point clouds and create canopy height models (CHMs) with spatial resolution of 10 cm. To remove spurious local maxima and minima, the CHMs were smoothed using a 3 × 3-pixel window Gaussian filter. The CHMs created using the RGB dataset and the multispectral dataset are hereafter referred to as CHM_{RGB} and CHM_{MICA}.

Hedgerow delineation and extraction of structural parameters

Thresholding of CHMs was used to extract hedgerow extents. A minimum height threshold of 1.5 m was chosen to facilitate comparison with in-situ width measurements and exclude herbaceous vegetation. The resultant raster extents were converted to polygons; nearby forest

Figure 2. Example photograph of a sampling quadrat (left) alongside classification result used for estimation of flower fraction, i.e. flower count = 172, flower fraction = 25% (right).

patches were removed from the dataset. Next, hedgerow polygon centrelines were created by generating a skeletal line representation with Voronoi tessellation following Nyberg et al., (2015). The centrelines were then smoothed and used to create perpendicular polylines originating from GNSS locations of in-situ height and width measurements. For width measurements, polylines were clipped to hedgerow extents; lengths of these clipped polylines were recorded as widths. In the case of hedgerow heights, the maximum CHM pixel values intersecting the created polylines were recorded. The whole workflow is visualized in Figure 3. Additionally, the geometric area and the volume under CHM extrapolated to ground level were computed for each detected hedgerow; for comparison purposes, CHM_{RGB} hedgerow polygons were clipped to the length covered by CHM_{MICA}. To assess the performance of hedgerow extents extraction, the absolute and relative mean bias error (MBE) and RMSE were computed for height and width measurements.

Mapping flowering abundance

Hedgerow flowers were classified using RF classifier (Breiman, 2001), which is a widely used algorithm for data mining. Classification was performed for six chosen classes: flower, green vegetation, woody vegetation (representing woody material of hedgerows), dry soil, water and sampling frame. The training dataset was built with polygons that were manually delineated based on visual interpretation; the polygons were spread across the whole extent of the hedgerows to capture spectral variability of classes with the exception of quadrat interiors that were used for validation. The same training polygons were used for both datasets to facilitate direct comparison. The classifier was trained on points extracted from the photogrammetric point clouds using these polygons. The number of points used for each class is provided in Table 1; differences are due to different point density of the two datasets. For the multispectral dataset B, G, R and NIR reflectance bands were used to build the RF model, whereas in the case of Phantom imagery, we used B, G and R digital numbers. The generated RF models were used to perform variable importance analysis, and then to classify orthomosaic and model texture files. The processing was performed in R using the Rminer package version 1.4.1 (Cortez, 2019).

The flower detection performance was assessed by two approaches: (i) using points from the training set and applying K-Fold cross validation and (ii) validating against ground measurements. For validation against ground measurements, only the ‘flower’ class was retained. For each quadrat, area covered by flowers (%) was computed using the classified textured models. These were compared against ground flower counts and flower cover estimates.

Results

Hedgerow delineation and extraction of structural estimates

The workflow identified five hedgerows in the study area, yielding similar results for both datasets as shown in Figure 4. Although visually the used approach appears to have identified hedgerow extents well, in some cases tall understorey vegetation was misclassified as part of a hedge. In general, hedgerows extracted from CHM_{MICA} were narrower than those from CHM_{RGB} resulting in smaller total surface area (by 4.97%) – 1762.15 m^2 as opposed to 1854.33 m^2 (Table 2). Likewise, hedgerows

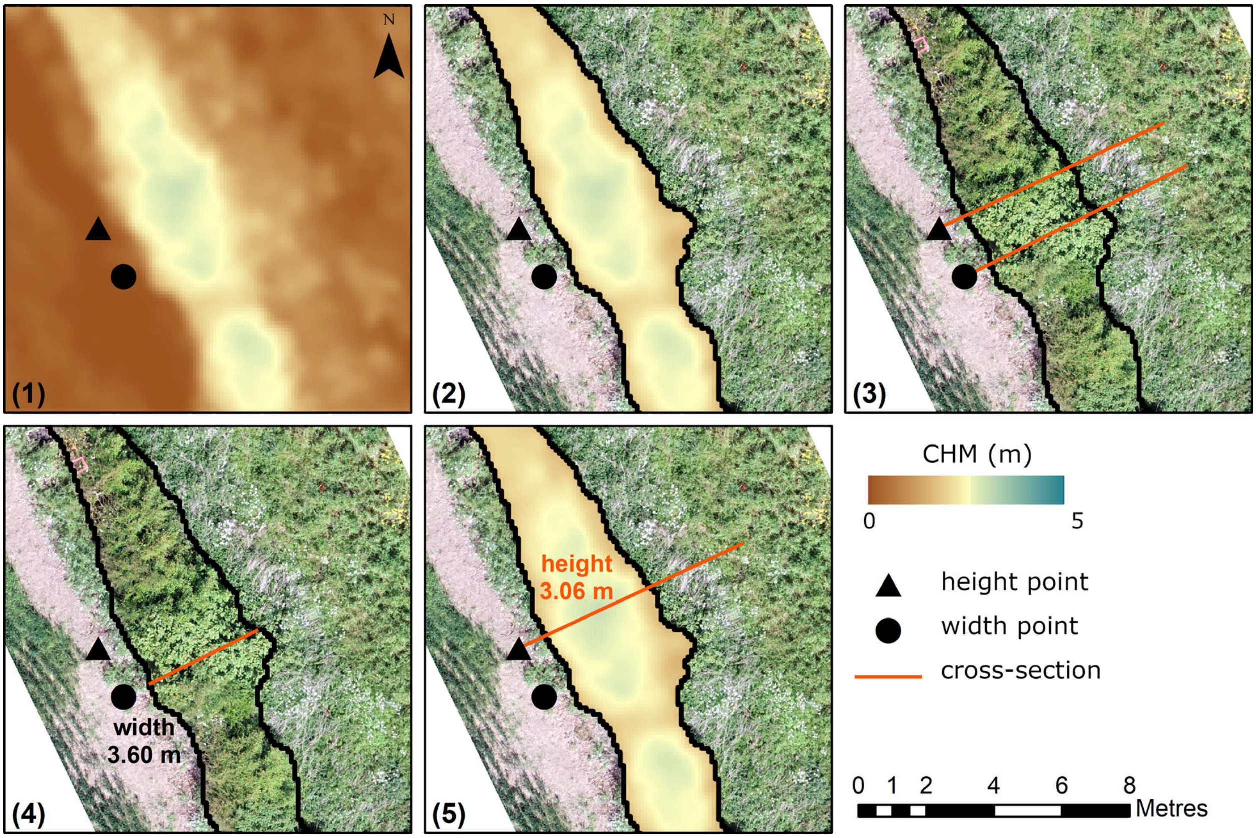

Figure 3. Hedgerow structural parameters were extracted using the following workflow: first, a height threshold of 1.5 m was applied to the initial CHM (1) to derive hedgerow extents (2); nearby forest patches were then manually removed from the dataset. GNSS locations of ground measurements were used as origins for polylines perpendicular to the hedgerow's centreline (3). For width measurements, these polylines were clipped to the extracted hedgerow extents (4), whilst for height measurements, the largest CHM pixel values along the polylines were recorded (5). Background: RGB orthomosaic.

Table 1. Number of training points per category used for classification.

Class	Multispectral points	RGB points
Flower	340	5495
Green vegetation	4046	40 591
Woody vegetation	3291	25 633
Dry soil	1047	5882
Water	222	1240
Sampling frame	75	377

extracted from CHM_{MICA} were slightly shorter with an average recorded height of 3.15 m rather than 3.21 m (1.87% difference). Consequently, the extracted volumes were smaller for the CHM_{MICA}; the total volume under CHM differed by 6.67%–5552.15 m^3 as opposed to 5949.00 m^3 (Table 2), with the greatest relative difference of 10.98% recorded for hedgerow B1.

A comparison of the extracted hedgerow height and width estimates against ground reference measurements is shown in Figure 5 with additional statistics provided in Table 3. The derived structural estimates showed a high correlation with the ground truth data, with CHM_{RGB} being superior for width measurements (R^2 of 0.94 vs. 0.90). The RMSE values for both datasets were comparable, with higher errors observed for width estimates for both sensors: 0.11 m/0.14 m for height and 0.18 m/0.23 m for width (CHM_{RGB}/CHM_{MICA}). In the case of CHM_{RGB}, errors cancelled each other out, leading to MBE of 0.01 m for height and −0.02 m for width. In contrast, structural measures determined from CHM_{MICA} were underestimated as implied by the negative bias: −0.09 m for height and −0.07 m for width.

Contribution of individual spectral bands to detection of flowering

Relative importance of predictive variables for an RF model is based on mean decrease in classification accuracy following a variable removing procedure. Figure 5

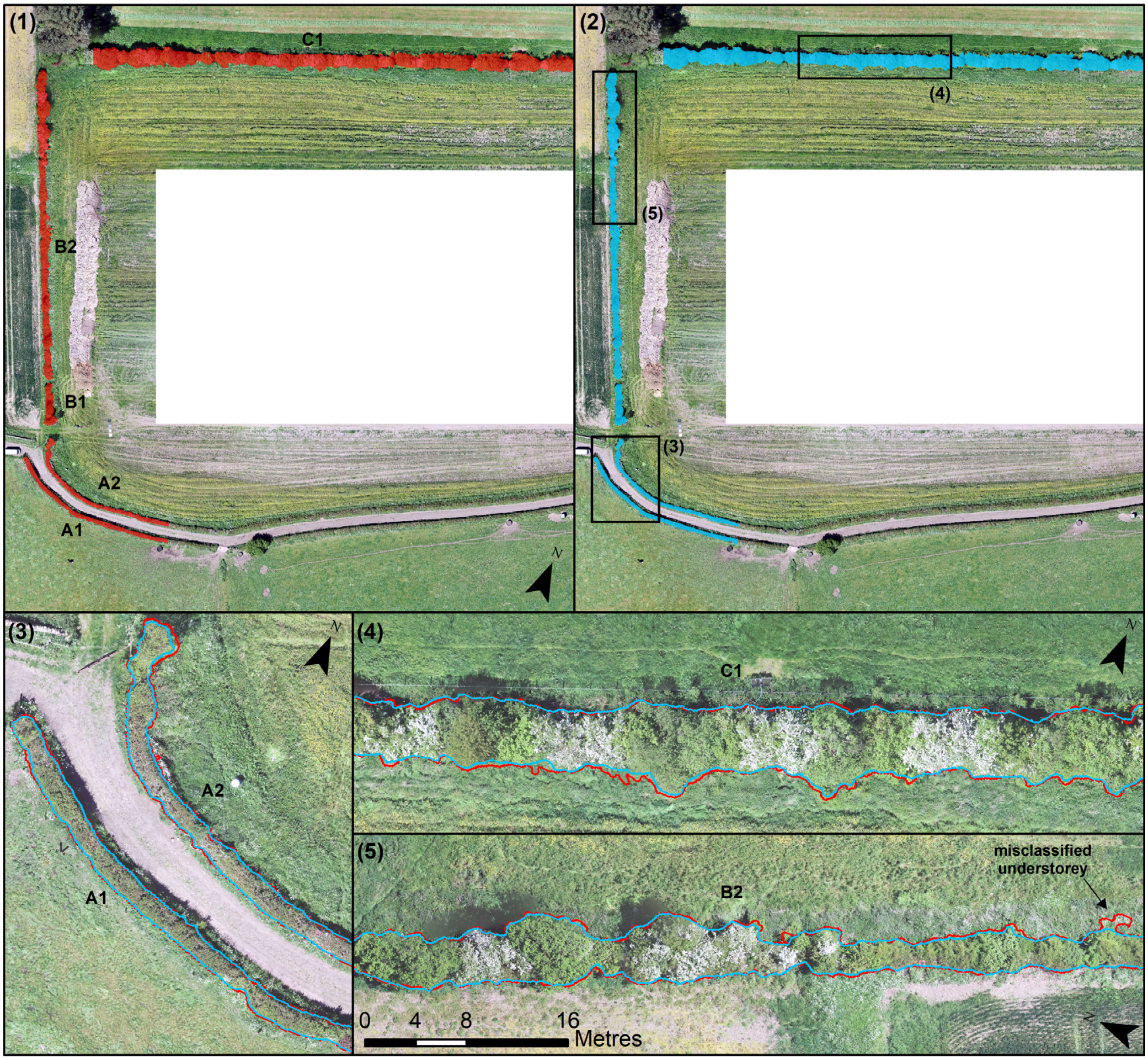

Figure 4. (1–2) Hedgerow maps created with CHM_{RGB} (shown in red) and CHM_{MICA}(shown in blue) clipped to the common data extent. (3–5) Magnified views comparing extracted hedgerow extents. Background: RGB orthomosaic.

shows predictor importance for the RGB and multispectral datasets used in this study. The model applied to the multispectral data identified near-infrared as the most important band for the whole classification, whereas in the case of the RGB data, all bands were of similar importance. Conversely, the near-infrared band was the weakest predictor for the 'flower' class, with blue and green bands identified as most important in both the multispectral and the RGB datasets.

Overall classification accuracies based on K-fold cross-validation of the training set for the multispectral and RGB datasets were 98.3% and 90.4%, respectively (confusion matrices are provided in the Appendix S1). As expected, inclusion of the near-infrared spectral band improved the performance across all classes. The greatest improvement was found for the 'flower' class: 2.4% in producer's accuracy and 36.1% in user's accuracy. The 'flower' class was primarily confused with the 'woody vegetation' class due to similarly bright appearance in the RGB imagery. Even though the near-infrared spectral band did not rank highly as a predictor for the 'flower' class, it was identified as the most important band for the 'woody vegetation' class, further signifying its importance.

Table 2. Area, volume and average height of identified hedgerows extracted from CHM_{RGB} and CHM_{MICA}. Corresponding hedgerow locations are shown in Figure 4.

		A1	A2	B1	B2	C1	All
Height (m)	CHM_{RGB}	1.96	2.04	3.38	2.75	3.63	3.21
	CHM_{MICA}	1.87	1.93	3.28	2.70	3.59	3.15
	Difference	0.09	0.11	0.10	0.05	0.04	0.06
	Difference (%)	4.59	5.39	2.96	1.82	1.10	1.87
Area (m^2)	CHM_{RGB}	124.22	117.97	58.62	418.65	1134.87	1854.33
	CHM_{MICA}	123.33	111.28	53.75	398.24	1075.55	1762.15
	Difference	0.89	6.69	4.87	20.41	59.32	92.18
	Difference (%)	0.72	5.67	8.31	4.88	5.23	4.97
Volume (m^3)	CHM_{RGB}	243.85	240.87	197.92	1149.5	4116.86	5949
	CHM_{MICA}	230.49	214.6	176.18	1073.49	3857.39	5552.15
	Difference	13.36	26.27	21.74	76.01	259.47	396.85
	Difference (%)	5.48	10.91	10.98	6.61	6.3	6.67

Table 3. Performance of hedgerow height and width estimation from the CHM_{RGB} and CHM_{MICA} compared with ground reference measurements.

	Reference width	CHM_{RGB} width	CHM_{MICA} width	Reference height	CHM_{RGB} height	CHM_{MICA} height
Average (m)	2.29	2.27	2.22	2.52	2.53	2.43
Median (m)	1.99	1.92	1.95	2.29	2.22	2.13
SD (m)	0.65	0.72	0.70	0.56	0.62	0.60
MBE (m)	–	−0.02	−0.07	–	0.01	−0.09
MBE_{rel} (%)	–	−1.06	−3.02	–	0.51	−3.75
RMSE(m)	–	0.18	0.23	–	0.11	0.14
$RMSE_{rel}$ (%)	–	7.82	10.12	–	4.31	5.55

CHM, canopy height model; RMSE, root-mean-square error; MBE, mean bias error.

Mapping flowering abundance

Flower coverages extracted from RGB imagery were poorly related to ground measurements as shown in Figure 6. Regarding multispectral imagery, we found a strong relationship (R^2 of 0.68–0.75), indicating its suitability for mapping flowering abundance. Reference estimates of flower cover derived from field photographs were better correlated than flower counts. This is due to flower cover being more applicable for comparison because optical remote sensing records objects as 2D surfaces. Although 3D scene reconstruction can be achieved with UAV SfM-MVS approaches, it is limited to the outer envelope of hedgerows and consequently cannot provide any indication on arrangements of overlapping flowers. Although count, being a direct measure, is preferable for estimating floral resource amounts, we found it was strongly correlated with flower cover in our study ($R^2 = 0.83$, Fig. 7), suggesting flower cover could serve as its proxy. Flower cover estimates derived from multispectral imagery were on average higher than the reference values (MBE = 2.67%, RMSE = 10.23%), with differences being more pronounced in higher flower fractions. The MBE and RMSE for quadrats with flower area of ≤20% were 0.04% and 5.50%, whereas for quadrats with >20% flower area they were 8.95% and 17.21%, respectively.

Visually, the RF model performed well at identifying flowers on the multispectral model's texture. Figures 8.1–8.2 show a sample section of hedgerow B2 prior to and after classification. All bright white pixels, which captured flowers, were correctly identified, and only few cases of misclassification appeared to be present. The multispectral dataset was subsequently used to compute relative flower abundance for each hedgerow. The lowest flower fractions were found in hedgerows B1 (0.7%) and A1 (3.3%), whereas the highest were found in hedgerows C1 (6.2%) and A2 (5.7%). Figures 8.3–8.4 show how the applied methodology can be used to analyse the relative variability in abundance of flower resources within individual hedgerows and across the study area. Although we presented relative flower cover in 10 m hedgerow stretches here, these can be converted to coverage in square metres to provide an absolute measure.

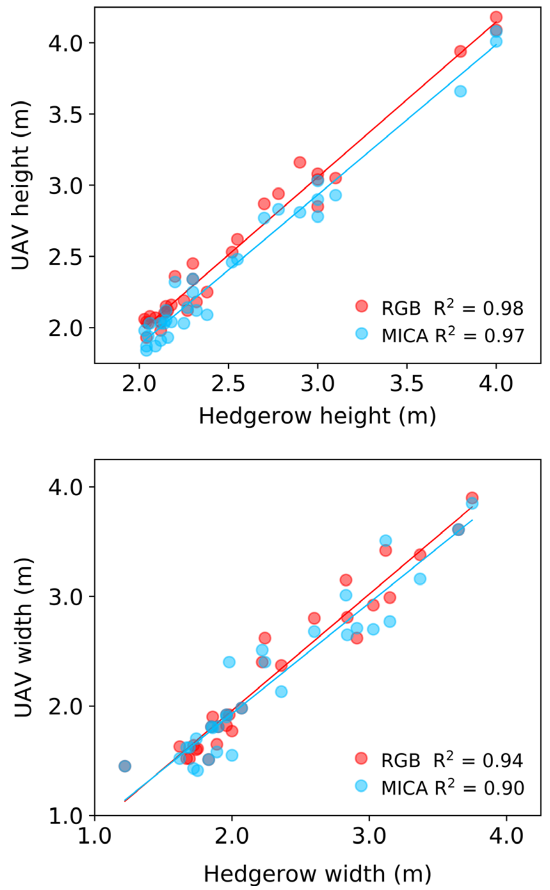

Figure 5. Relationship between UAV-derived height (top) and width (bottom) estimates against ground reference measurements.

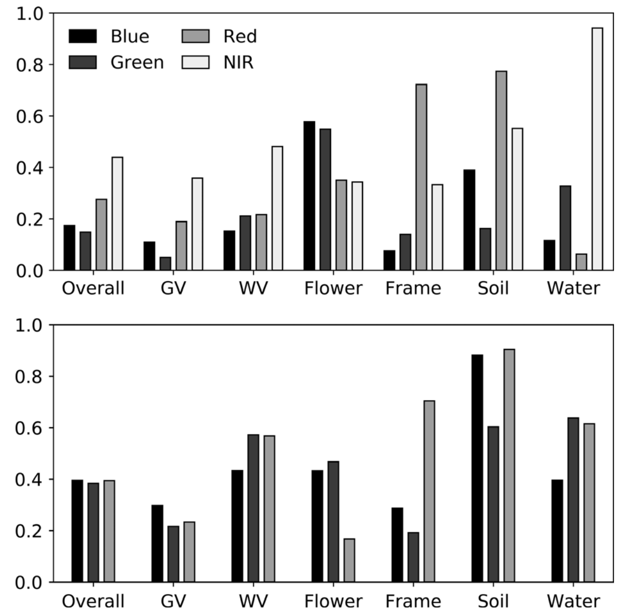

Figure 6. Predictor importance for the random forest model based on multispectral (top) and RGB data (bottom). GV and WV refer to "green vegetation" and "woody vegetation" classes.

Discussion

Our study showed the potential of UAVs for performing detailed surveys of hedgerows. We have demonstrated that UAV remote sensing products can provide accurate measurements of hedgerow structure and be used to map abundance and distribution of flowering (Fig. 8).

Hedgerow structural metrics this study focused on were height and width because taller and wider hedgerows were previously found to positively affect the population of birds, bats and small mammals due to provision of wider selection of nest sites, better shelter and greater food availability (Graham et al., 2018). Measurements of height and width extracted from CHMs yielded small errors, with RMSE between 0.11 and 0.23 m. Higher spatial resolution of the RGB camera resulted in more detailed reconstruction (point density of 974.76 pts/m^2 as opposed to 123.89 pts/m^2), which allowed for more accurate characterization of plant extremities, reducing MBE and RMSE. In contrast to CHM_{RGB}, CHM_{MICA} often underestimated both dimensions, yielding MBE of −0.09/−0.07 m for height/width. In both cases, the width dimension was less accurate, which can be attributed to a number of causes. Firstly, the used minimum height threshold of 1.5 m in some cases failed to exclude adjacent herbaceous vegetation. Performing the survey earlier in the season would resolve this problem; however, the timing would no longer coincide with flowering. Alternatively, an additional threshold based on the curvature of a hedgerow could potentially be introduced under the assumption that a break of slope would occur in the presence of adjacent low vegetation.

Although the height thresholding approach excluded most herbaceous vegetation, it extracted a number of non hedgerow features, such as forest patches and stone walls, which were manually removed. If applied at larger scales, the applied methodology could be further automated by implementation of a decision tree determining if an extracted feature is a hedgerow. Only linear features of a specified width and length could be retained. For instance, in the UK, the field survey guidance could be followed, which specifies hedgerows must be over 20 m long and less than 5 m wide (Defra, 2007). Spectral information could also be used to eliminate any non hedgerow linear features meeting the above criteria, such as fences and walls. Such automation would obviate the need for manual processing prior to computation of hedgerow parameters.

Hedgerow flowers and berries are crucial resources for invertebrates and birds. However, their availability can be

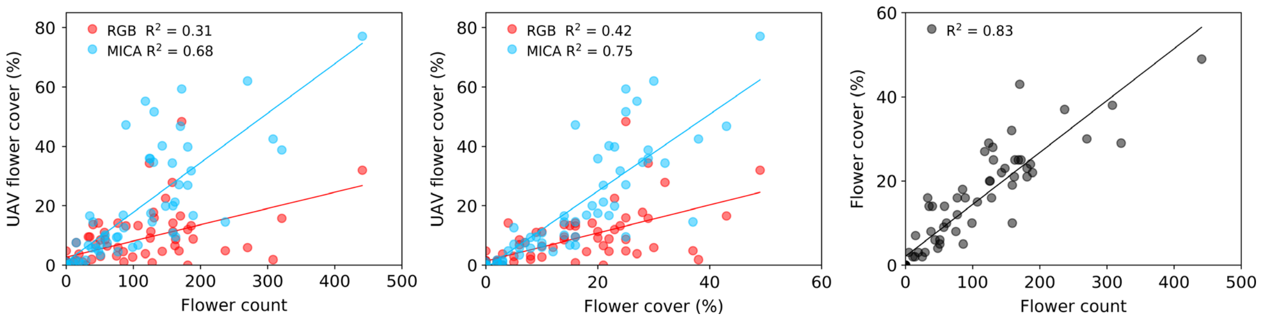

Figure 7. Relationship between UAV-derived flower cover estimates and flower counts (left), and reference flower cover estimates extracted from field photographs (middle). Also provided is relationship between the reference flower count and flower cover measurements (right).

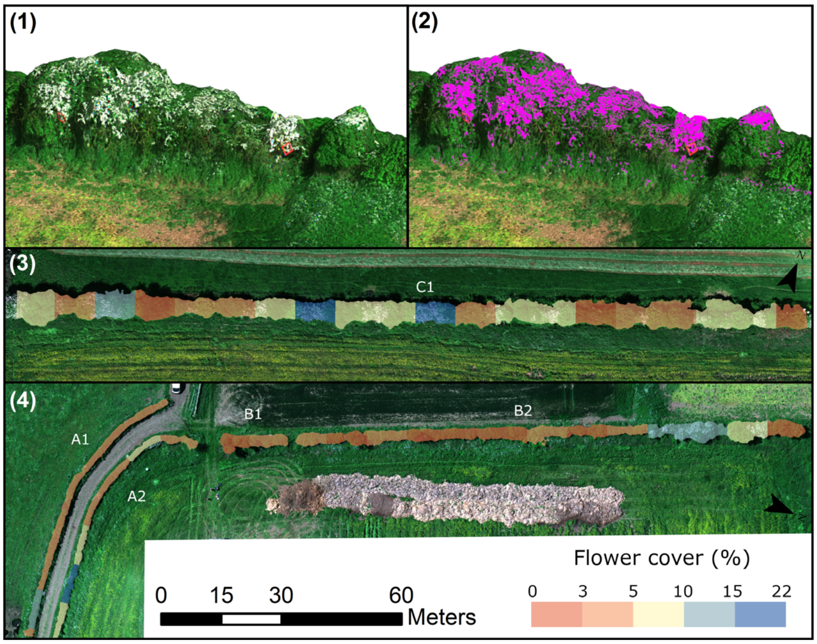

Figure 8. Sample hedgerow section of the textured 3D model created using multispectral imagery (1) with areas identified as flowers shown in pink (2). (3–4) Flower abundance, given as a fraction of total hedgerow surface, mapped in 10 m sections along hedgerow lengths. The average flower fractions for the investigated hedgerows were: A1 – 3.3%, A2 – 5.7%, B1 – 0.7%, B2 – 3.8%, C1 – 6.2%. Background: multispectral orthomosaic.

significantly impacted by cutting regimes; Staley et al., (2012) observed a 75% reduction in floral resources on annually cut hedgerows. Here we attempted to map the available floral resources by applying RF models to RGB and multispectral photogrammetric products. RGB flower classification showed poor relationships with ground measurements (R^2 = 0.31–0.42). Others who used UAV RGB imagery also observed mixed results when comparing flowering classifications to ground measurements. In *Acacia longifolia* de Sá et al., (2018) reported R^2 of 0.00–0.16, whereas in pear trees Vanbrabant et al., (2020) obtained R^2 of 0.41–0.44 (relative RMSE = 23%) on individual tree level and R^2 of 0.54–0.70 (relative RMSE = 15%–18%) at plot level. Inclusion of near-infrared spectral band in this study significantly improved the performance by helping differentiate between flowers and woody material of hedgerows. In the RGB imagery, these two classes were often confused due to similarly bright appearance. Although RF model indicated blue and green spectral bands were most important for classifying flowers, the near-infrared band was the strongest predictor for the woody material. Similarly, Xu et al., (2019) observed that although flowers in cotton plants could be distinguished using RGB channels, the near-infrared band was required for clear separation of the ground; using red, green, blue and near-infrared bands 73% of flowers were correctly identified, with misclassifications being caused by shadowing of flowers, and leaves that appeared bright due to high specular reflectance. We observed similar effects, with flower fraction being underestimated in quadrats located in shadowed hedgerow parts. Reflectance values depend not only on surface properties but also on the solar zenith and viewing angles. By incorporating oblique imagery and classifying 3D models rather than orthomosaics, the variability of reflectance in our study was further exacerbated. However, the applied approach allowed more representative mapping of floral resources as the hedgerows were assessed from multiple perspectives. Furthermore, there was a strong relationship with field measurements, all but two of which were performed on hedgerow sides (R^2 = 0.68–0.75, RMSE = 10%). Here, flowering was predominantly limited to hawthorn, with white flowers. The methodology may perform better in hedgerow species that flower in more distinctive colours, such as spindle *Euonymus europaeus*, which would allow for clearer separation from the woody material. Conversely, flowering prior to the leaf onset as in blackthorn's case could complicate the classification. Further research is therefore required to assess the feasibility of mapping flower coverage in hedgerows consisting of other woody species or in more species diverse hedgerows.

The size of hedgerow flowers necessitates the use of ultra-high spatial resolution imagery, which can capture even a small number of flower clusters. Currently, UAVs are the only airborne platforms that can deliver such level of detail. Depending on the required level of detail for investigating a given ecosystem, the UAV flight plan can be easily adjusted with lower flying heights resulting in higher spatial resolution. What has to be kept in mind though, is that higher spatial resolution comes at an expense of coverage. Multiple flights or even multiple survey days may therefore be needed to cover larger sites. Furthermore, consideration has to be given to the type of data to be acquired. Although just nadir imagery could be sufficient for extracting structural metrics, additional oblique imagery is necessary to capture hedgerow sides in detail and facilitate flowering detection. In our study area, we obtained oblique imagery from an altitude of 30 m, which was deemed the minimum flying height allowing safe operation above any obstacles (i.e. forest patches) and retaining a visual line of sight.

Although height, width and flowering are the focus of this study, there is potential to extract additional variables of interest in assessing hedgerow condition and habitat value from UAV data. The ability to calculate surface area and volume directly from the derived CHMs is demonstrated here and these parameters are important to a number of taxa in determining habitat value, for example, in predicting habitat area and availability of refuge from predators for small mammals or habitat suitability for shade-tolerant herbaceous plant species (Graham et al., 2018). However, a number of other descriptive variables can be directly derived which may be of use for specific taxa or to allow a more complete monitoring of hedgerow condition. For example, the CHMs or point clouds allow derivation of metrics of heterogeneity in height or surface roughness, which can influence the value of a hedge as an acoustic landmark for foraging bats (Froidevaux et al., 2019), and indicate the presence and abundance of trees, which are important to bird taxa (Hinsley & Bellamy, 2000).

Multispectral UAV data have been shown to have the ability to allow tree species classification (Franklin, 2018), suggesting potential for application in mapping woody vegetation species within hedgerows. Whereas multispectral vegetation indices or analysis of hyperspectral data can be used to derive leaf biochemistry information (Thomson et al., 2018) of importance as an indicator of foliage quality for herbivorous invertebrate groups. Inclusion of additional sensors, such as UAV-borne laser scanning may have future potential in assessing hedgerow density, vertical structural complexity and biomass, although at the potential cost of affordability. In addition to derivation of metrics characterizing hedgerow condition, UAV-borne spectroscopy and laser scanning could also considerably aid with their up-scaling, helping facilitate regional assessments; although airborne LiDAR has been shown to accurately map hedgerow networks (Vannier & Hubert-Moy, 2014), the derivation of condition-related metrics is still under development. Further research to fully evaluate this potential is necessary and timely. Even though the use of UAV-borne technologies can allow the derivation of a set of valuable metrics describing structural condition, the predictive value and reliability of such metrics for estimating habitat suitability or species richness of different taxa needs to be assessed. Significant research to integrate these with detailed field survey is, therefore, needed to both facilitate assessment and relate such metrics to other hedgerow functions such as carbon storage.

UAV data acquisitions over larger areas, potentially integrated with satellite remote sensing, can allow assessment of hedgerow connectivity over farm to landscape scales, contributing to better understanding of the hedgerow network and its role as a wildlife corridor (Davies & Pullin, 2007). For national-scale surveys, classification maps derived from high spatial resolution satellite imagery are likely to be the most cost-effective solution. Accuracy of such products depends heavily on spatial and spectral resolution of input imagery (Vannier & Hubert-

Moy, 2014), which affect the ability to differentiate and extract hedgerows from other vegetation elements. UAV-derived products could provide more comprehensive ground truth data than field surveys, helping validate hedgerow presence, extent and connectivity. Beyond validation, UAV surveys can provide a more in-depth representation of hedgerow condition in a given area through intensive sampling of a representative subset of hedgerows initially identified through satellite-based analysis. In particular, information on flower abundance, rarely available due to the time-consuming nature of ground surveys, could contribute to ecological intensification. Multitemporal UAV surveys of both flowering intensity and hedgerow structure of such a subset would allow tracking of hedgerow development and identification of hedgerows whose condition is declining, which can enable better informed decisions on hedgerow habitat management and biodiversity conservation in rural areas. However, the relatively short time window for the capture of flowering events may limit the number of hedgerows that can be investigated with a single UAV platform. Furthermore, in species diverse hedgerows multiple flight campaigns within a single year may be needed if flowering times do not overlap. Although surveys of structure do not face the same time restrictions, they may still be limited by flying regulations or lack of landowner's permission.

Despite these limitations, UAV remote sensing offers an attractive monitoring solution not only for hedgerows but also for other types of vegetated buffer strips, that is, forested shelterbelts, shrubs, grassy strips and wildflower margins. Within the agri-environmental setting, the establishment and management of vegetated strips is a commonly advocated, and in some cases mandatory, mitigation measure for the negative environmental impacts of intensive agriculture. UAV surveys can provide information on their condition and can potentially be used to investigate whether legal requirements are met. The SfM workflow can also be readily used to characterize farm woodland structure as evidenced by a number of forestry studies (Eugenio et al., 2020), whereas flower detection and mapping can be extended to wildflower margins that tend to be implemented to enhance pest control and pollination services in adjacent fields. Although clear enhancements to pest control are evident, effects on crop pollination can be more variable, with perennial and older flower strips with higher flowering plant diversity enhancing pollination more effectively (Albrecht et al., 2020), in addition to benefiting rare pollinator species and pollinator diversity (Sutter et al., 2017). The flowering abundance detection could therefore be extended to mapping flowering plant diversity to assess quality of wildflower margins in terms of their ecological importance and ecosystem services they can provide. However, further research would be necessary to investigate this potential.

Conclusions

Our study shows that UAV remote sensing has high potential for performing detailed surveys of hedgerows by allowing accurate measurement of structure and mapping of floral resources. We tested low-cost RGB and multispectral cameras for their performance. Although the RGB dataset characterized hedgerow structure more accurately owing to the higher spatial resolution, it was not capable of mapping flower abundance. Structural metrics extracted from the multispectral dataset yielded small errors, and the floral maps were highly correlated to field measurements, making multispectral cameras preferable for performing comprehensive hedgerow condition surveys.

UAV surveys are more time-efficient as they can cover larger spatial extents than traditional ground surveys. Consequently, they can provide better characterization of structural variations and distribution of flowers. The main advantage of UAV remote sensing is preservation of a high level of detail, which is required to capture flower clusters and is unattainable with airborne or satellite sensors. At local scale more comprehensive understanding of hedgerow conditions offered by UAV surveys can enable better informed decisions on hedgerow habitat management and biodiversity conservation in rural areas. Whereas acquisitions over larger areas and integration with satellite or airborne remote sensing can allow assessment of hedgerow connectivity over farm to landscape scales, contributing to better understanding of the hedgerow network and its role as a wildlife corridor.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1. Complementary tables.

