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Automated identification of hedgerows and hedgerow gaps using deep learning

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Abstract

Hedgerows are a key component of the UK landscape that form boundaries, borders and limits of land whilst providing vital landscape-scale ecological connectivity for a range of organisms. They are diverse habitats in the agricultural landscape providing a range of ecosystem services. Poorly managed hedgerows often present with gaps, reducing their ecological connectivity, resulting in fragmented habitats. However, hedgerow gap frequency and spatial distributions are often unquantified at the landscape-scale. Here we present a novel methodology based on deep learning (DL) that is coupled with high-resolution aerial imagery. We demonstrate how this provides a route towards a rapid, adaptable, accurate assessment of hedgerow and gap abundance at such scales, with minimal training data. We present the training and development of a DL model using the U-Net architecture to automatically identify hedgerows across the East Riding of Yorkshire (ERY) in the UK and demonstrate the ability of the model to estimate hedgerow gap types, lengths and their locations. Our method was both time efficient and accurate, processing an area of 2479 km^2 in 32 h with an overall accuracy of 92.4%. The substantive results allow us to estimate that in the ERY alone, there were 3982 ± 302 km of hedgerows and 2865 ± 217 km of hedgerow gaps (with 339 km classified as for access). Our approach and study show that hedgerows and gaps can be extracted from true colour aerial imagery without the requirement of elevation data and can produce meaningful results that lead to the identification of prioritisation areas for hedgerow gap infilling, replanting and restoration. Such replanting could significantly contribute towards national tree planting goals and meeting net zero targets in a changing climate.

Introduction

The UK alone produced an estimated 339.5 million tonnes of CO_2e in 2021 (BEIS, 2023), and aims to become carbon net neutral by 2050 (IPCC, 2023). As part of the roadmap to net zero, the UK plans to increase forest stock by 30 000 ha annually by 2025, increasing woodland cover from 13% to up to 20% by 2050 (Ares et al., 2021), whilst also extending hedgerows by 40% (Climate Change Committee, 2020). Hedgerows are defined as linear woody features that are composed of shrubs that can contain trees, with a degree of management and are often over 20 m long and less than 5 m wide (Baudry et al., 2000; Staley et al., 2020). Hedgerows are nationally distributed features with approximately 477 000 km of total length estimated in 2007 (Carey et al., 2007), which is notably reduced from the 800 000 km estimated in the 1950s, driven by rising demand for food production and expansion of land use (O'Connell et al., 2015) and, crucially lack of suitable management, resulting in hedgerows degrading or turning into tree lines (Carey et al., 2007). Well-managed hedgerows offer numerous benefits to biodiversity and are a key semi-natural habitat in agricultural regions (Staley et al., 2016); they can also benefit agricultural activities by creating habitats for essential insects, including pollinators and natural enemies of pests (Morandin et al., 2014), thus providing a range of ecosystem services. As one of the most abundant linear features at the landscape scale, hedgerows represent an important habitat for the dispersal of individual organisms (Coulthard et al., 2016).

Hedgerow structure and structural diversity can greatly influence their functionality (Hinsley & Bellamy, 2019). Hedgerow gaps can damage their utility as connected ecological corridors and may even lead to hedgerows functioning as ecological sinks for species dispersing along them (Alderman et al., 2011). Often gaps are defined as the space between the hedgerow that is <20 m, but this measurement is included in the total length measurement of the hedgerow itself, and areas >20 m are not classed as hedgerow, nor gap, potentially omitting hedgerow planting potential (Department for Environment, Food and Rural Affairs, 2007). Here we define a gap in the hedgerow as any length along a boundary that contains a hedgerow, with a maximum unit length of 30 m. Hedgerow gaps can be found nationwide, whether for access to adjacent land parcels, or due to over trimming, disease and poor management (Amy et al., 2015; Croxton & Sparks, 2002). Gaps reduce the connectivity of the landscape for migrating species, as well as reduce the amount of available habitat and food sources for wildlife (Graham et al., 2018; Staley et al., 2015). Hedgerow planting at the landscape scale could increase the agroecosystem's ability to biosequester CO_2, but empirical data that robustly quantifies this potential is currently lacking, and sequestration is highly dependent on soil type and seasonality (Axe et al., 2017; Biffi et al., 2022; Ford et al., 2021). Nevertheless, increased hedgerow planting could stabilise the soil and aid in its conservation (Baudry et al., 2000), thus benefiting carbon retention. Hedgerow can also increase soil permeability compared to adjacent fields resulting in increased water storage during storm events (Herbst et al., 2006; Holden et al., 2019). Contour hedgerow (i.e., hedgerow planted along the landscape contour) can also interrupt surface flow pathways, reducing hydrological surface connectivity and thus flood risk during rainfall events (Wallace et al., 2021).

The advent of readily available high-resolution satellite and aerial imagery has enabled desk-based classification of hedgerows using geographic information systems (GIS). Identifying hedgerows remotely has the advantage of being able to cover more land efficiently compared to manual, field-based surveys, with automatic landcover classification of multiband imagery over large areas commonly used in remote sensing applications (Graham et al., 2019; Scholefield et al., 2016; Thornton et al., 2007; Tong et al., 2020). However, the resolution of the imagery and size of the feature of interest can limit classification effectiveness (Blaschke, 2010; Woodcock & Strahler, 1987). As hedgerows are often less than 15 m in width, pixel resolution of available data must be high enough to discern between the field margin and the hedgerow (Lechner et al., 2009; Neumann et al., 2016; Vannier & Hubert-Moy, 2014). In addition, linear features including hedgerow can appear spectrally similar to other features such as tree lines, ditches, fences and walls, resulting in complications when identifying and classifying features of interest (Broughton et al., 2024; Scholefield et al., 2016). In the absence of available high-resolution data, Thornton et al. (2007) deployed sub-pixel mapping combined with fuzzy classifiers to identify hedgerows, while others have favoured active (emits its own light source and measures the return of that wavelength) remote sensing such as LiDAR (light detection and ranging)-derived digital elevation models (DEMs) over imagery, using the height differential from the surrounding area to classify hedgerows, trees and woodland habitats (Broughton et al., 2024; Luscombe et al., 2023). DEMs and underpinning LiDAR data often have relatively fine resolutions (1 m^2 pixel resolution with four guaranteed LiDAR returns, for example), but require a sensor capable of receiving multiple returns from the vegetation surface and from the bare ground to build a canopy height model. Additionally, as LiDAR requires a surface to reflect off to capture a measurement, the absence of leaves in winter reduces the surface area that is present to intercept the laser, and may result in the underrepresentation of hedgerow and other leaf-bearing features. Structure-from-motion may also be used to evaluate woody structure (e.g., Broughton, Bullock, et al., 2021) in addition to capturing rich detail such as flowering abundance (Smigaj et al., 2021), yet is impractical to deliver across the landscape-scale.

Unlike active sensing such as LiDAR, passive sensing such as satellite and aerial imagery reduce the aforementioned potential for data loss as they do not require a light source to be emitted, however fine resolution imagery can quickly become impractical to manage particularly when needing to manually classify features, especially at the landscape-scale. However, passively captured imagery can contain multiple bands that represent 100s of wavelengths of light that can lead to new insights, and often has greater spatial coverage and availability than actively sensed data. Automated image analysis is common in remote sensing (e.g., Kaushik et al., 2022; LaRue et al., 2024; Robson et al., 2020), with a recent shift towards deep learning (DL). DL is often used in remote sensing alongside other forms of artificial intelligence to perform land use land cover assessments, alongside object detection, classification and image segmentation (Blaschke, 2010; Li et al., 2018; Ma et al., 2019; Zhang et al., 2016). DL has started to gain interest for hedgerow identification owing to its ability to identify high-level, abstract patterns at both landscape and plot-scales, with the ability to extract the boundary of hedgerows through object identification or pixel classification (Ahlswede et al., 2021). DL lends itself to scalability in terms of spatial extent, resolution and ability to leverage computing power, which is especially important when considering the landscape and national scales. Often, object-based image analysis approaches are used for hedgerow remote sensing, with Tansey et al. (2009) identifying hedgerows and field margin cover from multispectral, very high-resolution airborne imagery, in combination with Digital Terrain and Digital Surface Models. Similarly, Broughton, Bullock, et al. (2021) and Broughton, Chetcuti, et al. (2021) utilised LiDAR data to generate a canopy height model to identify woody linear boundaries, while Ahlswede et al. (2021) implemented DL on approximately 1 m resolution IKONOS satellite imagery to identify hedgerow boundaries and evaluate temporal change in a 984 km^2 area in Bavaria, Germany. However, the IKONOS data only ranges up to 2008, and critically the authors did not quantify gap sizes.

Despite the presence of hedgerow gaps in the agroecosystem and understanding of the importance of gaps, there is a distinct lack of effective gap identification at the landscape scale. Identifying hedgerow gaps and their locations can support prioritisation activities and help with detecting suitable planting locations on unutilized land, contributing towards carbon net neutrality, increasing habitat connectivity, improving soil health and for surface water management. Moreover, planting hedgerows into gaps would help meet planting targets while not encroaching on valuable agricultural land. Herein, we present the training and application of a DL model to perform high-resolution image segmentation and pixel classification of rural hedgerows, combined with automated processing steps to differentiate between access and unutilized gaps. We additionally highlight some ground-truthing activities to demonstrate the skill of the DL and show how the model can be used to extract feature lengths and locations across the East Riding of Yorkshire (ERY) local authority district in the UK.

Materials and Methods

Study area and training data

The ERY covers 2479 km^2 of Northern England (Fig. 1) with a mixture of Jurassic and Cretaceous chalk geology overlain to the east by a last glacial maximum-derived deposit of boulder clay. As such, the area is generally flat and low-lying away from the west with rolling chalk hills to the west. The ERY has a median elevation of 13 m a.s.l (above sea level) and maximum of 246 m a.s.l with $<10\%$ of elevations being greater than 118 m a.s.l (Ordnance Survey, 2024). Over 2000 km^2 (81%) of this area is dedicated for agriculture, including arable (68%) and permanent pasture (13%), as of June 2021 (Department for Environment Food & Rural Affairs, 2023). The region has one of the lowest forest covers in the UK (3.85%), substantially lower than the national average of 10.16%, yet has a large proportion of agricultural land with hedgerows, presenting potential opportunities for planting and gapping up. The ERY was considered by Rackham (1986) as 'planned' countryside rather than ancient. Planned countryside was shaped during the Enclosure Act (18th century) and represented a strong tradition of open fields and little woodland (Rackham, 1986), suggesting that the hedgerows present in ERY are relatively young (<200 years old). Furthermore, previous studies have shown that hedgerow density in the ERY has a moderate density of 1.64–5.44 km km^{-2} (Carey et al., 2007; Scholefield et al., 2016) with lower densities to the east of the region (the Holderness Plain) and to the north and west (Vale of Pickering), both of which are low-lying, flat landscapes. The Vale of Pickering has been identified specifically as a priority area for hedgerow replanting and management action (Simonson et al., 2024). Hedgerows in Yorkshire have a distinctive regional style: a very thin, layered hedge used in sheep/arable rotation, cut close to the ground (National Hedgelaying Society, n.d.).

The ability to differentiate features in remotely sensed data is largely a function of the resolution of the image and the size of the feature of interest, i.e., the minimum mapping unit required, as well as its spectral properties and those of neighbouring pixels. As hedgerows in the ERY are often less than 2 m wide and can be 100 s of metres long, this requires a high-resolution dataset for training and inference. As such, we utilised one of the highest resolution national imagery datasets available in Great Britain: 0.25 m pixel resolution orthorectified aerial imagery captured in July and October 2018 (Getmapping, 2018). Images were available in 1 km^2 tiles ($\sim$10 MB in size each) and were mosaicked in ArcGIS Pro with a 50 m overlap either side of the tile boundary to ensure contiguous surface representation ($\sim$560 GB total size, upscaled to 16-bit depth from the original depth of eight). These data are both commercially available and through existing UK Government and academic agreements.

Hedgerows were identified manually in ArcGIS Pro and extracted by tracing a polygon around the feature. Nine 4 km^2 areas were selected for training (six tiles; 24 km^2) and validation (three tiles; 12 km^2; Fig. 1) that were distributed within the study area. These areas were chosen using a semi-random, pragmatic approach to ensure even distribution throughout the ERY. Within each tile,

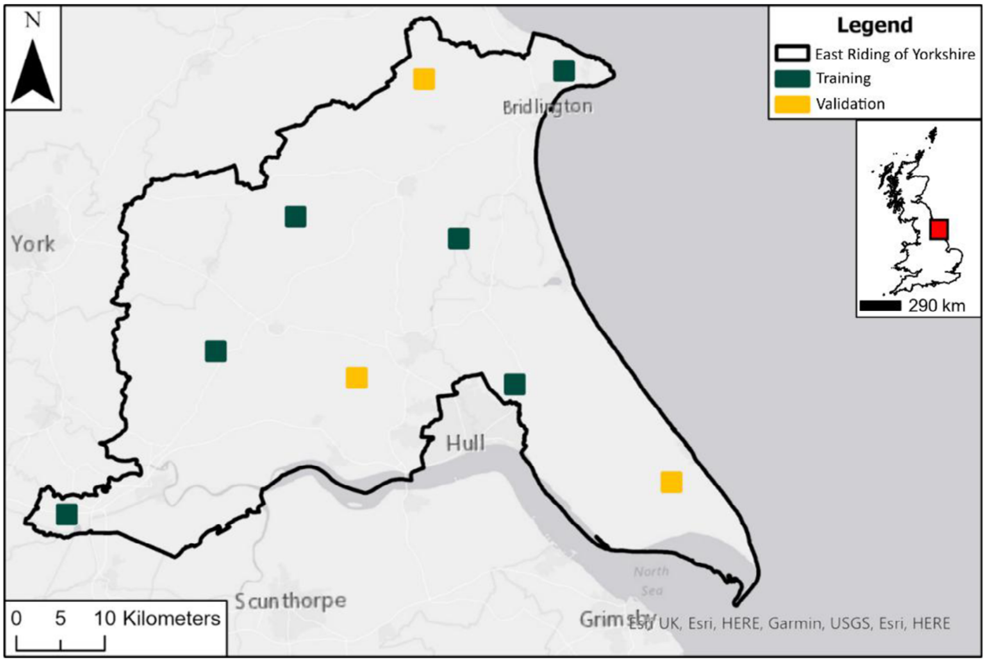

Figure 1. Outline of the East Riding of Yorkshire (ERY), UK area of interest with training and validation sites highlighted. Each site was randomly selected and equitably distributed throughout the area of interest.

hedgerow were manually identified by determining spectral differences between the hedgerow and the landscape through interpreting shadows, supported by a canopy height model (the difference between a DEM and a digital terrain model) for the area derived from 2 m LiDAR provided by the Ordnance Survey to reduce misclassifications. A total of 5770 individual features were identified, of which 3884 were classified as hedgerow (85 km) and 1789 as gap (9.2 km) that was further divided into for access (584 features, 2.8 km) or unutilised (1302 features, 6.4 km) as described below. 2137 (48.3 km) unique hedge features were used for training and 1747 (36.7 km) for validation (67%:33% split by area).

Model architecture

The U-Net architecture (Ronneberger et al., 2015) was utilised for semantic segmentation of aerial imagery with a preconfigured neural network that was 34 layers deep (ResNet-34) to increase the efficiency of the model. U-Net was initially developed for biomedical applications, such as identifying microscopic structures automatically. It was deployed herein for its speed, ability to localise classifications in pixel space and its high performance working with limited training data resulting in reduced training requirements (Ronneberger et al., 2015). U-Net is a fully convolutional neural network that is split into two phases, each with successive layers of differing resolutions: an encoding phase and a decoding phase. The encoding phase downsamples (i.e., reduces the resolution of) input data to gather classification context, whilst the decoding phase localises that context, enabling the output classification to be the same resolution as that of the input (Stoian et al., 2019). The DL model used herein had four pooling layers that reduced the spatial dimensions by half (i.e., an input image of 256 px became 128 px), resulting in a maximum resolution of 4 m. The decoder of the U-Net performed the inverse operation to return the image to its original resolution. This ultimately enables the model to 'learn' at different resolutions, recognising relationships at multiple levels, an important requirement when considering small features across a large landscape. To compensate for the reduction in resolution.

The DL model was trained on a high-specification desktop computer (Intel Core i7-9700, 64 GB RAM) with an NVIDIA GeForce RTX 2080 to leverage the GPU's ability to perform parallel processing. A batch size of eight was used to balance efficiency with required computer power and the model was trained for a maximum of 20 epochs. Training stopped when the model ceased to improve, and did not progress beyond 20 epochs. A total of 9214 training 'chips' (i.e., images with associated classification labels) that were 256 × 256 pixels in size (representing 64 × 64 m on the ground) were used as training data built from the manually classified hedgerow, as described above. Step size (the distance between training chips) was chosen to be 128 pixels in the X and Y directions to ensure at least a 50% overlap between training chips, resulting in approximately 22 000 unique features (instances of hedgerow) across all training chips. The model was trained across 17 500 batches in approximately 120 min of processing time.

Evaluation metrics

The DL model was evaluated statistically by comparing manually classified data to the validation sites. Four metrics were calculated for the dataset. The proportion of correctly classified hedgerows (precision) and the ratio of correctly identified hedgerows to the total number of actual hedgerows (recall) were calculated by randomly distributing 1500 sample points equally throughout each class (i.e., hedgerow or not hedgerow). Random spatial distribution within each class reduced potential bias resulting from unequal class sizes. The F1 score (harmonic mean of the model's precision and recall) was calculated to provide a meaningful representation of the two metrics rather than each in isolation (Dice, 1945; Vasilakos et al., 2020). When $F1 = 1$, the model has perfectly predicted all classes correctly. Second, the Jaccard index (commonly referred to as the intersection over union and herein IoU) was calculated for each hedgerow, comparing the total overlap between the model and ground truth data to the total area classified (Jaccard, 1912). For perfect predictions, $IoU = 1$, with lower IoU-values indicating less accurate predictions. The mean IoU (mIoU) was calculated to quantify overlap across the three validation areas. Finally, Cohen's kappa coefficient, κ, was calculated for each class (hedgerow or not hedgerow) in the dataset (Cohen, 1960). κ measures observed accuracy against random chance when considering data in multiple classes that are unbalanced and the classified data may be biased.

Extraction and differentiation of hedgerow gaps

The process for extracting and differentiating hedgerow gaps is shown in Figure 2 and described here in detail. Hedgerows identified by the DL model were converted from the raster format produced by the model to unique polygons following the removal of erroneous pixels and misclassified areas using the 'Boundary Clean' tool in ArcGIS Pro. Polygons were chosen to integrate with vector data that formed the linear framework for gap identification, the Ordnance Survey MasterMap (OSMM) Topography boundary layer (Ordnance Survey, 2017). OSMM is a polyline dataset that contains over 500 million real world objects for Great Britain, each with their own unique topographic identifier, including field boundaries. OSMM contains many classifications irrelevant to this study (including archaeological boundaries, overhead lines, slopes, cliffs, etc.) that were removed, retaining only the 'land' and 'roads, tracks and paths' themes, and those that do not reference water. Additionally, as the study does not consider urban hedgerows, urban areas were removed using the 'built up areas' classification from the Sentinel-derived land use layer (Karra et al., 2021). These steps reduced the OSMM ERY dataset from 2.3 million unique features to 420 000, substantially reducing computational expense during gap extraction.

Filtered OSMM data were divided into equal 30 m sections, reducing processing time and the maximum hedgerow gap size to 30 m. However, since the OSMM provides a unique identifier, when gaps were extracted the total length of hedge along each boundary line was extracted and lines rejoined. Gaps were extracted by first selecting all 30 m segments that intersected a hedge polygon. Where these lines intersected the polygon boundary, a point was placed, and the 30 m lines were further split at these points. Finally, all lines that were completely within the hedge polygon were classified as hedgerows and their inverse as hedgerow gaps. Gaps were further classified into those for access (i.e., those required to access a field), and 'unutilized' gaps. The spatial relationship of the gap to the field corner was used, with the assumption that most access gaps are close to a field corner or where two OSMM lines with different unique topographic identifiers intersect, corroborated by validation data from the training sites in Figure 1 and shown in Figure 3. Points were automatically placed at the boundary intersect and then evaluated against the hedgerow layer; a point was removed if it was not within 10 m of a classified feature to ensure only field corners near hedgerows or gaps were preserved. Remaining points had a 7.5 m buffer applied, enabling identification of access gaps of up to 15 m (chosen as larger gaps are unlikely to be for field access), at which point the location where the buffer intersected the classified line data was extracted. Finally, the classified data was split at these points to extract hedgerow gaps.

Results

Model performance

Processing and classification of the ERY study area took 32 h and produced a 357 GB raster layer. Following boundary cleaning as described above, the data was then binarized (not hedge/ hedge), resulting in a final 10 GB classified raster. The model had an *F1* score of 0.924, indicating that it was very effective at identifying hedgerow as shown in the confusion matrix (Table 1). There was excellent agreement between validation and inferred data with a κ of 0.85. Despite these positive metrics, mIoU was 0.481

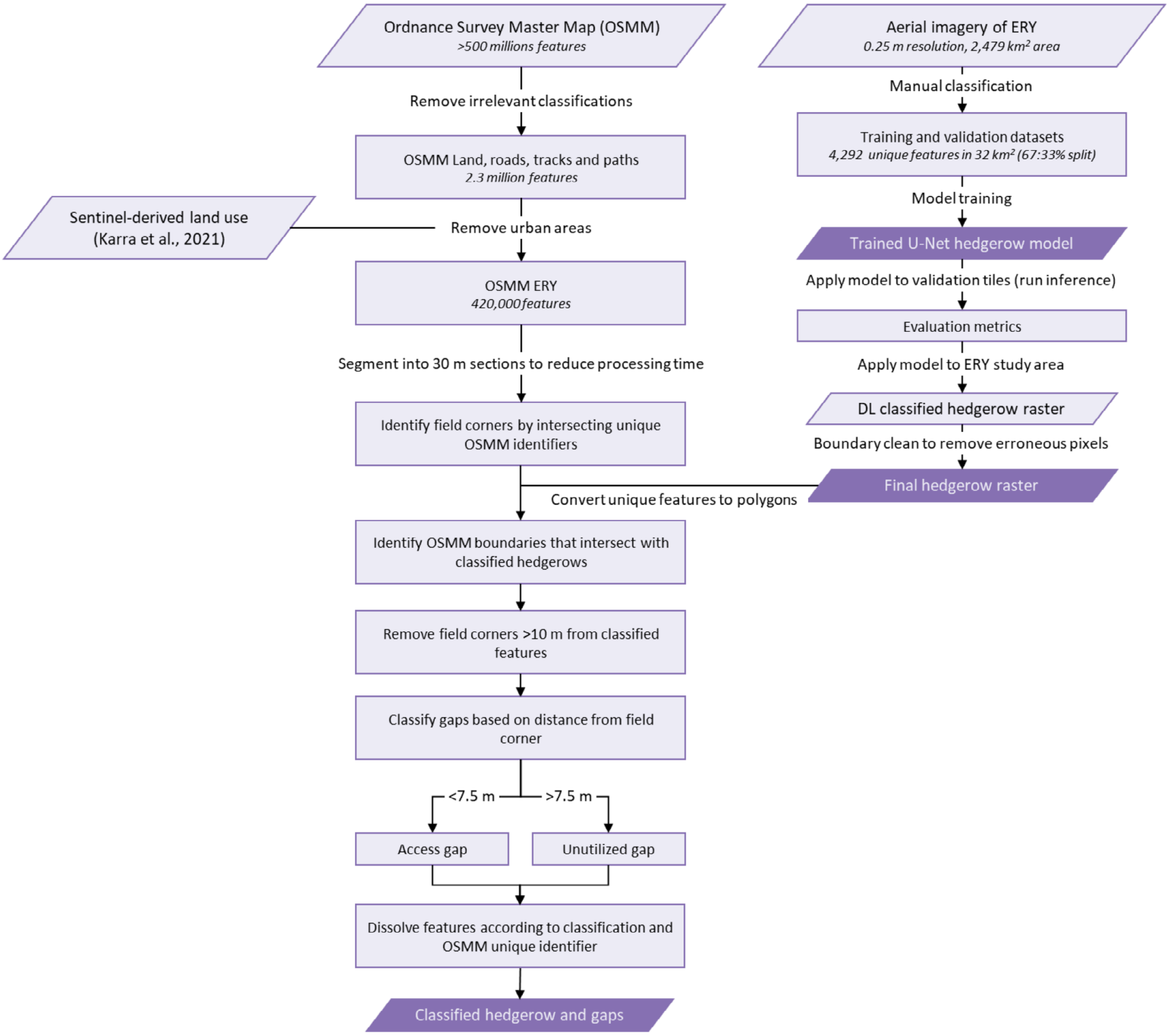

Figure 2. Process diagram for generating the DL model and detailing the extraction of hedgerow gaps from the OSMM dataset.

(where 1 is perfect overlap), a moderate result suggesting that the actual size of the hedgerow was systematically underestimated, However, upon manual comparisons of the classified data to the aerial imagery it was clear that hedgerow width was overestimated due to difficulties differentiating between the hedgerow and shadows, but length was unaffected. Comparisons between aerial imagery and classified hedgerow and gaps are shown in Figure 3.

Spatial distribution of identified hedgerow and gaps

61 822 unique features with a total length of 6847 km were identified as boundaries that contain hedgerows across the ERY region. 3982 ± 302 km (58%) were classified as hedgerows and 2865 ± 217 km (42%) as gaps within hedgerows. Features with lengths less than 0.25 m were removed since this was lower than the imagery resolution.

Individual features were aggregated into a 1 km^2 tessellated hexagonal grid (Fig. 4A,B). Hedgerow density was greatest to the east of the north–south central belt of the region—the Yorkshire Wolds—where the elevation is higher than the surrounding region (Fig. 4C). Land here was dominated by cereal and leguminous crops in 2018 (Fig. 4D), and the area is generally dominated by chalk deposits and is free of drift (glacial deposits) resulting in land dominated by barley, turnips and sheep farming in the 20th century (Sheppard, 1961), having transitioned from sheep dominated practices in the early 19th century

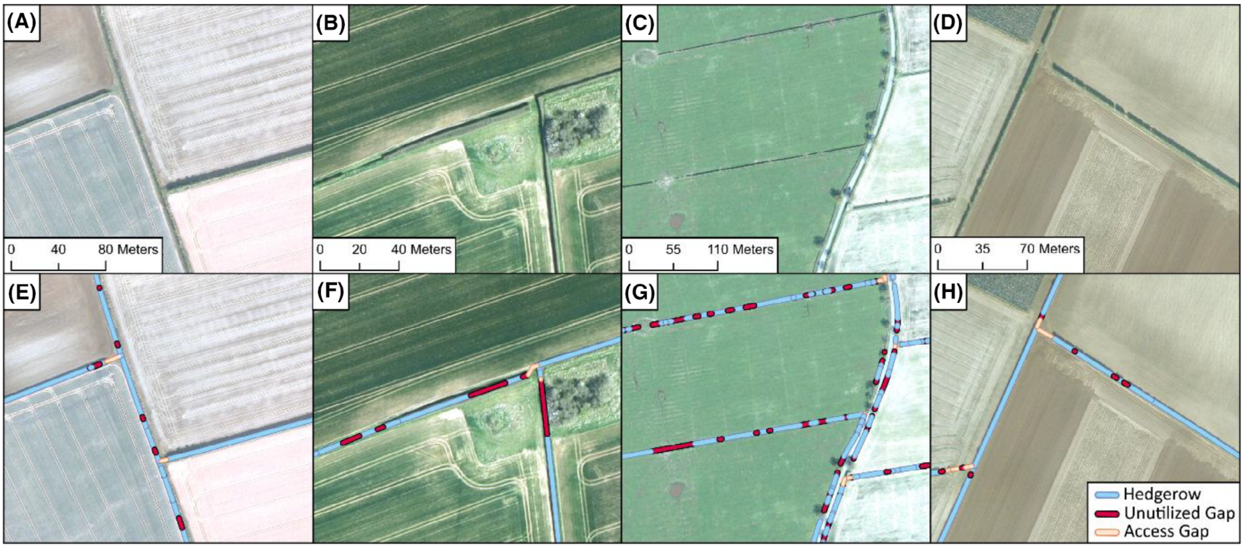

Figure 3. Examples of classified aerial imagery before (A–D) and after (E–H) hedgerow identification. Hedgerow boundaries were classified in 30 m segments to reduce processing time. Contains imagery provided by Getmapping (2018).

Table 1. Confusion matrix for hedgerow or not hedgerow predictions in the study area. The confusion matrix shows the precision and recall ability based on 1500 equitably distributed points in the three validation zones.

	Hedgerow	Not Hedgerow	Total	Recall
Hedgerow	**637**	52	689	0.925
Not Hedgerow	62	**749**	811	0.924
Total	699	801	**1500**	
Precision	0.911	0.935		**0.924**.

Bold values indicates the sum values of the row and column.

(Adams, 1977). The density of each feature also varies, with hedgerows often having a density greater than 2.4 km km^{-2} (Fig. 4A). In contrast, the density of all gaps was more evenly distributed, with a maximum density of 3 km km^{-2} (Fig. 4B). The proportion of hedgerow to gaps varied less across the region, however generally lower gap densities were present in the lowlands of the south and east (Fig. 4B) closer to the Humber estuary where drains and ditches dominate (Bankoff, 2024).

The mean aggregated hedgerow density was 1.5 km km^{-2} (std 0.105), while mean aggregated gap density was 0.56 km km^{-2} (std 0.053) as shown in Figure 5A. Over 60% of aggregated gap densities were less than 0.5 km km^{-2}. In contrast, aggregated hedgerow ranged up to 7.7 km km^{-2} but have a flatter distribution across the histogram than gaps (Fig. 5A). The length of individual hedgerow segments ranged up to 1800 m and fewer than 1% of features were larger than 500 m. Similarly, total gap size was up to 1000 m. However, fewer than 1% of features were larger than 260 m. Mean hedgerow length was 67 m (standard deviation, herein SD = 104 m) along a single unique boundary, and gap size was slightly lower, with a mean of 48 m (SD = 53 m; Fig. 5B).

Gap differentiation

Within the training and validation dataset there were 1789 individual gap features (i.e., a gap between two hedgerows), with 81.1% (6367 m) categorised as unutilized and 18.9% (2771 m) for access. The ratio varied across the survey sites, with unutilized gaps being as high as 91% in the southeast and as low as 63% in the northeast. Applying our method to the study region resulted in 2526 km of unutilized gaps (88%) and 339 km of access gaps (12%). The proportion of gaps for access is shown in Figure 6, where there was a relatively even spatial distribution across the study area. Furthermore, when considering the aggregate gap densities, there was no more than 0.60 km km^{-2} of access gap in any individual aggregate hexagon grid, with a mean of 0.13 km km^{-2} (SD = 0.1; Fig. 7A). In contrast, the density of unutilized gaps was much larger, with a maximum of 3 km km^{-2} (SD = 0.59). Individual boundaries shown in Figure 7B also highlight this, with access gaps of 10 m or less contributing to 77% of the gap population, while larger, unutilized gaps were more common (mean of 48 m, SD = 4.7).

Discussion

This study has shown that hedgerows and hedgerow gaps can be efficiently mapped at the landscape scale with high

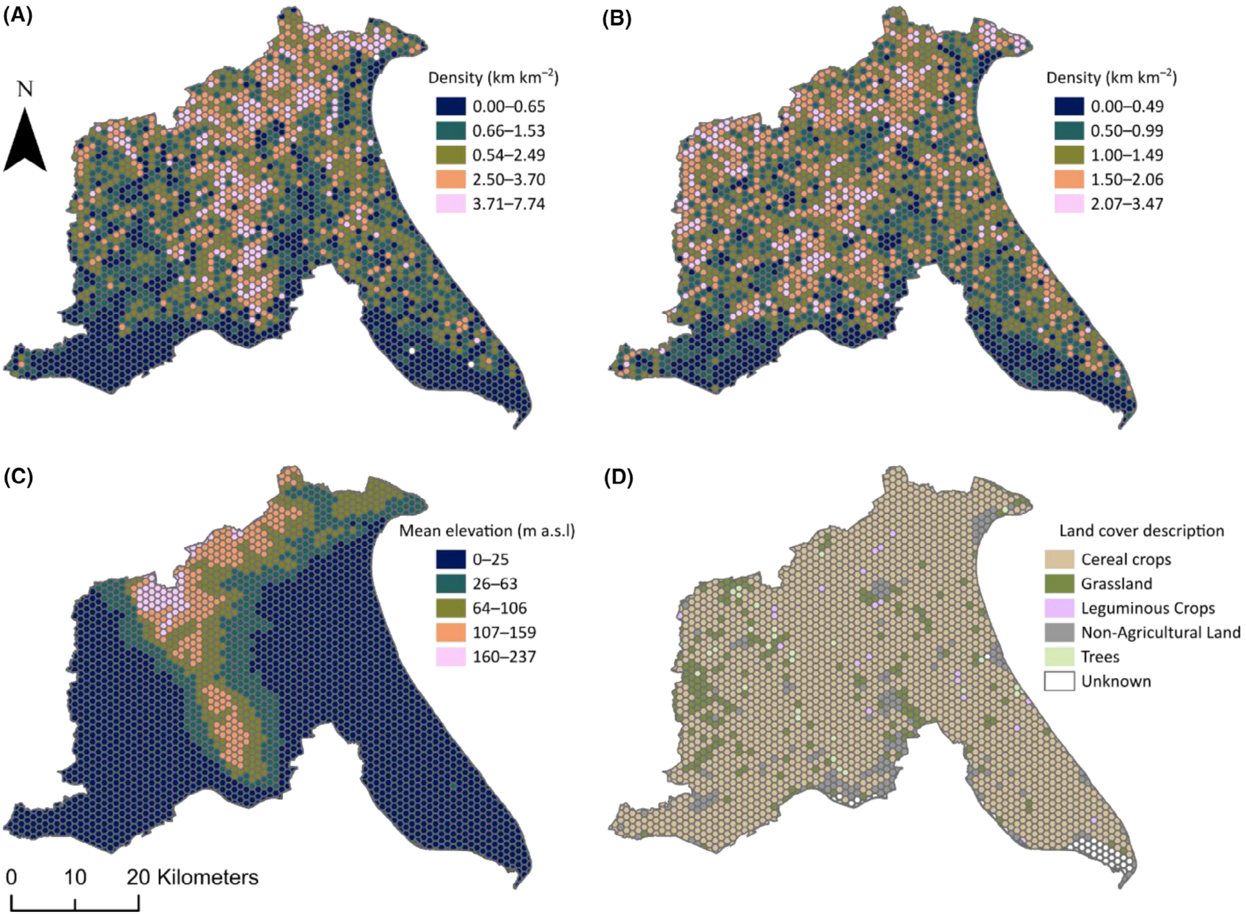

Figure 4. 1 km hexagon aggregate of (A) hedgerow density; (B) gap density; (C) mean 50 m resolution elevation (Ordnance Survey, 2024) and (D) dominant land use description from the Crop Map of England 2018 (Rural Payments Agency, 2018) for the ERY region.

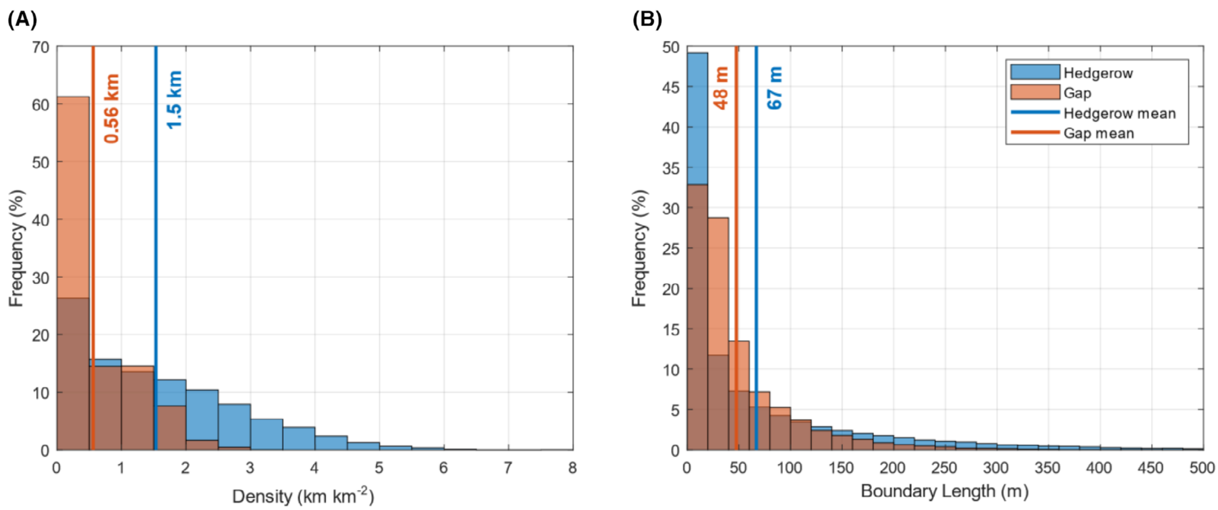

Figure 5. (A) Aggregated hexagon grid hedgerow and gap densities and (B) unique identifier lengths < 500 m. Less than 1% of values were >500 m and are not visualised here to retain clarity.

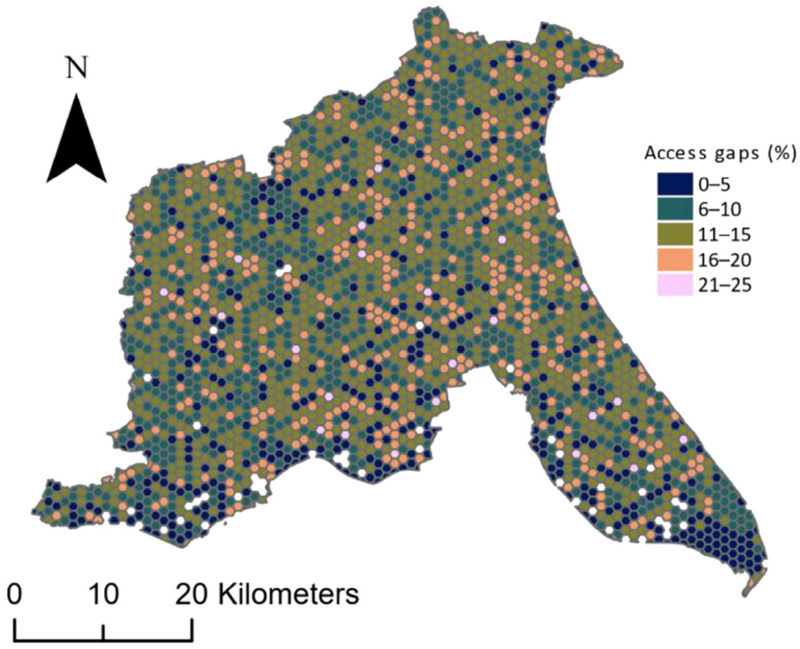

Figure 6. Hedgerow gaps are classified for access as a percentage of the total gap length in the area.

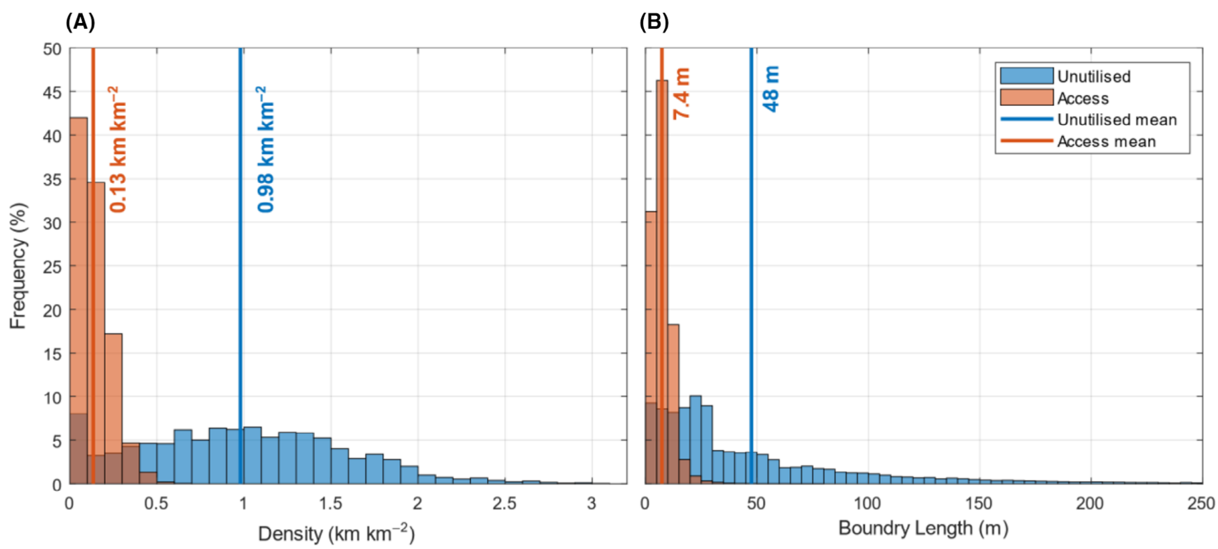

Figure 7. Hedgerow gap differentiation for (A) aggregate hexagons and (B) individual boundaries.

accuracy using high-resolution aerial imagery and DL. This discussion: (1) compares the performance of our method against previous approaches that have employed satellite and high-resolution imagery; (2) discusses the cause of underestimated hedgerow widths and potential alternative solutions; (3) highlights the novel outcomes of the present research (i.e., the identification of 'access' and 'unutilized' hedgerow gaps based on the presumed proximity to the field corner); and (4) highlights the implications of these results in the context of hedgerow restoration, net-zero targets and incentives to encourage sustainable land management practices.

The use of high-resolution imagery in this study was essential for training the DL model and ultimately the identification and determination of the area and spatial locations of hedgerow gaps across the ERY. Previous remote sensing studies of hedgerows have commonly used satellite imagery, but this can lead to underrepresentation of hedgerows (especially thin hedgerows that are often the most important class to identify for restoration) due to coarser resolutions, especially those > 10 m. Accuracy at such resolutions can be as low as 28% (IRS; 23 m) or 70% (Aster, 15 m) compared to 74–88% for Orthophotos (0.5 m) and the SPOT satellite system (5–10 m) respectively (Vannier et al., 2011) and 92.4% herein. Leveraging high-resolution aerial imagery enabled the confident detection of smaller hedgerow sections and gaps < 5 m, producing a useful overview of both hedgerow and gap density at the landscape scale. Scholefield et al. (2016) used a satellite-derived 25 m land cover map and achieved a poor to fair agreement with Countryside Survey (2007) observations, with a mean κ value of 0.016–0.053 across the ERY (vs 0.85 herein) but a 58–66% agreement across the entirety of Great Britain (vs 91.1–93.5% herein for the ERY). In contrast, O'Connell et al. (2015) used 0.5 m resolution colour infrared aerial photography to perform object-based image analysis of small-scale features in the agroecosystem and produced similar results to those presented here ($\kappa = 0.794$–0.920), but their approach produced lower precision/recall values than our method (77.14% vs. 91.1–93.5% herein; F1 score 0.924). Since the aim of this study was specifically on hedgerows, the binary model was able to focus purely on hedgerow inference, resulting in a more accurate output dataset without the requirement of multispectral data.

Our method is generous in its estimation of hedgerow width compared to validation data upon manual visual inspection. The complexity of the hedgerow canopy produces a shadowing effect, resulting in the classifier either not identifying areas of shadow as hedgerow within and beyond the hedgerow, an issue also experienced by others (Aksoy et al., 2010; Fauvel et al., 2013; Vannier et al., 2011). The pixel segmentation model overrepresented hedgerow width and intrusion into the gap, highlighted by the relatively low mIoU (0.481), but this issue did not impact hedgerow length estimates. LiDAR or SAR could be used to mitigate this issue since they do not rely on the visual spectrum of light, as well as to extract width and height (e.g., Luscombe et al., 2023; Broughton, Bullock, et al., 2021; Broughton, Chetcuti, et al., 2021; Broughton et al., 2024), but these data often have coarser resolutions when used at the landscape-scale (≥ 1 m; 1.5–2.2 m, respectively) that may omit hedgerow sections depending on the swath angle and point density relative to the hedgerow. Despite the resolution discrepancy, such data if collected at a similar time could be used in future studies integrated with the DL model herein, alongside multi- or hyperspectral imagery, to mitigate the influence of shadowing and more effectively constrain the hedgerow. Luscombe et al. (2023) achieved a similar high accuracy and κ coefficient to this study for both mature and managed hedgerow (91 and 94% respectively, $\kappa = 0.94$ and 0.97) yet did not differentiate between canopy gaps. Broughton et al. (2024) also achieved a reasonably high accuracy ($76 \pm 15\%$ SD) overall by evaluating identified woody linear features against 38 countryside survey squares, however their total feature length had a 96% agreement across the same squares. Furthermore, high-resolution LiDAR that provides a terrain and surface elevation model is less common than equivalent, or greater resolution, aerial imagery, to which the method could be adapted. Indeed, in the UK aerial imagery is updated at least every three years, while LiDAR is updated less frequently. However, UK-based LiDAR (both surface and terrain products) are currently freely available to use including commercial use (Environment Agency, 2024) whereas most high-resolution (< 10 m) aerial and satellite imagery is not. For example, a single 1 km^2 imagery tile used in this study is priced at £51.60 at the time of writing (Getmapping, 2024). The timing of the data captured will also likely influence the model herein (and would also influence other approaches including LiDAR) due to leaf cover and fluctuating spectral properties (i.e., it is likely that the hedgerow will be greener in summer). The influence of leaf cover was mitigated by using data from 2 months in the image capture year, however, including data collected at different times in the year would likely strengthen the model classification and expand its capability and robustness.

Hedgerow gaps are important for agroecosystems since they reduce landscape connectivity and the available habitat for small mammals and food supply for nesting birds (Graham et al., 2018) but the location, size and quantity of hedgerow gaps are often omitted from remotely sensed products due to difficulty differentiating between field margins, scrubland and hedgerows. Herein, hedgerow gaps were extracted and classified into 'access' and 'unutilized' by coupling the outcome of convolutional neural network processing with existing unique boundary vector information. The methodology is reliable and rapid. It revealed 2865 ± 217 km of hedgerow gaps across the study region, with a mean total gap length of 48 m per boundary. By differentiating between gaps for access and unutilized gaps, our method presents an opportunity to determine priority locations for hedgerow restoration, reducing bias from access gaps that are vital for agriculture or informing ecological connectivity studies. Further work is required however to more robustly differentiate between gap types, especially within the hedgerow and not at field boundaries. The method could easily be adapted to smaller areas of interest or to ultra-high resolution uncrewed aerial vehicle-derived datasets, perhaps with some additional training to increase reliability if the landscape mosaic is substantially different spectrally. Of potentially greater significance, it could be applied nationally through the use of a high-performance computing cluster to leverage parallel processing. Previous studies (Broughton et al., 2024; Scholefield et al., 2016) highlighted difficulties when differentiating hedgerow from other features with elevation such as drystone walls and banks due to their similar elevations and spectral properties. Although we do not statistically evaluate this, upon visual inspection dykes that are common in the east of the ERY are rarely misclassified as hedgerow, likely due to the exclusion of all non-hedgerow areas in the training data described above. Combining available LiDAR and multi- or hyperspectral remote sensing with high-resolution imagery may be a route forward to reduce misclassifications of similar features.

In the ERY alone, 10–15 million new hedgerow plants (whips) could be added to the 2526 km (±7.6%) of gaps, assuming that every 1 m hedgerow gap can accommodate four to six plants (Gregg et al., 2021), thus significantly contributing to the UK Government's net zero strategy (HM Government, 2023). This could equate to annual carbon sequestration of up to 0.75 t, or 1% of the current estimated hedgerow carbon stock, not including soil organic carbon (Crossland, 2015). Since the study area is 1% of the total UK area, gap infilling would thus meet the ERY targets for tree planting without needing to remove land from agricultural production. Furthermore, the financial contribution of the UK Government to hedgerow infilling is £17.22 per metre, whereas newly planted hedgerow is over 20 m long (BN7; Natural England, 2023). The analysis herein therefore highlights that the financial incentive for landowners to infill and restore hedgerows across the ERY amounts to £43.5 million. In addition, gap infilling provides additional ecosystem services and biodiversity net gain, including improved functionality as a windbreak, a more structurally diverse hedgerow and increased species richness (Tresise et al., 2023; Weninger et al., 2021).

Despite the clear opportunity for hedgerow gapping up and planting in the ERY, hedgerows often become gappy in the first instance due to a lack of appropriate management. For example, agricultural intensification (Staley et al., 2013) and the increased use of chemicals has resulted in some degradation of hedgerow conditions (Graham et al., 2018). Additionally, the management of hedgerow is often viewed as a source of lost productivity (Mills et al., 2013; Staley et al., 2023), and large mammals such as deer can further damage the hedgerow through grazing, leading to increased gaps (Vanhinsbergh et al., 2003). The availability of hedgerow sapling stock in the UK may also pose a barrier to increased hedgerow planting, especially when considering ambitious planting targets required to contribute towards net-zero targets (Biffi et al., 2022).

In conclusion, the approach presented herein provides a rapid and scalable solution for identifying hedgerows and hedgerow gaps at the landscape scale and provides an accurate assessment of their distribution. Tools, such as our method, help further current understanding of the hedgerow network, its influence on landscape connectivity, and potential for gap infilling to contribute towards net zero in an evolving climate. With the advent of repeat high-resolution aerial imagery and ultra-high resolution satellite missions, such as the Planet Labs' 0.5 m resolution SkyDoves and hyperspectral Tanager-1 system (Planet Labs, 2024a, 2024b), the method presented herein could form the basis of a monitoring framework for hedgerows and gaps, both in the UK and globally.

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Author Contributions

JMW: Conceptualisation, methodology, formal analysis, writing. FC: Methodology, formal analysis, writing. RET: Methodology, formal analysis, supervision, writing – review and editing. JA: Resources, writing – review and editing. KJP: Resources, writing – review and editing. DRP: Conceptualisation, resources, writing – review & editing.

Data Availability Statement

This study utilised existing data that are available under licence from https://digimap.edina.ac.uk/ or directly from Getmapping PLC.

References

Adams, M.G. (1977) *Agricultural change in the East Riding of Yorkshire, 1850–1880: an economic and social history*. University of Hull.

Ahlswede, S., Asam, S. & Röder, A. (2021) Hedgerow object detection in very high-resolution satellite images using convolutional neural networks. *Journal of Applied Remote Sensing*, **15**(1), 1–28.

Aksoy, S., Akçay, H.G. & Wassenaar, T. (2010) Automatic mapping of linear Woody vegetation features in agricultural landscapes using very high resolution imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **48**(1), 511–522. Available from: https://doi.org/10.1109/TGRS.2009.2027702

Alderman, J., Hinsley, S.A., Broughton, R.K. & Bellamy, P.E. (2011) Local settlement in woodland birds in fragmented habitat: effects of Natal territory location and timing of fledging. *Landscape Research*, **36**(5), 553–571. Available from: https://doi.org/10.1080/01426397.2011.556714

Amy, S.R., Heard, M.S., Hartley, S.E., George, C.T., Pywell, R.F. & Staley, J.T. (2015) Hedgerow rejuvenation management affects invertebrate communities through changes to habitat structure. *Basic and Applied Ecology*, **16**(5), 443–451.

Ares, E., Coe, S. & Uberoi, E. (2021) Tree Planting in the UK. Available from: https://researchbriefings.files.parliament.uk/documents/CBP-9084/CBP-9084.pdf [Accessed 13 September 2023]

Axe, M.S., Grange, I.D. & Conway, J.S. (2017) Carbon storage in hedge biomass—a case study of actively managed hedges in England. *Agriculture, Ecosystems & Environment*, **250**, 81–88.

Bankoff, G. (2024) Wartime drainage and water level management in the east riding of Yorkshire 1939–1945. *Water History*, **16**, 115–140. Available from: https://doi.org/10.1007/s12685-024-00337-6

Baudry, J., Bunce, R.G.H. & Burel, F. (2000) Hedgerows: an international perspective on their origin, function and management. *Journal of Environmental Management*, **60**(1), 7–22.

BEIS. (2023) 2021 UK greenhouse gas emissions, final figures. Available from: https://www.gov.uk/government/statistics/final-uk-greenhouse-gas-emissions-national-statistics-1990-to-2021 [Accessed 7 February 2023]

Biffi, S., Chapman, P.J., Grayson, R.P. & Ziv, G. (2022) Soil carbon sequestration potential of planting hedgerows in agricultural landscapes. *Journal of Environmental Management*, **307**, 114484.

Blaschke, T. (2010) Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, **65**(1), 2–16.

Broughton, R.K., Bullock, J.M., George, C., Hill, R.A., Hinsley, S.A., Maziarz, M. et al. (2021) Long-term woodland restoration on lowland farmland through passive rewilding. *PLoS One*, **16**, e0252466. Available from: https://doi.org/10.1371/journal.pone.0252466

Broughton, R.K., Burkmar, R., McCracken, M., Mitschunas, N., Norton, L.R., Pallett, D.W. et al. (2024) UKCEH Land Cover Plus: Hedgerows 2016–2021 (England).

Broughton, R.K., Chetcuti, J., Burgess, M.D., Gerard, F.F. & Pywell, R.F. (2021) A regional-scale study of associations between farmland birds and linear woody networks of hedgerows and trees. *Agriculture, Ecosystems & Environment*, **310**, 1–10.

Carey, P.D., Wallis, S., Chamberlain, P.M., Cooper, A., Emmett, B.A., Maskell, L.C. et al. (2007) Countryside Survey: UK Results.

Climate Change Committee. (2020) The sixth carbon budget: the UK's path to net zero.

Cohen, J. (1960) A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, **20**, 37–46.

Coulthard, E., McCollin, D. & Littlemore, J. (2016) The use of hedgerows as flight paths by moths in intensive farmland landscapes. *Journal of Insect Conservation*, **20**, 345–350. Available from: https://doi.org/10.1007/s10841-016-9864-z

Crossland, M. (2015) *The carbon sequestration potential of hedges managed for woodfuel*. Organic Research Centre.

Croxton, P.J. & Sparks, T.H. (2002) A farm-scale evaluation of the influence of hedgerow cutting frequency on hawthorn (*Crataegus monogyna*) berry yields. *Agriculture, Ecosystems & Environment*, **93**, 437–439.

Department for Environment Food & Rural Affairs. (2023) Structure of the agricultural industry in England and the UK at June.

Department for Environment, Food and Rural Affairs. (2007) *Hedgerow survey handbook: a standard procedure for local surveys in the UK*. London: DEFRA.

Dice, L.R. (1945) Measures of the amount of ecologic association between species. *Ecology*, **26**(3), 297–302.

Environment Agency. (2024) National LIDAR Programme. [Dataset]. Available from: https://www.data.gov.uk/dataset/f0db0249-f17b-4036-9e65-309148c97ce4/national-lidar-programme. [Accessed 21 October 2024]

Fauvel, M., Arbelot, B., Benediktsson, J.A., Sheeren, D. & Chanussot, J. (2013) Detection of hedges in a rural landscape using a local orientation feature: from linear opening to path opening. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **6**(1), 15–26. Available from: https://doi.org/10.1109/JSTARS.2012.2227464

Ford, H., Healey, J.R., Webb, B., Pagella, T.F. & Smith, A.R. (2021) Hedgerow effects on CO_2 emissions are regulated by soil type and season: implications for carbon flux dynamics in livestock-grazed pasture. *Geoderma*, **382**, 114697.

Getmapping. (2018) High Resolution (25cm) Vertical Aerial Imagery [JPG geospatial data], Scale 1:500, East Riding of Yorkshire Local Authority District. Updated: 29 October 2018, Using EDINA Aerial Digimap Service. Available from: https://digimap.edina.ac.uk [Accessed 14 January 2021]

Getmapping. (2024) UK aerial photography: aerial maps, digital aerial photos, aerial photo prints. Available from: https://www1.getmapping.com/Webshop/ [Accessed 21 October 2024]

Graham, L., Gaulton, R., Gerard, F. & Staley, J.T. (2018) The influence of hedgerow structural condition on wildlife habitat provision in farmed landscapes. *Biological Conservation*, **220**, 122–131.

Graham, L., Broughton, R.K., Gerard, F., Gaulton, R. (2019) Remote sensing applications for hedgerows. In: *The Ecology of Hedgerows and Field Margins*. Routledge.

Gregg, R., Elias, J., Alonso, I., Crosher, I., Muto, P. & Morecroft, M. (2021) Carbon sequestration by habitat: a review of the evidence.

Herbst, M., Roberts, J.M., Rosier, P.T.W. & Gowing, D.J. (2006) Measuring and modelling the rainfall interception loss by hedgerows in southern England. *Agricultural and Forest Meteorology*, **141**, 244–256. Available from: https://doi.org/10.1016/j.agrformet.2006.10.012

Hinsley, S.A. & Bellamy, P.E. (2019) Birds of hedgerows and other field boundaries. In: *The ecology of hedgerows and field margins*. Routledge, pp. 210–232.

HM Government. (2023) Environmental Improvement Plan 2023: First revision of the 25 Year Environment Plan.

Holden, J., Grayson, R.P., Berdeni, D., Bird, S., Chapman, P.J., Edmondson, J.L. et al. (2019) The role of hedgerows in soil functioning within agricultural landscapes. *Agriculture, Ecosystems & Environment*, **273**, 1–12. Available from: https://doi.org/10.1016/j.agee.2018.11.027

IPCC. (2023) Summary for Policymakers. In: Intergovernmental Panel on Climate, C (Ed.) *Climate Change 2021—the physical science basis: working group I contribution to the sixth assessment report of the intergovernmental panel on climate change*. Cambridge: Cambridge University Press, pp. 3–32.

Jaccard, P. (1912) The distribution of the flora in the alpine zone. *The New Phytologist*, **11**(2), 37–50.

Karra, K., Kontgis, C., Statman-Weil, Z., Mazzariello, J.C., Mathis, M. & Brumby, S.P. (2021) Global land use/land cover with Sentinel 2 and deep learning. IEEE International Geoscience and Remote Sensing Symposium IGARSS. 11–16 July 2021.

Kaushik, S., Singh, T., Joshi, P.K. & Dietz, A.J. (2022) Automated mapping of glacial lakes using multisource remote sensing data and deep convolutional neural network. *International Journal of Applied Earth Observation and Geoinformation*, **115**, 103085. Available from: https://doi.org/10.1016/J.JAG.2022.103085

LaRue, M., Iles, D., Labrousse, S., Fretwell, P., Ortega, D., Devane, E. et al. (2024) Advances in remote sensing of emperor penguins: first multi-year time series documenting trends in the global population. *Proceedings of the Royal Society B: Biological Sciences*, **291**(2018), 20232067. Available from: https://doi.org/10.1098/rspb.2023.2067

Lechner, A.M., Stein, A., Jones, S.D. & Ferwerda, J.G. (2009) Remote sensing of small and linear features: quantifying the effects of patch size and length, grid position and detectability on land cover mapping. *Remote Sensing of Environment*, **113**(10), 2194–2204.

Li, Y., Zhang, H., Xue, X., Jiang, Y. & Shen, Q. (2018) Deep learning for remote sensing image classification: a survey. *WIREs Data Mining and Knowledge Discovery*, **8**(6), e1264. Available from: https://doi.org/10.1002/WIDM.1264

Luscombe, D.J., Gatis, N., Anderson, K., Carless, D. & Brazier, R.E. (2023) Rapid, repeatable landscape-scale mapping of tree, hedgerow, and woodland habitats (THaW), using airborne LiDAR and spaceborne SAR data. *Ecology and Evolution*, **13**(5), e10103.

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G. & Johnson, B.A. (2019) Deep learning in remote sensing applications: a meta-analysis and review. *ISPRS Journal of Photogrammetry and Remote Sensing*, **152**, 166–177.

Mills, J., Gaskell, P., Reed, M., Short, C., Ingram, J., Boatman, N. et al. (2013) *Farmer attitudes and evaluation of outcomes to on-farm environmental management*. Report to Department for Environment, Food and Rural Affairs (Defra). Gloucester: CCRI.

Morandin, L.A., Long, R.F. & Kremen, C. (2014) Hedgerows enhance beneficial insects on adjacent tomato fields in an intensive agricultural landscape. *Agriculture, Ecosystems & Environment*, **189**, 164–170. Available from: https://doi.org/10.1016/j.agee.2014.03.030

National Hedgelaying Society. (n.d.) Regional Styles. Available from: https://www.hedgelaying.org.uk/pg/info/styles.aspx [Accessed 21 October 2024]

Natural England. (2023) Countryside Stewardship Scheme 2016 Management Options.

Neumann, J.L., Griffiths, G.H., Foster, C.W. & Holloway, G.J. (2016) The heterogeneity of wooded-agricultural landscape mosaics influences woodland bird community assemblages. *Landscape Ecology*, **31**(8), 1833–1848.

O'Connell, J., Bradter, U. & Benton, T.G. (2015) Wide-area mapping of small-scale features in agricultural landscapes using airborne remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, **109**, 165–177.

Ordnance Survey. (2017) OS MasterMap Topography Layer: Product Guide.

Ordnance Survey. (2024) OS Terrain 50 DTM [ASC geospatial data], Tile(s): East Riding of Yorkshire, Updated: April 2020. Contains public sector information licensed under the Open Government Licence v3.0.

Planet Labs. (2024a) High-Resolution Imagery with Planet Satellite Tasking. [Website]. Planet Labs. Available from: https://www.planet.com/products/high-resolution-satellite-imagery/ [Accessed 16 October 2024]

Planet Labs. (2024b) *Hyperspectral Imaging Satellites [Website]*. Planet Labs. Available from: https://www.planet.com/products/hyperspectral/. [Accessed 16 October 2024]

Rackham, O. (1986) *The history of the countryside*. London: Dent.

Robson, B.A., Bolch, T., MacDonell, S., Hölbling, D., Rastner, P. & Schaffer, N. (2020) Automated detection of rock glaciers using deep learning and object-based image analysis. *Remote Sensing of Environment*, **250**, 112033. Available from: https://doi.org/10.1016/J.RSE.2020.112033

Ronneberger, O., Fischer, P. & Brox, T. (2015) U-net: convolutional networks for biomedical image segmentation. International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer.

Rural Payments Agency. (2018) Crop Map of England 2018. Contains public sector information licensed under the Open Government Licence v3.0.

Scholefield, P., Morton, D., Rowland, C., Henrys, P., Howard, D. & Norton, L. (2016) A model of the extent and distribution of woody linear features in rural Great Britain. *Ecology and Evolution*, **6**(24), 8893–8902.

Sheppard, J.A. (1961) East Yorkshire's agricultural labour force in the mid-nineteenth century. *The Agricultural History Review*, **9**, 43–54.

Simonson, W., Tosh, C. & Gossel, C. (2024) *Aiming high for hedgerows*. Organic Research Centre.

Smigaj, M., Gaulton, R., Horning, N. & Poursanidis, D. (2021) Capturing hedgerow structure and flowering abundance with UAV remote sensing. *Remote Sensing in Ecology and Conservation*, **7**(3), 521–533. Available from: https://doi.org/10.1002/rse2.208

Staley, J.T., Amy, S.R., Adams, N.P., Chapman, R.E., Peyton, J.M. & Pywell, R.F. (2015) Re-structuring hedges: rejuvenation management can improve the long term quality of hedgerow habitats for wildlife in the UK. *Biological Conservation*, **186**, 187–196.

Staley, J.T., Botham, M.S., Chapman, R.E., Amy, S.R., Heard, M.S., Hulmes, L. et al. (2016) Little and late: how reduced hedgerow cutting can benefit lepidoptera. *Agriculture, Ecosystems and Environment*, **224**, 22–28.

Staley, J.T., Bullock, J.M., Baldock, K.C.R., Redhead, J.W., Hooftman, D.A.P., Button, N. et al. (2013) Changes in hedgerow floral diversity over 70 years in an English rural landscape, and the impacts of management. *Biological Conservation*, **167**, 97–105. Available from: https://doi.org/10.1016/j.biocon.2013.07.033

Staley, J.T., Wolton, R. & Norton, L. (2020) *Definition of favourable conservation status for hedgerows*. Natural England.

Staley, J.T., Wolton, R. & Norton, L.R. (2023) Improving and expanding hedgerows—recommendations for a semi-natural habitat in agricultural landscapes. *Ecological Solutions and Evidence*, **4**, e12209. Available from: https://doi.org/10.1002/2688-8319.12209

Stoian, A., Poulain, V., Inglada, J., Poughon, V. & Derksen, D. (2019) Land cover maps production with high resolution satellite image time series and convolutional neural networks: adaptations and limits for operational systems. *Remote Sensing*, **11**(17), 1–26.

Tansey, K., Chambers, I., Anstee, A., Denniss, A. & Lamb, A. (2009) Object-oriented classification of very high resolution airborne imagery for the extraction of hedgerows and field margin cover in agricultural areas. *Applied Geography*, **29**(2), 145–157.

Thornton, M.W., Atkinson, P.M. & Holland, D.A. (2007) Sub-pixel mapping of rural land cover objects from fine spatial resolution satellite sensor imagery using super-resolution pixel-swapping. *International Journal of Remote Sensing*, **27**(3), 473–491.

Tong, X.-Y., Xia, G.-S., Lu, Q., Shen, H., Li, S., You, S. et al. (2020) Land-cover classification with high-resolution remote sensing images using transferable deep models. *Remote Sensing of Environment*, **237**, 111322.

Tresise, M.E., Reed, M.S. & Chapman, P.J. (2023) Effects of hedgerow enhancement as a net zero strategy on farmland biodiversity: a rapid review. *Emerald Open Research*, **1**(10), 1–25. Available from: https://doi.org/10.1108/EOR-10-2023-0011

Vanhinsbergh, D., Fuller, R.J. & Noble, D. (2003) *A review of possible causes of recent changes in populations of woodland birds in Britain (report no. 245)*. Norfolk, UK: British Trust for Ornithology.

Vannier, C. & Hubert-Moy, L. (2014) Multiscale comparison of remote-sensing data for linear woody vegetation mapping. *International Journal of Remote Sensing*, **35**(21), 7376–7399.

Vannier, C., Vasseur, C., Hubert-Moy, L. & Baudry, J. (2011) Multiscale ecological assessment of remote sensing images. *Landscape Ecology*, **26**, 1053–1069. Available from: https://doi.org/10.1007/s10980-011-9626-y

Vasilakos, C., Kavroudakis, D. & Georganta, A. (2020) Machine learning classification ensemble of multitemporal sentinel-2 images: the case of a mixed Mediterranean ecosystem. *Remote Sensing*, **12**(12), 1–25.

Wallace, E.E., McShane, G., Tych, W., Kretzschmar, A., McCann, T. & Chappell, N.A. (2021) The effect of hedgerow wild-margins on topsoil hydraulic properties, and overland-flow incidence, magnitude and water-quality. *Hydrological Processes*, **35**, e14098. Available from: https://doi.org/10.1002/hyp.14098

Weninger, T., Scheper, S., Lackóová, L., Kitzler, B., Gartner, K., King, N.W. et al. (2021) Ecosystem services of tree windbreaks in rural landscapes—a systematic review. *Environmental Research Letters*, **16**(10), 1–20. Available from: https://doi.org/10.1088/1748-9326/ac1d0d

Woodcock, C.E. & Strahler, A.H. (1987) The factor of scale in remote sensing. *Remote Sensing of Environment*, **21**, 311–332.

Zhang, L., Zhang, L. & Du, B. (2016) Deep learning for remote sensing data: a technical tutorial on the state of the art. *IEEE Geoscience and Remote Sensing Magazine*, **4**(2), 22–40. Available from: https://doi.org/10.1109/MGRS.2016.2540798

