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SURVEY

Hedgerows Monitoring in Remote Sensing: A Comprehensive Review

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ABSTRACT This comprehensive review delves into the importance of hedgerows in urban green spaces, emphasizing their significant role in sustainable development and providing ecological benefits. Accurate identification and characterization mapping of hedgerows are vital for effective land management, urban planning, and conservation efforts. The article explores the challenges associated with identifying hedgerows in urban environments and the complexities they present for automatic detection. It discusses the limitations of traditional methods and showcases the potential of advances in remote sensing technologies and artificial intelligence (AI) methods, such as deep learning algorithms. Results indicate that deep learning can generally achieve an accuracy of 75% for hedgerow identification. This review article sets out a vision for the future of hedgerow detection and monitoring.

INDEX TERMS Hedgerow, remote sensing, machine learning, deep learning, synthetic aperture radar, LiDAR.

I. INTRODUCTION

Hedgerows are essential features in many landscapes of the world [1], [2], [3], [4]. Hedgerows comprise various elements, including hedges, trees, walls, fences, and gates. These features can vary greatly, from ancient to newly planted, and may consist of a single or multiple species. However, the definition of hedgerows varies according to studies, and this disparity is a problem for extracting hedgerows from satellite images because the maps obtained are based on different characteristics, often making them incomparable [5]. Different studies use various names and criteria to define hedgerows. Some studies may focus on specific aspects, such as mapping woody vegetation or delineating linear features adjacent to fields, without considering the specific species composition. This lack of standardized terminology and criteria makes it difficult to compare and integrate the results from different studies. Hedgerows fall into two categories:

- Managed: where trees no longer take their natural shape
- Relict: where trees were planted as hedges but are no longer managed.

To provide a more nuanced understanding of hedgerow types, Neumann et al. [6] further categorized them into four distinct types based on their structural characteristics and the intensity of management:

- Type 1: this category includes low-lying, intensively managed hedges, typically flailed. These hedges contain no trees or woody elements and are characterized by a height of up to approximately 1.5 meters and an average width of 2.5 meters. Their primary functions are often aesthetic or boundary-setting, rather than ecological.
- Type 2: hedges in this category contain small or juvenile trees, as well as taller, shrub-like species. They are less intensively managed than Type 1 and typically exceed 1.5 meters in height, with an average width of 7 meters. Their increased structural complexity provides enhanced habitat opportunities compared to Type 1.
- Type 3: this type features hedges with mature trees, which, when viewed from above, resemble linear strips of broadleaved woodland. With an average width of

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15 meters, these hedges offer significant ecological benefits, including habitat for various wildlife species and improved landscape connectivity.
- Type 4: this type consists of a line of usually planted trees, which may not conform to traditional hedge characteristics. These may have clear spaces between individual trees or represent a defunct hedge with noticeable gaps. While they provide some ecological value, their fragmented structure limits their effectiveness as habitat corridors.

Often planted as boundary lines around areas like farm fields or gardens, hedges are much more than valuable dividers. In agricultural landscapes, it is widely recognized that features such as trees outside forest (hedges, copses, scattered trees, small remnant woodlots, Bocage, etc.) play an essential role in the conservation and restoration of biodiversity [7]. Hedgerows play a critical role in providing food resources for wildlife, serving as habitats for important species like pollinators and natural enemies of pests [2], [8]. Flowers, in particular, are essential sources of nectar for pollinators, producing berries that are a food source for resident and overwintering birds [9]. However, agricultural intensification can negatively impact hedgerows, resulting in habitat loss and disruption of connectivity [10]. These green veining elements serve as essential habitats, movement corridors, and refuges for various species that rely on hedgerows for survival [11], [12], [13], [14], [15]. However, hedgerows can act as barriers for some species while providing corridors for others. For example, hedgerows can act as barriers for butterflies like Lysandra bellargus [16] but serve as corridors for forest carabid beetles [17]. The scale of these corridors can vary, from kilometers for mammals to meters for insects [18], [19].

Research on the impacts of increasing hedgerow extent has shown primarily positive effects on the studied species, although there have been relatively few publications on this topic. For example, doubling the total length of hedgerows has significantly improved connectivity for European hedgehogs (Erinaceus europaeus), a species of conservation concern [20]. Studies also suggest that having a high density of flowering hawthorn and blackthorn hedgerows, combined with later-flowering habitats, can support healthy populations of six wild bee species [21]. For birds, there is an increase in species richness with hedgerow extent up to 8 km/km2 [22]. Additionally, hedges are considered crucial structures for promoting bird diversity [13]. To ensure that grassland bird species are supported, having approximately 9.5 km/km2 of hedgerow is recommended, allowing for the retention of large enough grassland patches [23].

In addition to its positive impact on biodiversity, hedgerows serve various functions, including controlling physical, chemical, and biological flux (such as protecting water and preventing erosion), acting as a windbreak, and serving as a barrier [24]. These semi-natural elements are crucial in agricultural landscapes and hold cultural and historical significance. They play a vital role in connecting landscapes and contribute significantly to halting biodiversity decline and addressing climate change. While the definition of a hedge may vary depending on the involved species, it typically refers to a dense row of small trees, shrubs, and bushes [25]. Some alternative definitions include those from Forman and Baudry [7], who describe hedgerows as narrow strips of woody plants that separate fields, and French and Cummins [26], who define it as a combination of a hedge and a hedge-bottom used for farming boundaries. Baudry and Jouin [5] defined a hedgerow as "a linear element of the landscape composed of trees or shrubs and managed by man". In the National Forest Inventory, hedgerows are classified as woody treelines found at the edges of forests, around agricultural fields, or near settlements [27].

FIGURE 1. Different types of hedgerows identified through aerial photography [28].

Given the advantages of hedgerows, there is an increased interest in identifying them as a means to protect them. The use of satellite remote sensing in detecting hedgerows has received increasing attention in the last decade [29], [30], [31]. This growing interest is motivated by the critical ecological role of such natural objects [24]. However, hedgerows can vary significantly in structure at both the tree and hedgerow scales, depending on the landscape [32]. This is due to differences in species composition, vegetation density, and management practices as shown in Fig 1. The functions of hedgerows are heavily influenced by their structure [33]. Despite their positive impact, the abundance of hedgerows in Europe has decreased due to factors such as agricultural intensification and the effects of World War II [34], [35], [36]. Several European countries have implemented financial incentives to combat this decline to promote sustainable farming practices, including hedgerow maintenance [35], [37]. For example, in France, there is a need for the mapping of "green belt networks" or green infrastructures, as highlighted in the "environment round table" [38].

Farmers in the European Union must maintain hedges on their farms to be eligible for funding [30], and several other countries have integrated the protection of hedgerows into their Good Agricultural and Environmental Conditions [39], [40]. However, enforcing and monitoring these regulations

FIGURE 2. Examples of different hedgerow classes in an urban area (Photo credit: M. A. Pirbasti).

at regional, national, and international levels is necessary to prevent the ongoing loss of biodiversity and the services and natural capital supported by biodiversity [41], [42]. For example, the UK's Research and Innovation (UKRI) investment in the Land Use for Net Zero (LUNZ) initiative, which encompasses the protection and restoration of woodlands, including hedges, underscores their ongoing significance in achieving sustainability objectives such as the target of net zero emissions by 2050 [43]. Moreover, hedges are pivotal in three United Nations Sustainable Development Goals (SDG): sustainable cities and communities (No. 11), climate action (No. 13), and life on land (No. 15) [44]. Their contribution to these goals, promoting biodiversity, mitigating climate change, and fostering a healthier environment for humans and wildlife, cannot be overstated. Hence, prioritizing the preservation and conservation of hedges is paramount to advancing these global aspirations.

A. HEDGEROWS IN URBAN ENVIRONMENTS

While there are many studies focusing on hedgerow detection and analysis in rural landscapes, we have identified a lack of research for understanding hedgerows in the urban environment. Urban green spaces play a crucial role in enhancing the quality of life in cities by providing various environmental, social, and economic benefits [45]. Diverse vegetation types, including trees, shrubs, and herbaceous plants, often characterize these spaces. One important feature of urban green spaces that has gained increasing attention in recent years is the presence of hedgerows [46]. Hedgerows, traditionally used in rural landscapes for delineating boundaries and providing wildlife habitat, are now recognized for their significance in urban settings [46].

As in the rural context, hedgerows in urban green spaces serve as important corridors and refuges for biodiversity. They provide habitat and shelter for various species, including birds, small mammals, insects, and plants [22], [47]. The linear structure of hedgerows creates connectivity between fragmented patches of green spaces, enabling the movement and dispersal of wildlife across urban landscapes. These green corridors can act as stepping stones, facilitating species migration and colonization, thus promoting biodiversity resilience in urban environments. Furthermore, hedgerows harbor diverse plant species, contributing to local plant biodiversity and supporting pollinators, such as bees and butterflies, essential for urban agriculture and ecosystem functioning [48].

Hedgerows in urban green spaces offer various ecosystem services that benefit humans and the environment. Firstly, hedgerows act as natural windbreaks, reducing wind velocity and providing shelter to nearby areas, including residential neighborhoods and gardens. This wind mitigation function is essential in urban areas prone to strong winds and storms. Additionally, hedgerows play a crucial role in regulating microclimates by providing shade and reducing the urban heat island effect, thus mitigating heat stress and enhancing urban climate resilience [49]. Moreover, hedgerows act as effective filters [50], [51], mitigating air pollution by capturing particulate matter and absorbing gaseous pollutants, thereby improving air quality in urban environments. Lastly, hedgerows enhance water management by reducing soil erosion, promoting groundwater recharge, and improving stormwater management through their ability to absorb and retain excess rainfall [52].

Beyond their ecological functions, hedgerows in urban green spaces also have a positive impact on human well-being [53]. Green infrastructure, such as hedgerows, has been associated with various mental and physical health benefits. Research has shown that exposure to green spaces and natural environments can reduce stress, improve mood, and enhance cognitive function [27]. With their aesthetic appeal and diverse flora and fauna, hedgerows provide nature-based recreation and relaxation opportunities, contributing to improved mental well-being and overall quality of life for urban residents. Furthermore, hedgerows act as visual screens, creating a sense of privacy and tranquility in densely populated urban areas.

However, it is crucial to detect and map hedgerows to comprehend their ecological impact in urban environments and promote the development of sustainable spaces. By identifying and mapping hedgerows, we can preserve valuable habitats, enhance urban biodiversity, improve ecosystem services, mitigate the effects of climate change, and create visually appealing and livable cities. Urban environments present unique challenges for hedgerow detection due to the complexities of the landscape. Unlike rural areas with more prevalent and distinct hedgerows, urban landscapes are characterized by fragmented and mixed vegetation types. In urban areas, vegetation is often fragmented, with smaller patches of green spaces scattered throughout the built environment [54]. This fragmentation makes it challenging to identify and delineate hedgerows accurately [55]. Moreover, urban landscapes often contain a mixture of vegetation types, including trees, shrubs, and grass, which further adds to the complexity of distinguishing hedgerows from other forms of vegetation [56].

Another challenge in urban hedgerow detection is the presence of man-made structures, such as buildings, roads, and infrastructure. These structures can cause occlusions, obstructing the view of hedgerows from remote sensing platforms. As a result, the identification and mapping of hedgerows become more challenging, as they may be partially or entirely hidden by these structures [57]. Traditional methods, such as field surveys and aerial photography, often struggle with accuracy and scalability, frequently requiring extensive data labeling due to the complexities of urban environments. However, recent advances in remote sensing technology and machine learning have significantly enhanced detection and classification capabilities [58]. Various data sources and methodological strategies have been developed in recent years to map urban tree cover or green vegetation [59]. Many studies have used a combination of very high spatial resolution (VHSR) imagery and/or airborne LiDAR to map green vegetation, including hedgerows [60], [61], [62]. However, they did not examine the extracted classes in detail so that the accuracy of their work could be compared.

Advanced remote sensing techniques and data fusion approaches can be employed to address this challenge. These techniques involve integrating data from multiple sensors, such as high-resolution optical imagery, synthetic aperture radar (SAR), and Light Detection and Ranging (LiDAR) [28]. Combining data from different sensors makes mitigating the occlusion effects caused by buildings, roads, and other structures possible, thus improving the detection and mapping of hedgerows in urban environments. Developing innovative algorithms and methodologies tailored explicitly for urban hedgerow detection can also help overcome occlusion challenges. These algorithms can leverage advanced techniques like machine learning [63], [64] and computer vision algorithms [65], [66], [67] to extract hedgerow features from remotely sensed data, even in the presence of occlusions.

The remainder of this paper is organized as follows. Section II describes the review methodology. Section III describes state-of-the-art hedgerow mapping with remote sensing sensors. In this Section, we discuss multispectral and radar remote sensing in hedgerow mapping. The separate task of identification of hedgerows in remote sensing imagery is introduced and reviewed in Section IV; Characteristics of hedgerows with remote sensing, textural features, fractal analysis, spatial auto-correlation, and wavelet transforms are presented in this Section, followed by a description of detecting hedgerows using AI techniques in remote sensing imagery. Finally, we conclude this article in Section V with a discussion of how the field can advance.

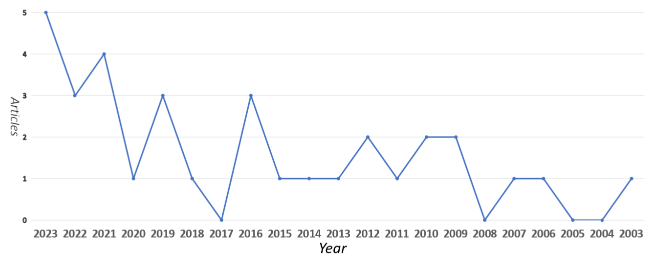


FIGURE 3. Graph depicting the annual publication count of research papers on hedgerow mapping using remote sensing observations.

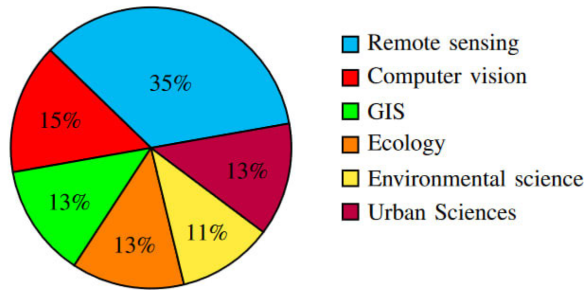


FIGURE 4. The number of articles (percent) published in the field of hedgerow mapping by subject area.

II. REVIEW METHODOLOGY

The methodology for selecting papers for this review article follows a rigorous and systematic approach. The initial step involved conducting a comprehensive literature search using reputable academic databases, such as ResearchGate, IEEE Xplore, and Google Scholar. To ensure a comprehensive search, a range of relevant search terms were employed, including "Hedgerows", "Remote Sensing", "Machine Learning", "Deep Learning", "Woody Vegetation", "Detection", "Very High Resolution", "Hedges", "LiDAR", "SAR", "Object Detection", and "Convolutional Neural Networks". The search was limited to papers published between 1985 and 2024 to encompass classic and more recent advancements in the field.

The inclusion criteria for paper selection were stringent and carefully applied. Only papers directly relevant to hedgerow monitoring using remote sensing observations and techniques were considered, while those focusing on unrelated topics or lacking substantial insights into hedgerow detection and characterization were excluded. Only peer-reviewed journal articles were included to ensure the reliability and validity of the research findings, while conference papers, book chapters, and non-peer-reviewed sources were not included. Finally, papers published within the specified time frame were considered.

Following the literature search, the selected papers underwent a meticulous review and evaluation process, taking into account their research content, methodology, and relevance to the objectives of this review article. As seen in Figs. 3 and 4, the papers were grouped based on their thematic focus and key findings. This approach allowed for a structured and coherent presentation of the research findings, enabling the identification of common themes, challenges, and opportunities in hedgerow monitoring using remote sensing. The rationale behind grouping the papers into sections was to provide readers with a well-organized and comprehensive review of the literature. Each section addresses a specific aspect of hedgerow monitoring, such as challenges related to identification, the utilization of machine learning and deep learning algorithms, the complexities of landscapes, and so on. This systematic arrangement enables readers to navigate through the different topics and gain a comprehensive understanding of the current state of research in the field.

III. HEDGEROW MAPPING WITH REMOTE SENSING SENSORS

A. OPTICAL REMOTE SENSING IN HEDGEROWS MAPPING

Optical remote sensing, employing passive sensors, has emerged as a pivotal tool for mapping hedgerows with enhanced precision and efficiency [68]. These sensors capture electromagnetic radiation reflected or emitted by objects on the Earth's surface, providing valuable insights into various ecological parameters of hedgerow landscapes. By capturing data across multispectral bands, optical sensors facilitate the analysis of phenology and biodiversity dynamics within hedgerow networks [69]. These satellite sensors offer superior spectral resolution compared to other remote sensing technologies, enabling detailed characterization of vegetation types, health, and structure within hedgerow ecosystems.

Mapping different vegetation cover types and measuring their biodiversity primarily relies on vegetation indices that combine reflectance values at two or more wavelengths [70]. For instance, multispectral satellites are equipped with a few spectral bands, allowing for the discrimination of subtle differences in vegetation composition and health. Moreover, advanced passive satellites like hyperspectral sensors feature even higher spectral resolutions, boasting over 200 bands [71]. This expanded spectral coverage empowers researchers to conduct in-depth analyses of hedgerow dynamics, including spatial distribution, species composition, habitat quality, and ecological interactions.

In recent years, passive satellite sensors have been engineered to record a higher number of carefully selected wavelengths [72]. For example, the red edge band of the Pleiades Neo satellite, where there is a rapid increase in reflectance from the red to near-infrared (NIR) reflectance, correlates strongly with hedge chlorophyll content and can indicate vegetation change [73]. The inclusion of measurements made in a red-edge channel serves as a reliable indicator of foliar chlorophyll content and vegetation change, aiding in the assessment of plant chlorophyll concentration, leaf area index, and change status. Hyperspectral remote sensing data, recording a larger number of wavelength bands, can offer

FIGURE 5. Spatial resolution comparison (false color composite: R = NIR, G = RED, B = GREEN) among QuickBird (A), RapidEye (B) and Landsat-8 (C) [75].

the opportunity to define new vegetation indices tailored to specific species and/or parameter applications [74].

Although increased spectral resolution benefits species composition analysis at a single point in time, a time series of imagery acquired throughout the growing season provides maximum information on yields and management [75]. The phenological stages of hedgerows progress rapidly during the growing season due to factors such as weather, germination, management strategies, and pruning [76]. Leveraging temporal data allows researchers to assess spatial distribution, monitor changes over time, and inform conservation strategies aimed at preserving these vital landscape features [77].

Increased temporal frequency of image acquisition is advantageous in countries with cloud-dominated climates, where multiple overpasses may fail to generate ground images [75]. However, there is typically an inverse relationship between the frequency of image acquisition and the swath width of the sensor and its spatial resolution. This often results in sensors acquiring daily images at resolutions of 300–1000 meters, which may be sufficient for large range land areas but too coarse for imaging urban areas. In such cases, *in-situ* data validation discrepancies arise during up and downscaling for multisensor data integration [75].

Access to images with high spatial resolution is essential for hedge identification Fig. 5 illustrates the false-color composite of the target area, where small-scale differences in growth are more evident in a 2.4m Quickbird image than in a 6.5m RapidEye image and almost impossible to detect in a 30m Landsat-8 scene.

Several high and very high-resolution sensors launched in the last decade enable the detection of intrafield variations. When multiple identical instruments are in a constellation, a time series of cloud-free imagery can be maintained. However, the imaging scale remains a complex and dynamic topic in remote sensing, which will be further discussed in the following sections.

B. LIDAR REMOTE SENSING IN HEDGEROWS MAPPING

LiDAR, an acronym of ''light detection and ranging'' is a remote sensing technology that utilizes laser pulses to measure distances and create detailed three-dimensional representations of the earth's surface. By emitting short pulses of laser light and measuring the time it takes for these pulses to bounce back after hitting an object, LiDAR systems can accurately determine the distance to various surfaces, such as buildings, trees, and the ground. This technology provides information about objects' shape, elevation, and even composition within their line of sight [78].

An airborne or ground-based LiDAR system is employed to collect LiDAR data. The system emits laser pulses and records the time for the reflected pulses to return. Combining these time measurements with the known speed of light can calculate the distance to the objects [79]. Additionally, LiDAR systems often include scanners that allow the laser beam to be directed in multiple directions, enabling the creation of highly detailed 3D point clouds. These point clouds can be further processed to generate digital elevation models and terrain maps or extract information about vegetation density [80]. For example, as shown in Fig. 6, scientists at the UK Center for Ecology and Hydrology (UKCEH) recently reprocessed high-resolution LiDAR data collected by the UK Environment Agency to create this new map of hedgerows. Their development produced the first hedgerow length and height map with this data.

Laser scanning and LiDAR have long been recognized as valuable tools for national biomass inventories. For instance, Rosier et al. [81] developed a workflow using LiDAR data to delineate and characterize hedgerows and tree lines in agricultural landscapes. However, the need for aircraft-mounted systems poses a cost barrier to operational use. A green low-carbon agri-environment scheme (GLAS) and an experimental space-borne laser scanner have been utilized for biomass retrieval. However, its footprint size and acquisition geometry are unsuitable for fragmented landscapes like Western Europe.

Malinowski's research utilizes LiDAR datasets (DK-DEM/Point Cloud) alongside their derivatives to identify and delineate selected landscape components, such as hedgerows, single trees and groups of trees, stone and earth dikes, and ditches [82], similar to the previous EPA study [25]. Airborne Laser Scanning data collected during 2014–2015 in Denmark, featuring 0.15m horizontal precision and 0.05m vertical precision, were employed to generate a normalized digital surface model (DSM) and FieldBlocks, the Danish adaptation of the Land Parcel Identification System (LPIS). Condition assessment requires high-resolution LiDAR derived point cloud data (to derive hedge height, width, and gap). Various methods of how ground-based LiDAR can be used for monitoring hedge conditions have been proposed to date [83], [84].

Also, the SAR X-band has shown promise for estimating forest/hedgerow biomass by deriving above-ground elevation information. Information on the vegetation height is extracted by calculating the difference between the radar-extracted elevation values and the ground surface elevations from an existing digital terrain model (DTM) [85]. Additionally, polarimetric indicators from RADARSAT-2 or TerraSAR-X are valuable for estimating crop phenological stages, height, and biomass [86], [87], [88], [89]. Betbeder et al. [1] conducted a study using SAR imagery to detect hedgerow networks and characterize the heterogeneity of hedgerow canopies. They utilized an object-oriented (OO) method with two polarimetric parameters, single bounce and Shannon entropy, extracted from a TerraSAR-X image. The study compared field measurements of hedgerow canopy heterogeneity with backscattering coefficients and three polarimetric parameters derived from the same image. The findings indicate a high classification kappa accuracy of 0.92 for identifying hedgerow networks and their fragmentation. The high kappa value obtained in this study should be interpreted cautiously due to concerns regarding the suitability of point samples for capturing linear features accurately [90], [91]. The accuracy assessment was based on whether a point intersected with a hedge rather than correctly identifying it as an object. It is crucial to note that a sampling ratio of 50/50 between hedges and non-hedges is not appropriate, as it does not reflect the actual distribution of hedgerows in the study area. The authors highlight that errors may arise from some hedges falling below the pixel threshold and from layover artifacts caused by hedge/sensor orientation. Furthermore, the study did not include the hedges' height, volume, or biomass measurements.

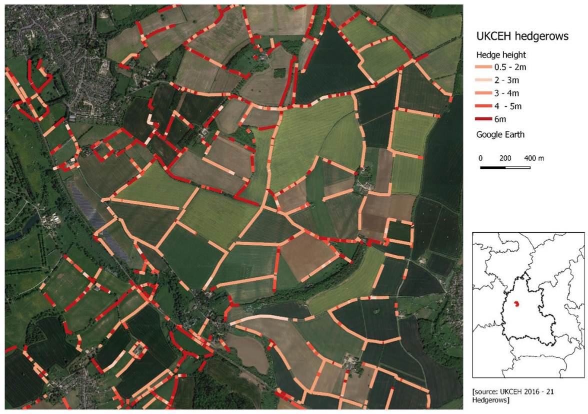


FIGURE 6. The extent and height of woody linear features, including hedgerows, tree lines, and semi-natural thickets of shrubs and trees, on field boundaries in West Oxfordshire, England [94]. This was produced by the UK Center for Ecology and Hydrology (UKCEH) based on the Environment Agency's LIDAR product, captured in 2016-2021, to create a model of woody field boundaries classified by height [95].

A recent literature review examining the constraints of object-oriented classification discovered that OO techniques yielded results that closely aligned with the spatial arrangement of non-forest trees, surpassing visual interpretation. However, pixel-based methods were deemed more precise in generating comprehensive coverage estimates [92], [93]. The authors identified the lack of an accepted accuracy method for OO approaches and recommended "targeted assessment", looking at small sub-rates in an image to see how well the sub-map mirrors reality using patch metrics.

C. RADAR REMOTE SENSING IN HEDGEROWS MAPPING

Radar, an acronym for Radio Detection and Ranging, Radar remote sensing utilizes electromagnetic energy backscattered from ground targets to extract physical and dielectric behavior. The advantage of radar imaging lies in its capability of all-hour and all-weather imaging [96].

Radar systems like SAR emit radio waves, typically in the microwave portion of the electromagnetic spectrum, and analyze the echoes reflected back from objects on the Earth's surface. The radio waves penetrate the atmosphere and interact with the target, causing a portion of the energy to be scattered back toward the radar system. The time the echo returns to the radar receiver provides information about the distance to the target [97]. However, radar remote sensing goes beyond distance measurement. The intensity and phase of the echo carry valuable information about the physical properties of the target, including its surface roughness, composition, and geometry. The data is collected as SAR images, representing the backscattered energy from different targets. By analyzing these properties, SAR can create detailed images or extract specific interest features or maps of the observed area [98], [99].

Radar data acquisition involves transmitting radio waves in a specific frequency band and detecting the echoes using sophisticated receivers. The data is collected as radar images, representing the backscattered energy from different targets. These images can be further processed to enhance the information content or extract specific interest features [99].

As shown in Fig. 7 radar technology operates in various frequency bands, such as X-band, C-band, and L-band, each with its own advantages and trade-offs. For example, lower frequency bands like L-band can penetrate vegetation and soil, providing information about subsurface features [100]. Higher frequency bands like the X-band offer better resolution, allowing the detection of smaller objects or finer details on the Earth's surface [101].

There are several recent reviews of forest biomass estimation in the remote sensing literature. Lu et al. [102] give a general review of all remote sensing methods, but several radar-specific methods have also been published [103], [104]. A radar biomass review by Sinha et al. [105] comprehensively overviews current systems, particularly emphasizing biomass saturation and methods to overcome it. Literature covering the extensive use of C, L, and X-band obtained from satellite platforms (differing wavelength and frequencies) radar data, from fine to coarse resolution, for forest resource monitoring and biomass retrieval. However, more research must be conducted using X-band SAR data to examine Non-forest woody biomass (NFWB). In radar systems, the microwaves' wavelength determines the spatial and geometric properties of the resulting imagery. Forests with high Above-ground biomass (AGB) or a high stem volume are difficult to detect as the sensitivity of the radar backscatter to biomass saturates above a certain point [106], [107].

The level of saturation in biomass observations is influenced by factors such as sensor frequency, polarization, and angle of incidence, as well as the characteristics of the forest itself, including type, structure, and moisture content. Various studies have reported biomass saturation limits ranging from 20 to 200 Mg/ha [108], [109]. Radar

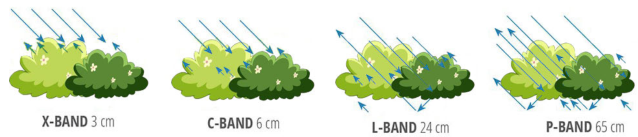


FIGURE 7. The responsiveness of SAR measurements to the configuration of hedgerows and their ability to penetrate vegetation cover at various wavelengths employed in land surface remote sensing observations.

signals at longer wavelengths (e.g., L- or P-band) saturate at higher biomass levels compared to shorter wavelengths like X-band. Decreasing radar signal wavelengths leads to improved spatial resolution, enabling the detection of smaller targets and reducing sensitivity to changes in biomass levels. Although much of the literature on biomass retrieval using radar is concerned with forestry, some literature does exist around mapping heterogeneous wooded landscapes that are applicable. For instance, Betbeder et al. [1] utilized the SAR data from TerraSAR-X, aerial photography, and a SPOT 5 optical image to map species distribution in France. Their research focused on identifying hedgerows using VHSR TerraSAR-X dual-polarization data. They processed the data by employing Shannon entropy and backscattering analysis to classify and extract the hedgerow network based on single and double bounce signals. The accuracy assessment revealed a 92% match for SPOT 5 and a 90% match for TerraSAR-X in identifying the hedgerow network. Recent studies suggest that the saturation phenomenon observed in biomass measurements is not solely due to biomass levels but is also influenced by the forest's structure. Understanding the forest structure may enable the extraction of additional biomass parameters, such as stem density, beyond the saturation thresholds previously reported [110].

1) X-BAND SAR IN HIGH VEGETATION

X-band SAR refers to a specific frequency range in the electromagnetic spectrum in radar systems. This frequency range typically spans from 8 to 12 gigahertz (GHz). Regarding data collection, X-band SAR systems work similarly to other radar technologies. They emit radio waves in the X-band frequency range and receive the echoes reflected by objects in the environment [97]. By analyzing these echoes, X-band radar systems can generate detailed images and maps, providing valuable insights into the observed area. X-band SAR's high resolution and accuracy are beneficial for applications requiring fine-scale observation or detecting small objects, such as aircraft, ships, or vegetation monitoring [111], [112].

In recent years, radar satellite data's spatial and temporal resolution capabilities have improved rapidly. Using extra-high-resolution TSX-SS mode data (0.25 m spatial resolution) will allow for better characterization of NFWB than previously possible with existing sensors and modes. This will be compared with the more established imaging modes (Spotlight and Stripmap) to determine the improvements in using the higher-resolution data [28]. The use of VHSR radar to detect hedgerows and individual trees and to measure their structure is a very recent development, but published work has indicated its success. Betbeder et al. [1] utilized a similar technique to examine the structure of hedgerows using TSX-SS data and concluded that "very high spatial resolution radar images can precisely detect the presence of wooded hedgerow networks and characterize their structure". Current literature strongly suggests that when working with vegetative targets, coherence is unlikely to be achieved when using radargrammetry approaches to estimate elevation data [113].

Literature about woody vegetation/hedgerow mapping via X-band data remains relatively limited yet progressively expanding (with approximately 70+ publications). Some insights can be gained from the literature on mapping Savannah woodlands. Although quite different from typical agriculture, these semi-arid habitats present some aspects of NFWB mapping. One observation, demonstrated in experiments, is that the scattering center (the apparent source of volumetric scattering in a woodland) is lower because of a more significant ground component, and this is increased with the use of high-resolution X-band data [114]. This sensitivity to ground signals could potentially account for the superior performance of L-band data in mapping cover and AGB in barren Savanna woodlands relative to X-band data/methodologies [115]. One of the main obstacles faced when mapping heterogeneous or scarcely wooded environments stems from confounding backscatter signals emanating from landscape constituents. Such effects can be mitigated by selecting appropriate retrieval algorithms, improving spatial resolution, and incorporating priori data on the spatial distribution of targets [116]. VHSR X-band backscatter imagery has successfully mapped hedgerows within conventional image classification frameworks. Betbeder and colleagues [1] implemented an OO classification approach using TerraSAR-X HH/VV (polarization) imagery, achieving 90–92% extraction accuracy for hedgerows.

IV. IDENTIFICATION OF HEDGEROWS IN REMOTE SENSING IMAGERY

In remote sensing, detection refers to the process of recognizing the presence of an object in image, while identification goes a step further by assigning labels or classifications based on features such as spectral and spatial characteristics. Previously, the manual identification and mapping of small and linear woody elements were conducted through visual interpretation of aerial photographs or traditional field-based methods [117], [118], [119]. The reason for advancing this method at the local level was to enhance the understanding of hedgerow conditions through UAV surveys, enabling more informed decisions on hedgerow habitat management and biodiversity conservation due to their ability to cover larger spatial areas compared to traditional ground-based surveys. Previous research has shown that combining data from larger areas with satellite or aerial remote sensing can evaluate hedge connectivity at landscape scales, contributing to better

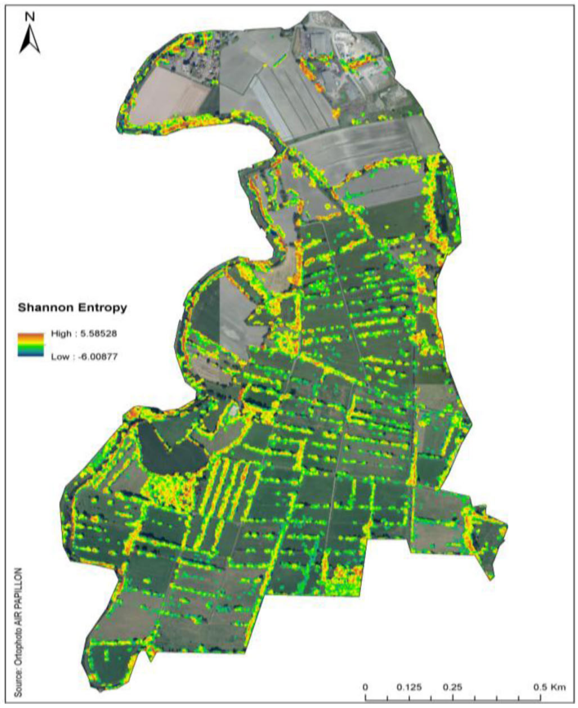


FIGURE 8. Examples of hedgerow map with the Shannon entropy index extracted from the TerraSAR-X image [1].

comprehending the hedge network and its significance [9]. However, this approach was time-consuming and unsuitable for extensive areas [120].

Furthermore, hedgerows were sometimes not adequately represented in spatial databases produced by national mapping agencies or were not categorized appropriately. The cartographic representation of these objects may not always align with user requirements as green features like hedgerows have varying applications. For example, the minimum length required to define a linear object as a hedge may vary based on the species being studied and its dispersal characteristics [31]. For example, an investigation revealed an intriguing disparity regarding the UK National Forest Inventory (NFI). While approximately 90% of trees with canopies taller than 15 meters are documented, merely around half of those ranging from 3 to 15 meters are incorporated into NFI records. This finding underscores a concerning oversight in present estimations of tree distribution, as it disregards smaller or less connected tree, hedgerow, and woodland habitats (THaW) canopies. These neglected habitats constitute a substantial portion of overall THaW habitat coverage, landscape carbon storage capacities, and ecological interconnectedness [121]; and so should be identified, understood, and analyzed. The automatic extraction of hedgerows from remotely sensed images has gained attention in recent years. Remote sensing provides a viable solution for automatically extracting hedges over large areas with an adequate temporal periodicity. Hedges can be identified visually from sensors with a finer spatial resolution, such as SPOT-5, WORLDVIEW, and

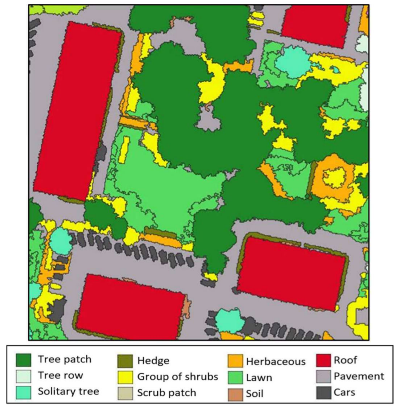
Vision-1. This study investigated the impact of different temporal and spatial resolutions on hedgerow monitoring. Experiments were conducted using data at resolutions of 20m, 10m, 5m, 2.5m, and 50cm. Findings revealed that at 20m spatial resolution, only larger hedgerows and riparian forests were discernible. Classification results demonstrated that 10m resolution was optimal for agricultural and hedgerow applications, enabling the detection of most hedges, forest edges, and thickets. While a 2.5m resolution offered increased precision and detail, it also complicated characterization. Remarkably, the 50cm resolution emerged as the most effective for classification purposes [122].

However, making the extraction of hedges automatic or semi-automatic is problematic because spatially, a hedge is a linear object similar to a road or a path, while spectrally, they closely resemble woody vegetation like forests. Its local contrast with the surrounding objects can also complicate the detection and its position. For instance, city hedges are usually located along roads or connected to house patches. When the target is hedgerows, that literature can be broadly split into two themes: the **detection** of hedgerows and the **characterization** of hedgerows. This review demonstrates that the literature is developing, and technology is outpacing the methodologies needed to use and assess it correctly.

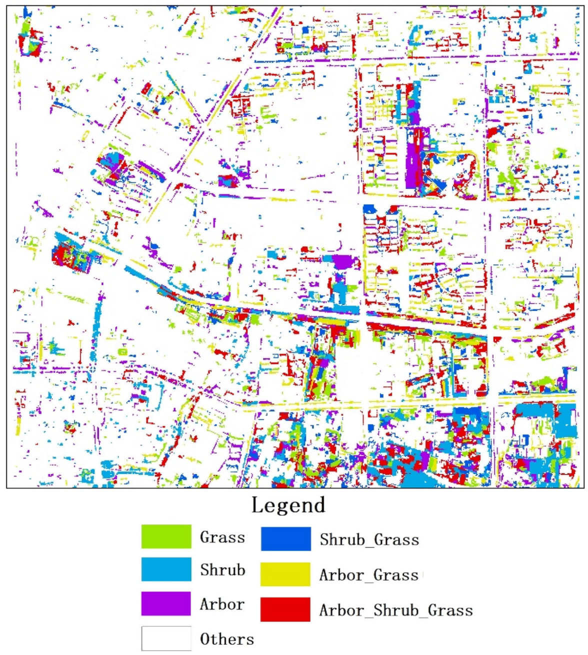
A. CHARACTERIZATION OF HEDGEROWS IN REMOTE SENSING

The two main characteristics of the hedgerows are **"vegetation index"** and **"texture"**. The vegetation index is a simple and effective measurement of the status of surface vegetation, which can effectively reflect the vitality of vegetation and vegetation information. It becomes a necessary technical means for remote sensing inversion of biophysical and biochemical parameters such as chlorophyll content, NDVI (normalized difference vegetation index), RVI (radar vegetation index), FVC (fractional vegetation coverage), LAI (leaf area index), biomass, net primary productivity, and photosynthetic effective radiation absorption [123], [124], [125].

The reflectance spectrum of healthy green vegetation in the visible band is characterized by significant absorption of blue and red light, strong reflection of green light, and intense reflection in the near-infrared band. Various vegetation indices have been developed based on these spectral characteristics to facilitate vegetation remote sensing. Common indices include the radar vegetation index (RVI [126]), differential vegetation index (DVI [127]), normalized difference vegetation index (NDVI [128]), and Leaf Area Index (LAI) [129]. These indices are crucial for assessing vegetation health and density, comparing reflectance in the red and near-infrared bands. The operational bands typically focus on the visible and near-infrared spectral ranges. Obtaining near-infrared spectrum data necessitates high-altitude remote sensing technology. VHSR images offer high resolution,



(a)



(b)

FIGURE 9. Examples of classification map of urban vegetation types taken from [61] and [62], respectively.

detailed texture features, and easy accessibility and contain visible band data.

The vegetation index can accurately distinguish vegetation and non-vegetation. However, the vegetation index of shrubs and herbs is similar, so the vegetation index cannot be used to distinguish vegetation [70]. Discriminating between instances of the "same object, different spectrum" and the "same spectrum, different object" solely based on pixel information in images is challenging [130]. High-resolution remote sensing often yields low accuracy, and single-scale object-oriented segmentation classification methods are susceptible to issues like over-segmentation and under-segmentation [131]. Researchers must rely on their expertise to determine the optimal scale level for object segmentation. Various geospatial techniques have been developed to address these challenges to enhance classification accuracy beyond traditional spectral-based classifiers. These techniques include utilizing textural features [132], fractal analysis [133], spatial auto-correlation, and wavelet transforms [134].

1) TEXTURAL FEATURES

Texture pertains to the visual impact produced by tonal variation in small areas [135]. Textural features provide insights into the spectral variation present in the vicinity of a pixel or within a predetermined object. Various texture statistics can identify unique information and spatial patterns for features that are challenging to differentiate using spectral information alone [136], [137]. Texture has been utilized in several studies to differentiate between high and low vegetation [138], [139] and identify various vegetation types [140], [141]. Even texture derived from SAR backscatter images has proven to be a simple and effective approach that does not require additional data [142]. However, the relative importance of texture decreases when attempting to differentiate vegetation at more detailed levels [143]. For instance, textural information becomes useful for vegetation species mapping only if the spatial resolution of the imagery is sufficiently high [144].

Textural features can be computed in two distinct manners: either within a fixed-size window surrounding the central pixel of the vegetation object or by solely considering pixels that constitute the vegetation object (OBIA) [145], [146]. The former method applies primarily to areas with uniformly vegetated plots, rendering it less suitable for urban settings [59]. Consequently, the object-based approach is generally favored. However, parameterizing a segmentation algorithm or manually delineating vegetation objects can be laborious and may not always significantly enhance accuracy [146].

Since the spectral characteristics of the different species of vegetation in the urban zones are very similar and also present large individual variability, techniques based on textures have been developed. Textures refer to the microstructure pattern (coarseness, contrast, directionality, line-likeness, regularity, and roughness) that characterizes the image [147]. Numerous studies have focused on utilizing texture features in optic, multi-spectral, or hyperspectral imagery for classifying vegetation species, and texture analysis is commonly employed in processing HR images [148], [149], [150]. Incorporating texture has been shown to enhance classification accuracy [151]. Common methods for characterizing vegetation using textures involve color histograms and statistical measures (mean, standard deviation, skewness, kurtosis, entropy, etc.) [152], [153], we present the Shannon entropy index in Fig. 8 that are used to map hedgerows. Two primary techniques for texture extraction based on analyzing pixel neighborhood patterns are Local Binary Pattern (LBP) [154] and Gray-Level Co-occurrence Matrix (GLCM) [132]. More advanced texture methods utilize local invariant descriptors like Speeded-Up Robust Features (SURF) [155] and Scale-Invariant Feature Transform (SIFT) [156].

A classification chain utilizing textures can be integrated with various features derived from remote sensing satellites to enhance classification outcomes. These features include spectral characteristics, vegetation indices, and morphological measurements [157], [158]. In a study by [145], different methods for vegetation classification in multi and hyperspectral images based on texture extraction and Bag of Words (BoW) are compared. These techniques are categorized into codebook-based, descriptor-based, and spectrally enhanced descriptor-based approaches. CNNs can also be used to classify vegetation exploiting textures, but they entail higher computational complexity and longer execution times [159].

2) FRACTAL ANALYSIS

Fractals are essential in remote sensing as they provide valuable information about the structure of objects and surfaces. This information is crucial for object identification, size and shape measurement, and understanding spatial relationships [160]. In remote sensing, fractals have been widely used to study various features such as vegetation, soil, water, and urban areas [133], [161], [162].

Fractal analysis is instrumental in distinguishing between different types of vegetation [163]. By measuring the fractal dimension of leaves, which represents the complexity of a shape, fractal analysis can differentiate between different plant species, each plant species exhibits a distinct fractal dimension, enabling accurate identification and classification [101].

There are several methods available for calculating fractal properties, each with advantages and limitations. These methods include the correlation dimension, fourier transfor lacunarity, multifractal analysis, Isarithm, Triangular Prism, and Variogram [164], [165], [166], [167]. The choice of method depends on the specific application and data being analyzed. For example, the box-counting method is commonly used for calculating the fractal dimension, while the power spectrum method analyzes the spatial frequency of fractal patterns. Lacunarity measures the gappiness or heterogeneity of a fractal pattern, while multifractal analysis provides a more comprehensive characterization of the spatial distribution of fractal objects. These methods can be compared with existing methods such as morphological profiles [168] and gray level Co-occurrence matrix (texture features [132]).

To describe vegetation using fractals, researchers utilized various metrics such as fractal dimension, lacunarity, and spatial frequency [169], [170]. Fractal dimension quantifies the complexity of patterns, lacunarity measures the homogeneity of patterns, and spatial frequency captures the variability of an image at different scales. However, recently, by incorporating these fractal properties into deep learning classification algorithms, it is possible to improve the accuracy of species mapping in remote sensing; in this context, fractal convolution can be seen as a specific technique within the broader field of fractal analysis [171].

In complex environments such as urban areas, distinguishing between plant species based on their spectral characteristics can be challenging due to the high level of spectral heterogeneity. Fractal analysis offers a solution to this challenge by focusing on the structural properties of objects, which are less influenced by spectral variations [172]. This approach provides valuable information that can enhance the accuracy of the classification and interpretation of remote sensing data in such complex settings.

3) SPATIAL AUTO-CORRELATION AND WAVELET TRANSFORMS

Spatial auto-correlation measures the similarity between observations in spatial data [173]. For example, spatial auto-correlation exists when the value of a variable (like a hedge) at a location is correlated with the values of the same variable at neighboring locations due to the underlying spatial processes. There are different methods to quantify spatial auto-correlation. Moran's I calculates the correlation of variates at locations with their average neighbors' values. Geary's C compares the variate of each location with the variate of neighboring locations, Getis-Ord General G measures the concentration of high or low values in a spatial dataset; researchers use these indices to identify spatial clustering and ensure diversity [174].

Wavelet transforms provide an alternative approach to analyze spatial auto-correlation structures [175]. They allow the decomposition of a spatial dataset into components at different scale levels by convolving the original data with wavelet basis functions. Common wavelet transforms used in spatial data analysis include the Haar, Daubechies, and Morlet wavelets [176]. One can detect spatial patterns and anomalies present at specific scale levels by examining the wavelet coefficients. For example, wavelet transforms have been applied to detect anomalies in spatial datasets by identifying locations where high variance exists only at fine scales [176]. They have also been used with spatial auto-correlation indices to perform multi-scale geostatistical modeling and kriging of non-stationary spatial processes [177]. Wavelet-based methods are particularly useful for analyzing geographic datasets with heterogeneous multi-scale spatial correlations [178].

In recent years, there has been a growing focus on multi-scale analysis, leading to the development of numerous methods aimed at investigating the impacts of varying spatial scales [179]. Discrete Wavelet Transform (DWT) is an advanced mathematical method to provide scale and location information for spatial variation [180]. Geographically Weighted Regression (GWR) unveils spatially varying relationships between dependent and explanatory variables, effectively addressing non-stationarity concerns [181]. Researchers have successfully applied GWR to discern the primary influences on NDVI across different scales [174].

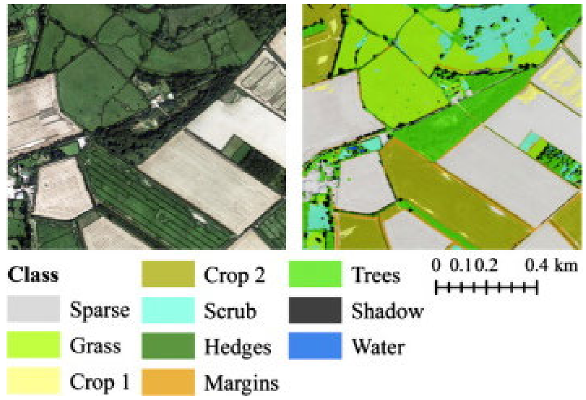


FIGURE 10. An instance of the shadow being used as an incorrect classification in a land-use study [185].

NDVI and topography exhibit scale dependencies, with terrain attributes affecting NDVI differently across distinct research areas [182]. Cross-wavelet analysis is a powerful tool for exploring correlations between two related time series through cross-spectral and wavelet analyses [183], enabling a comprehensive examination of their relationship in the time-frequency domain. Wavelet transforms (WT) are particularly suitable for detailed image analysis, serving as a potent tool for enhancing image details akin to a mathematical magnifier. This extraction capability of wavelet transforms proves valuable in addressing challenges encountered by CNNs, as they can efficiently capture intricate features by adjusting translations and scales. Integrating WT with CNNs allows for the acquisition of rich features. Recent studies have demonstrated the effective integration of Wavelet Neural Networks with diverse interdisciplinary algorithms like fuzzy logic, fractal analysis, and genetic algorithms [176], leading to notable advancements across various applications, notably in vegetation studies [184].

B. DETECTING HEDGEROWS USING AI TECHNIQUES IN REMOTE SENSING IMAGERY

The detection of hedgerows has evolved significantly with advancements in AI techniques applied to remote sensing imagery. Traditionally, hedgerow mapping relied on field surveys, manual digitization from aerial photography, and ground-based observations [186], [187]. For example, Back in 2008, it was reported in [188] that no accurate mapping of hedgerows existed at the landscape scale in the land cover maps of the UKCEH. Mapping every hedgerow across hundreds of 2 km by 2 km landscape sites would have been time-consuming and labor-intensive. At the time, they used digitization from aerial photography as the quickest method available. These methods, while accurate in small-scale or local studies, are labor-intensive, time-consuming, and prone to human error, particularly over large geographic areas. Traditional approaches like boundary maps, DTM, and DSM have been used for national-scale assessments of hedgerows [189], [190]. However, these techniques

TABLE 1. VHSR Satellites with < 1 m resolution.

Satellite	Spatial Resolution	Type of Sensor	launch Time	Operator
KeyHole-1	0.15-1m	Pan	1959	U.S. NRO
Vision-1	0.87m	Pan	2018	Airbus
IKONOS-2	0.82m	Pan	1999	Space Imaging
TripleSat	0.8m	Pan	2015	SDSC
SkySats	0.72m	Pan/MS	2013	Planet Labs
KOMPSAT-3	0.7m	Pan	2012	KARI
KOMPSAT-3A	0.7m	Pan	2015	KARI
QuickBird-2	0.61m	Pan	2001	DigitalGlobe
SuperView-1	0.5m	Pan	2018	TSLC
Pléiades-1A	0.5m	Pan	2011	Airbus
Pléiades-1B	0.5m	Pan	2012	Airbus
THEOS-2	0.5m	Pan	2023	GISTDA
WorldView-1	0.5m	Pan	2007	DigitalGlobe
WorldView-2	0.5m	Pan	2009	DigitalGlobe
WorldView-3	0.3m	Pan	2014	DigitalGlobe.
WorldView-4	0.3m	Pan	2016	DigitalGlobe
GeoEye-1	0.41m	Pan	2008	GeoEye
Pléiades Neo	0.3m	Pan	2021	Airbus
COSMO-SkyMed	1m	SAR (X-band)	2007	ASI
Capella SAR Satellites	1m	SAR (X-band)	2018	Capella Space
Kompsat-5	1m	SAR (X-band)	2013	KARI, TAS-i
TerraSAR-X	0.25-1 m	SAR (X-band)	2007	DLR
ICEYE (Strip mode)	0.5-2.5m	SAR (X-band)	2023	ICEYE
ICEYE (Spot mode)	0.5m	SAR (X-band)	2023	ICEYE
ICEYE (SLEA mode)	1m	SAR (X-band)	2023	ICEYE
PAZ (Spot mode)	0.25m	SAR (X-band)	2018	Hisdesat
CAPSTONE	0.25m	SAR (X-band)	2022	NASA

lack the precision and efficiency offered by modern AI-powered approaches. The advent of AI techniques, starting with algorithms like Random Forest [185], and progressing to deep learning models, has facilitated automated and highly accurate hedgerow detection, thereby transforming the applications of remote sensing.

The accurate detection of hedges through satellite imagery is an intricate task in the field of remote sensing. While hedges may appear similar to forests from a spectral standpoint [28], as discussed, they are linear in nature and can be compared to roads or dirt tracks in terms of spatial perspective. Furthermore, their placement along roads or at right angles to forest edges adds another layer of complexity to their detection. Cutting-edge VHSR remote sensors can capture images that provide both spectral and spatial information, making it possible to automatically detect hedges. There is a growing literature on using optical imagery, whether obtained from satellites, aircraft, or drones, to map the extent of hedgerows [191], [192]. The principal method applied is object-oriented segmentation. In segmentation, groups of contiguous pixels with similar properties are clumped together to create objects. These objects are then classified as a whole rather than being individually analyzed.

The authors in [193] utilized an object-oriented method to automatically identify and detect hedgerow networks in France using a combination of VHSR optical satellites, SPOT 5 and KOMPSAT. The segmentation process involved three hierarchical levels (tree, hedge, and field), and fuzzy logic was used for image classification. The results showed that SPOT 5 images were slightly more accurate than other classifications, with a detection accuracy of 84.5% for small wooded elements and 97% using Kompsat and SPOT 5 images, respectively. This study concluded that the object-oriented approach applied to satellite images with a VHSR of 1 m is a reliable and efficient method for detecting small wooded elements and characterizing hedgerows. To provide readers with specific information about VHSR satellites, we have included Table 1 in this article. This table serves as a valuable addition, allowing researchers, professionals, and enthusiasts interested in satellite imagery and remote sensing to easily identify and compare the capabilities of different VHSR satellites. The table includes details such as the satellite's name, spatial resolution, type of sensor, launch time, and operator. It covers various VHSR satellites from various operators and launch times. The satellites listed in the table include those equipped with panchromatic sensors and those utilizing multispectral and X-band SAR technologies. The spatial resolutions of these satellites range from 0.25-1 meters, providing a comprehensive overview of the available options for high-resolution satellite imagery.

In the UK, a national map of hedgerows was established using national-scale boundary maps, including a DTM and a DSM [190]. The length and height of hedgerows can be estimated by calculating the difference between the DTM and DSM at the boundaries. The study utilized NEXTMap DSM and DTM data with 5 m resolution. In Ireland, national DSM and DTM products with resolutions of 1 meter and 2 meters, respectively, are available from Bluesky2. The model's effectiveness was evaluated by comparing it to woody linear feature data from countryside surveys at different scales. Despite some limitations, this simple approach can provide helpful information about the extent and locations of woody linear features in both local and national contexts [28].

Aksoy et al. [30] utilized a multi-feature and multi-scale approach with a shape-based target detection algorithm to distinguish hedgerow pixels. They extracted hedgerow networks in six locations across three European countries by analyzing spectral and texture data from Quick Bird imagery. The researchers found that their model was successful and could be adapted for detecting natural boundaries of linear objects, including roads, rivers, and paths.

Fauvel et al. [31] utilized a support vector machine (SVM) analysis to detect hedgerows in VHR Worldview-2 images. By incorporating feature orientation, the NDVI, and texture analysis, they could accurately discriminate hedges from other woody elements, such as forests. The results showed that the local orientation was defined as the difference between the morphological directional profile's minimum and maximum. However, there were some false detections of non-woody elements with significant local orientation in the final results. Fauvel et al. [31] utilized a SVM analysis to detect hedgerows in VHR Worldview-2 images. By incorporating feature orientation, the NDVI, and texture analysis, they could accurately discriminate hedges from other woody elements, such as forests. The results showed that the local orientation was defined as the difference between the morphological directional profile's minimum and maximum. However, there were some false detections of non-woody elements with significant local orientation in the final results.

Burnett and Blaschke [194] applied multi-scale segmentation object relationship modeling and segmentation of color orthophotography to identify linear objects in the landscape. To tackle challenges related to heterogeneity, scale, connectivity, and quasi-equilibrium states in landscapes, they proposed a five-step framework employing the hierarchical patch dynamics (HPD) technique. This multi-scale segmentation/object relationship approach predominates linear feature extraction strategies. Hedgerow maps are pivotal in vast-scale ecosystem services investigations and automated techniques for delineating regions of high natural worth [195]. A study by Sheeren et al. [196] utilized a hybrid approach, incorporating aerial photography alongside ancillary coarse-resolution datasets, to distinguish minute wooded elements systematically. Firstly, the extraction of wooden elements was accomplished via textural analysis, which proved efficient in isolating wooded elements from orthophotos without confounding them with other classes sharing comparable pixel values (such as grasslands and crop fields). In contrast to the traditional per-pixel classification approach, the hybrid method allows for incorporating spatial and relational features in the classification process.

Tansey et al. [40] also used object-oriented classification of VHR airborne imagery in the UK to extract hedgerows. Despite successes, some criteria for defining hedgerows remained elusive. Object/segmentation approaches were consolidated in a study by O'Connell et al. [185], where a rural region of the UK was mapped with high-resolution airborne data, processed, segmented, and classified through a Random Forest model. Generally, the performance was good for all selected classes, with hedgerow achieving 77% production accuracy. Nonetheless, the paper's credibility is diminished by incorporating **shadow** as a land cover class. Though shadows are indeed present and extracted in the segmentation process, they are not actual land covers/uses.

Consequently, pixels labeled as shadows are erroneously classified for land-use studies, as shown in Fig. 10, many shadows are linked to hedgerows. As a consequence, the true user accuracy for the hedgerow class is probably far lower than reported. Ultimately, the outcomes from these studies indicate that the declared precisions must be handled cautiously and that the methods typically recognize parts of hedgerows rather than entire ones. Therefore, an automated and cost-effective approach would be preferred for regional monitoring of hedgerows. Automated hedgerow mapping from aerial or satellite imagery has focused on random forest or support vector machine methods using object-based image analysis (OBIA) [30], [31], [40], [185], [193], [197]. OBIA allows for incorporating object features such as size, shape, or context regarding neighboring objects. Although increased inclusion of features has been shown to improve hedgerow detection [30], [31], [185], [197], the lack of transferability of features across study sites limits the capacity of OBIA approaches [30], [193], [197]. This lack of transferability means that the features that worked well in one study site do not perform as effectively in another site. The reasons behind this could be variations in environmental conditions, different tree species compositions, or other factors specific to each location. As a result, the OBIA-approach's capacity to accurately classify and map the hedges in different study sites is limited.

Furthermore, manually designed features may be over-specified, incomplete, and time-consuming in design and validation [198]. Using manually engineered features is thus one of the main drawbacks of an OBIA approach for hedgerow mapping [30], [193], [197], [198]. To facilitate non-experts' ability in feature engineering and remote sensing to perform automated hedgerow mapping, the overhead of feature engineering must be reduced.

1) HEDGEROW DETECTION WITH DEEP LEARNING

In order to accurately map vegetation, manual labeling of training samples is often required to provide ground truth or masks. However, some studies utilize existing datasets like small woody features (SWF) [199], [200], [201] obtained from the Copernicus Land Monitoring Services.[1] The SWF dataset includes a raster layer with a spatial resolution of 5 m/pixel and a vector layer that classifies woody features into linear, patchy, and additional features. Additional features refer to those that do not fall into the linear or patchy categories but contribute to the connectivity of other features or represent isolated features with an area larger than 1500 m^2. The latter are features that are, according to the rules, neither linear nor patchy but enhance the connectivity of other features or represent isolated features with an area larger than 1500 m^2.

In recent years, deep learning (DL) models, particularly deep neural networks, have significantly improved semantic image segmentation compared to previous methods. Many DL-based approaches for semantic image segmentation utilize end-to-end CNNs, such as the fully convolutional network (FCN) [202], to classify individual pixels into predefined semantic classes. These models typically consist of an encoder-decoder architecture [203], [204], [205], where the encoder compresses the input image into a latent representation using a backbone feature extractor often a pre-trained CNN on a large dataset such as ImageNet [206]. The decoder reconstructs from the latent representation a segmented image of original size through a series of up-sampling operations and a final pixel-wise classification Encoder-decoder architectures have been successfully employed for vegetation mapping using both UAV [207], [208] and VHR imagery [209]. Further improvements have been made by incorporating dilated separable convolutions [210] and channel attention mechanisms [211]. Currently, DeepLab v3+ (for semantic segmentation) [210], [212], [213] and Mask R-CNN (for instance segmentation) [214], [215] are state-of-the-art models for their respective tasks and are openly available through public repositories as shown in in Fig 11.

When applying pre-trained networks to remote sensing data, there are restrictions on the input data, as pre-trained networks are typically trained on three-band images. Additionally, limited training data in remote sensing can lead to network overfitting, which can be mitigated through data augmentation techniques. A common technique used to offset small dataset sizes is data augmentation. Here, the original images are modified (*e.g.*, rotated and scaled) in order to increase the size of the dataset [159] and avoid overfitting

[1] https://land.copernicus.eu/pan-european/high-resolution-layers/small-woody-features

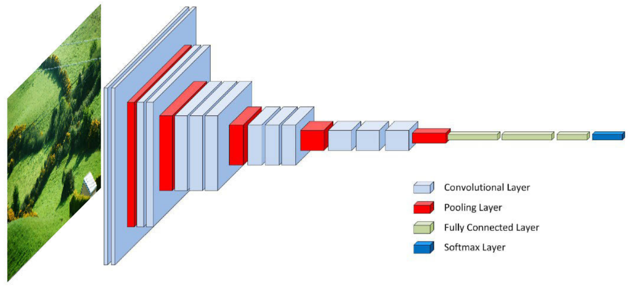


FIGURE 11. Example of the architecture of CNNs.

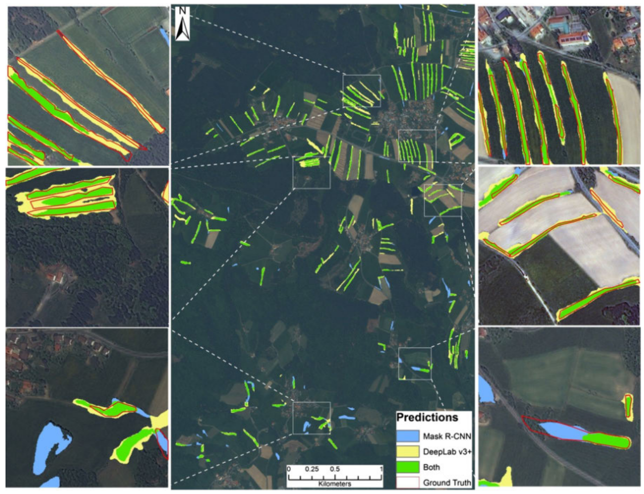


FIGURE 12. Map showing hedgerows detected with a CNNs algorithm at a landscape scale [68].

[216]. However, choosing the appropriate data augmentation strategy depends on the dataset and prediction targets, as an improper choice can negatively impact network predictions [217], [218]. While FCN and R-CNN architectures have been successfully applied to vegetation classification [219], [220], this presents an opportunity as these specific applications for hedgerow detection have not been extensively explored.

Nonetheless, studies have demonstrated the effectiveness of alternative FCN and R-CNN architectures for vegetation classification, and Mask R-CNN has shown superior performance compared to FCN in tree canopy segmentation tasks [221], with the downside being that Mask R-CNN required longer training time. While both networks have demonstrated exceptional accuracies on classification datasets like COCO (Microsoft Common Objects in Context) [222], this remarkable performance does not consistently transfer when these networks are utilized on novel datasets [221]. One contributing factor is linked to the accuracy of annotations employed during network training, as the precision of annotations has been revealed to impact network performance [223]. Creating the COCO dataset included multiple quality checks to ensure precise object annotations [222]. However, monitoring agencies often lack the resources to invest in precise dataset annotations, resulting in poorly annotated datasets from which the network must learn.

TABLE 2. Strengths and weaknesses of sensors.

Sensors	Strengths	Weaknesses
LiDAR	High-resolution 3D data	Costly
	Accurate estimation of vegetation structure	Limited availability
		Sensitivity to vegetation density
SAR	All-weather and day-night imaging	Limited spatial resolution
	Penetration through vegetation	Complex data interpretation
Hyperspectral	Fine spectral resolution	High data dimensionality
	Discrimination of vegetation types	Limited availability of sensors

TABLE 3. Strengths and weaknesses of techniques.

Technique	Strengths	Weaknesses
Object-based Image Analysis	Ability to capture spatial context	Relies on accurate image segmentation
	Suitable for complex landscapes	Sensitivity to parameter settings
AI Algorithms	Ability to learn complex patterns	Reliance on training data
	High accuracy	Limited interpretability

In 2021, Ahlswede et al. [68] explored the applicability of high-performance DL networks for remote sensing object detection using real-world datasets. Considering the challenges faced in implementing OBIA approaches and their poor performance across different study areas, this work aims to systematically evaluate the potential of pre-trained neural networks for accurate and precise hedgerow detection. The study compares the performance of Mask R-CNN and DeepLab v3+ networks. It investigates optimal data inputs for fine-tuning the networks, including the optimal three-band combination, seasonal imagery, and data augmentation strategies. The study demonstrates the scalability of neural networks for hedgerow detection using IKONOS 1-m data. This presents another opportunity to use DL methods in this context, which is still novel and relatively unexplored in hedgerow mapping from satellite imagery. There have been notable advancements in aerial and satellite image segmentation in recent years. These advancements include applying transfer learning from high-resolution satellite datasets [198], which allows leveraging pre-existing knowledge to improve segmentation accuracy. Another approach involves using ensembles of segmentation neural networks [224] to enhance the overall performance by combining multiple models. Hybrid architectures [4], [225], have also been explored, combining different neural network components to benefit from their respective strengths.

To address the classification challenges associated with easily confused classes, adaptive CNNs have been developed [226]. These adaptive CNNs alter their classification strategies based on the specific characteristics of the classes, leading to improved accuracy. Deformable convolutions [227], [228] have also been introduced to adjust the receptive field of the network to accommodate geometric deformations in shape and size, allowing for more precise segmentation. In addition to these techniques, graph neural networks (GNN) have emerged as an alternative approach for image segmentation in remote sensing [229], [230], [231]. GNNs operate on graph nodes constructed from an image in a preprocessing step, enabling them to capture spatial relationships and dependencies between image elements. This approach has shown promising results in remote sensing image segmentation tasks [62]. Specifically, graph convolutional networks (GCNs) are a type of GNN that can process graph-structured data directly. In remote sensing image segmentation, a graph representation is constructed by treating each pixel as a node and connecting adjacent pixels through edges. By utilizing GCNs, information can be propagated through the graph, enabling the capture of spatial dependencies and ultimately enhancing the accuracy of segmentation [232], [233].

Attention-based transformers have also gained attention, either replacing or supplementing the backbone CNN in segmentation architectures [234], [235], [236], [237]. Attention-based transformers are inspired by the Transformer model, which has been highly successful in natural language processing tasks. These transformers excel at capturing long-range dependencies in images and improving the modeling of complex spatial relationships. By leveraging self-attention mechanisms, they can assign different weights to different image elements, allowing them to focus on essential regions and effectively process contextual information [238]. When applied to remote sensing image segmentation, attention-based transformers have demonstrated the ability to enhance the accuracy of segmentations by effectively capturing global spatial dependencies and incorporating them into the segmentation process [239], [240]. This newer approach shows promise in overcoming some limitations of traditional CNN-based segmentation methods in remote sensing applications.

These recent advancements demonstrate the ongoing efforts to enhance aerial and satellite image segmentation techniques. By incorporating transfer learning, ensemble methods, adaptive CNNs, deformable convolutions, graph neural networks, and attention-based transformers, researchers are pushing the boundaries of segmentation accuracy and paving the way for improved remote sensing applications.

V. CONCLUSION

A. WEAKNESSES AND CHALLENGES IN HEDGEROW MAPPING

The hedgerow mapping field faces several weaknesses and opportunities, as we have shown in this review particularly in OBIA, deep learning, and texture analysis. Despite the existing challenges, we have compared the weaknesses and strengths of remote sensing sensors and existing methods in Table 2 and Table 3. One significant challenge in hedge detection is the absence of a standardized reference dataset. This gap hampers the evaluation and comparison of algorithms, making it difficult to assess the performance of various methods and establish consistent standards. As observed in the literature review, the lack of a standard benchmark impedes the seamless comparison of results across different approaches. To address this issue, there is a pressing need to develop a comprehensive and publicly accessible reference dataset specifically tailored for hedgerow detection. Such a dataset would enhance the comparability of research findings, foster collaboration, and accelerate progress in the field.

As noted in the review, traditional field-based methods for detecting and characterizing hedgerows are often time-consuming, subjective, and prone to human error. This limitation highlights the need for more automated and objective techniques. Machine learning approaches, OBIA and texture analysis, offer potential solutions, but they also come with their own challenges.

For instance, the review highlights that in OBIA, relying on manually engineered features can be a bottleneck. Developing feature sets that are robust, generalizable, and transferable across different study sites is a complex task. It requires expert knowledge in feature engineering and remote sensing and considerable time and resources. Overcoming this challenge would make the OBIA approach more efficient, automated, and cost-effective.

Similarly, the review shows us that DL methods, on the other hand, offer promising avenues for hedgerow Mapping. However, their application in this field is still relatively limited. DL models require large amounts of labeled data for training, which can be scarce or unavailable for specific study areas. Additionally, the complexity of deep learning architectures and the need for computational resources pose challenges for their practical implementation.

Texture analysis, another technique widely used in remote sensing, is also limited. While it can capture fine-grained details and patterns in images, accurately identifying and characterizing hedgerows solely based on texture features can be challenging. Vegetation density, species composition, and management practices can introduce variations that affect the reliability and accuracy of texture-based analysis.

Addressing these weaknesses and challenges in hedgerow mapping requires ongoing research and development efforts. It involves the creation of standardized reference datasets, the exploration of more automated and robust feature sets, the refinement and adaptation of DL models, and the integration of complementary techniques along with selecting the required remote sensing sensor. By overcoming these challenges, researchers can enhance hedgerow mapping methods' accuracy, efficiency, and reliability, supporting better understanding and management of these important ecological features.

B. FUTURE DIRECTIONS AND POTENTIAL DEVELOPMENTS IN HEDGEROW MAPPING

Developing standardized mapping protocols for detecting hedgerows is essential to guarantee uniformity and comparability among various research endeavors. These guidelines should cover crucial elements like hedgerow definition, data collection techniques, and accuracy evaluation methodologies. Standardization enables dependable comparisons and meta-analyses of hedgerow investigations. The field of hedgerow detection is continuously evolving, driven by advancements in remote sensing technologies and computational methods in machine learning and computer vision. As researchers strive to overcome the challenges associated with accurately detecting and characterizing hedgerows in complex environments, several future directions and potential developments emerge:

1) Integration of multi-source data: A promising direction is the integration of diverse data sources, such as satellite imagery, aerial photography, LiDAR data, and ground-based measurements, which we showed in Section III. By combining data from various sources, researchers can leverage the complementary strengths of each data type, leading to improved accuracy and reliability in hedgerow detection. This integration can help overcome the limitations of individual data sources and provide a more comprehensive understanding of hedgerow characteristics.
2) Fusion of VHR optical and SAR data: The fusion of optical and radar data presents an exciting opportunity for hedgerow detection. Optical data can provide detailed information about spectral properties and vegetation structure, while radar data can penetrate through vegetation, offering insights into hedgerows' vertical structure and biomass. Integrating these data modalities can lead to a more comprehensive understanding of hedgerow characteristics. This integrated approach can improve the accuracy and reliability of hedgerow detection algorithms by capturing a wider range of features and characteristics associated with hedgerows.

3) Texture analysis with SAR data: SAR data offers unique capabilities for hedgerow detection due to its sensitivity to surface roughness and backscatter properties. Texture analysis techniques, such as gray-level co-occurrence matrix (GLCM) and wavelet transforms, can be applied to SAR imagery to extract textural information related to hedgerow characteristics. These textural features can complement other data sources and improve discrimination between hedgerows and surrounding land cover types. Incorporating texture analysis with SAR data can enhance the accuracy and robustness of hedgerow detection algorithms in diverse environmental conditions. For instance, Luo and Mountrakis [241] demonstrated that using texture information from Landsat imagery increased the classification accuracy by at least 3.6%.
4) Advanced machine learning techniques: The application of advanced machine learning techniques, particularly deep learning algorithms such as CNNs and Mask R-CNN, hold great potential for enhancing hedgerow detection. These algorithms can effectively extract complex features and patterns from remote sensing data, enabling more accurate identification and characterization of hedgerows. In our detailed discussion of deep learning in Section IV, we explored how these models improve the reliability and automation of detection algorithms, resulting in enhanced precision and detailed analysis. Additionally, image captioning techniques can further enhance this process by generating detailed descriptions of hedgerow characteristics such as describe of height, length and etc, supporting automated monitoring and urban planning efforts.
5) Automated image captioning: Image captioning techniques, combining computer vision and natural language processing, can provide detailed descriptions of hedgerows based on remote sensing images. By automatically generating textual descriptions, these techniques can assist in data interpretation, enabling efficient analysis and decision-making in land management and conservation efforts [242]. This approach can make the results more accessible and facilitate communication between researchers, land managers, and policymakers.
6) Long-term monitoring and change detection: Temporal monitoring and change detection of hedgerows are essential for assessing their dynamics and evaluating the effectiveness of conservation measures. Integrating time-series data and developing automated algorithms for change detection can provide valuable insights into hedgerow dynamics and support adaptive management strategies.
7) Citizen science and crowd-sourcing: Engaging citizen scientists and leveraging crowd-sourcing platforms can significantly contribute to hedgerow detection efforts. Involving the public in data collection and validation processes allows for the collection of large-scale and geographically diverse datasets, fostering collaborative research and enhancing the accuracy of hedgerow mapping like: "TreeSnap" an APP developed by The University of Tennessee Forest Resources Research & Education Center that allows users to photograph and map trees, contributing to a comprehensive database for tree identification and monitoring [243]. "iNaturalist", a platform where users can upload photos of trees and other organisms, which are then verified by experts and added to a global biodiversity database [244]. "Treezilla" is a citizen science project in the UK that aims to map and measure urban trees using crowd-sourced data to better understand the benefits of urban forests [245].

The review of remote sensing technologies for hedgerow monitoring highlights the importance of accurately detecting and characterizing hedgerows, especially in urban environments. Hedgerows play a vital role in maintaining biodiversity and ecological balance in urban environments where they are importance in providing food resources, habitats, and movement corridors for wildlife, as well as their role in connecting landscapes and contributing to halting biodiversity decline and addressing climate change.

This review underscores the advantages of using remote sensing in detecting hedgerows, including monitoring large areas and providing valuable data for conservation and management purposes.

Overall, the review highlights the importance of preserving and conserving hedgerows, which is paramount to advancing global aspirations such as sustainability objectives and the United Nations Sustainable Development Goals. It also emphasizes the need to enforce and monitor regional, national, and international regulations to prevent the ongoing loss of biodiversity and the services and natural capital supported by biodiversity.

However, we note that hedgerows can vary significantly in structure at both the tree and hedgerow scales, depending on the landscape, making it challenging to detect and characterize them using remote sensing. As a result, we have identified the need for standardized terminology and criteria for defining hedgerows, which would facilitate comparing and integrating the results from different studies.

The review highlights that remote sensing technologies, combined with deep learning algorithms and image captioning techniques, offer promising hedgerow detection and monitoring solutions. However, the complexities of urban landscapes and their unique challenges for automatic hedgerow detection must be addressed.

In conclusion, future directions and potential developments in hedgerow detection involve integrating multi-source data, advanced machine learning techniques, optical and radar data fusion, automated image captioning, standardized mapping protocols, long-term monitoring and change detection, citizen science, and crowd-sourcing. By exploring these avenues, researchers can advance the field and improve our understanding of the ecological importance of hedgerows, supporting sustainable land management practices and biodiversity conservation.

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