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Field Margin Quantification and Characterization Using Very High Resolution Multisource Geospatial Data in Wallonia, Belgium

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List of Acronyms

CAP	Common Agricultural Policy
CHM	Canopy Height Model
CNN	Convolutional Neural Networks
DEM	Digital Elevation Model
DSM	Digital Surface Model
DTM	Digital Terrain Model
EODHaM	Earth Observation Data for Habitat Monitoring
EU	European Union
FN	False Negatives
FP	False Positives
FHD	Foliage Height Diversity
GSA	Geospatial Aid Application System
ICA	Independent Component Analysis
LiDAR	Light Detection and Ranging
LPIS	Land Parcel Identification System
MESH	Effective Mesh Size
MPI	Mean Proximity Index
nDSM	Normalized Digital Surface Model
NDVI	Normalised Difference Vegetation Index
NIR	Near-infrared
NP	Number of Patches
OBIA	Object based Image analysis
OA	Overall accuracy
PICC	Plan Informatique de Cartographie Continue
R-CNN	Region-based Convolutional Neural Network
RGB	Red, Blue, Green
RMSE	Root Mean Square Error
SPW	Le Service public de Wallonie
SIGEC	Système Intégré de Gestion et de Contrôle
TIN	Triangulated Irregular Network

TN	True Negatives
ToF	Trees Outside Forest
TP	True Positives
UAV	Unmanned Aerial vehicle
VHR	Very High Resolution

1. Introduction

Field margins are permanent or semi- permanent habitat features that contribute significantly to farmland heterogeneity, connectivity, and are widely recognized as biodiversity hotspot within a simplified agricultural system (Poschlod & Braun, 2017). In rural and peri-urban regions, these spaces comprise of hedgerows, ditches, grass strips and other semi-natural linear or patch elements. These in-between areas can play critical role in ecological resilience by enhancing the habitat connectivity, supporting the biodiversity and mitigating fragmentation by linking fragmented urban and rural landscapes (Baudry et al., 2000).

Belgium has a highly fragmented landscape, with around 84% of its area classified as highly fragmented habitats and an average habitat size of less than 0.02 km² (European Environment Agency, 2022). In Wallonia, Belgium, the gradual urban expansion has created a heterogenous landscape where agriculture land, settlement clusters and semi-natural features are interwoven. This mosaic structure elevates the presence of field margin and increases the fragmentation pressure around rural peri-urban zones (Mustafa et al., 2017). Fragmentation pressure describes the combined consequences of habitat loss and isolation, which can progressively lower population size and viability over time, frequently in a non-linear way that may not show up for many generations. Fragmentation pressure, in simple terms, occurs when rural landscapes are divided into smaller patches which increases competition for resources and causes habitat loss. Under these circumstances, identifying and characterizing these elements is essential to understand its ecological importance.



Figure 1.1: Examples of field margin types in agricultural landscapes of Wallonia, Belgium: (a) margin adjacent to a paved road; (b) margin along an agricultural track (credit: Prof. Pierre Defourny); (c) dry ditch with grass-covered embankments; (d) water-filled ditch with vegetated banks (credit: Farm Wildlife).

2. Literature Review

This chapter reviews the current scientific knowledge on agricultural field margins and recent developments in geospatial approaches for their mapping, characterization, and functional landscape analysis.

2.1 Field Margins in Agricultural Landscape

In most European intensively managed farming systems, the uncultivated linear features present in the landscape form field boundaries, boundary strips, and crop edges defined as field margins (Greaves & Marshall, 1987). The boundary may be a fence, shelterbelts of trees, hedge, wall, ditch, grass strip, or a combination of these types. Sometimes this boundary can be another habitat, like woodland. Field margins exist in enclosed agricultural landscapes. Also in the arable land, field margins delineate the field edge and land ownership. Field margins provide habitat and food for wildlife (Cederbaum et al., 2004), helps in conservation of native flora (Cœur et al., 2002) and reduce runoff, erosion and pesticide drift (USDA, 2000). Besides, the structural complexity and compositional heterogeneity of these field margin habitats significantly influence their capacity to support diverse flora and fauna, thus contributing to the overall connectivity of a given landscape. In rural areas, these spaces consist of hedgerows, scattered trees, and other pieces of uncultivated ground, and despite being often fragmented, they contribute substantially to landscape heterogeneity and ecological function (Mercier, 2021). Maintaining functional connections among these habitats across landscapes is crucial for survival and resilience among numerous populations. This heterogeneity of field margin incorporates biodiversity, offering critical refugia and corridors to many species. Structural diversity within such field margin elements, such as different heights or densities of vegetation, further enhances the ecological value by offering a wider array of microhabitats and resources (Kissling et al., 2017). The hedgerows, ditches, grass margin and trees outside forest are some of the important features of the field margin.

2.1.1 Hedgerows

Hedgerows areas are part of agroecosystems and play an important role in ecological processes, including biodiversity conservation and the provision of ecosystem services (Morin, 2022). The hedgerows, a prominent feature in Wallonian field margin vegetation, are very important in the overall ecological network, acting as conduits for species movements and providing the essential habitat structure (Allard et al., 2023). In other words, long, linear strips of woody vegetation mostly define boundaries between agricultural parcels, offering both shelter and grounds for wildlife to forage on. Such linear landscape elements are critical for maintaining ecological connectivity, especially in fragmented agricultural landscapes where they function as crucial ecological corridors and refugia for diverse taxa (Morin, 2022). Their complex internal structure, often characterized by multiple layers of vegetation, provides better biodiversity support compared to isolated trees or single-species plantings (Dufflot, 2013). Moreover, hedgerows embody stable habitats amidst agricultural matrices, which support several ecosystem functions such as pollination, pest control, carbon sequestration, and soil protection (Boinot & Alignier, 2022). Beyond these, they are also considered key biodiversity reservoirs, supporting metapopulations and facilitating the necessary gene flow for the survival of species (Rolland, 2020).

2.1.2 Grass Margins

Grass margins have potential ecological benefits and provide a positive impact on the farmland biodiversity being shown among the different range of taxa and species of flora (Cordeau et al., 2011) and fauna (Cordeau et al., 2012). In arable lands they enhance ecosystem services like pest control and soil fertility. Smith et al.'s (2008) study showed that the grass strips in the margins of the arable field will increase the soil macrofauna biodiversity both within and across the field. Grass margins have a positive effect on the hedge bottom vegetation by increasing the species richness (Moonen & Marshall, 2001). By decreasing runoff and raising the rate of soil infiltration, this vegetation prevents soil erosion. The pollinators had good feeding habitat in this non-crop habitat created by natural regeneration.

2.1.3 Ditches

Field margins often include ditches, which play an important role in regulating the water flow in agricultural landscapes. These ditches function as water channels but also as ecological habitats consisting of water courses, bottom substrate, bank slopes, and nearby vegetated margins (Herzon & Helenius, 2008). In many European agricultural systems, ditches are commonly distributed across fields. These networks within the cultivated catchment play an major role in regulating functions such as i) improving the transfer

of water and soluble nutrients from the field, ii) nutrient cycling and water retention, iii) modifying the erosion rate and transfer of soil-bound nutrients, and iv) supporting pest control. The relative importance of ditches depends on the availability of other non-cropped and wet structures like natural (wetland) and man-made (pond) habitat in the farmland. Most studies simply address margins; however, some offer information on the relative abundance and presence of species in ditches compared to other ecosystems (Biggs et al., 2007). These elements are the only non-cropped or moist ecosystems left in some heavily managed agricultural areas. Although ditches close to heavily maintained fields typically have poor quality, with the right management, their biological value can be increased. In homogeneous agricultural landscapes, even non-cropped elements, even species-poor ones, may contribute comparatively more to the overall species pool than in correspondingly diversified ones (Herzon & O'Hara, 2006). Animals and plants that are absent from farmland habitat are supported by ditches (Armitage et al., 2002).

2.1.4 Trees Outside Forest (ToF)

Complementary to these linear networks are the Trees Outside Forest (ToF) elements—small woodlots and scattered single trees that besides providing supplementary habitat and connectivity, are fundamental contributors to climate mitigation and soil and water protection, as well as the defense of agricultural crops (Bazzato et al., 2022). Altogether, this network, involving hedgerows and scattered trees, constitutes the green infrastructure that gives the landscape extra permeability and supports a high variety of ecological processes in agricultural areas (Roux et al., 2008). This field margin vegetation can mutually enhance the resilience and ecological stability of agroecosystems through an increased range of supported species and ecological functions (Lameed, 2012; Jumeau, 2017). They also support important ecosystem services, such as carbon sequestration, flood control, and microclimate moderation, among others, which will be instrumental in responding to climate change (Shetti et al., 2022). Therefore, the need for conservation and strategic expansion of these kinds of non-forest woody vegetations is crucial for improving biodiversity, fostering ecosystem services, and promoting sustainable land management in agricultural contexts (Diviaková, 2018). This framing in terms of green infrastructure accentuates the need for effective quantification and characterization of those elements of field margin for the purposes of proper conservation policy and land use planning (Rossi et al., 2015). The diverse interstitial rural mosaic enhances together landscape permeability and supports a high number of ecological processes within agricultural areas. This emphasizes the need for strong spatial quantification of methods that would capture complexity and distribution of these important landscape components, informing targeted conservation efforts and sustainable agricultural practices.

2.2 Field Margin as a Components of European Green Infrastructure

Several European countries have included explicit hedgerow protection as part of their Good Agricultural and Environmental Conditions requirement, recognizing their ecological value and encouraging their protection. Hedgerows also contribute to the broader EU biodiversity policy under the EU 2030 Biodiversity Strategy, which highlights enhancing habitat connectivity through rural landscapes, as well as the Natura 2000 network. Reliable information about the location, extent, and temporal changes of hedgerows is crucial for the guarantee of legality, guiding agricultural subsidies, and informing monitoring schemes.

Under the environment target plans of the Common Agricultural Policy (CAP) for 2023–2027, farmers are rewarded for enhancing ecological connections and making room for nature on agricultural land (European Commission, 2023). Agricultural regions that preserve or include additional landscape elements that are acknowledged as essential components of agricultural production systems will receive support. Farmers shall preserve and safeguard non-productive areas including hedges, ditches, trees, and fallow land on at least 3% of their arable land as part of the improved fundamental criteria. This might result in more than 3 million hectares of unproductive features and regions, which is far higher than the approximately 1.9 million hectares of unproductive features and areas that were identified as ecological emphasis areas prior to 2023.

Setting these landscape features in their wider context of green infrastructure underlines the urgent requirement for methods that allow field margins to be effectively quantified and characterized for sound conservation policy and spatial planning (Rossi et al., 2015). Hedgerows, tree lines, and other semi-natural components forming the heterogeneous rural mosaic enhance landscape permeability and support various ecological processes. The need for spatially explicit high-resolution mapping techniques that can capture the distribution, structure, and complexity of these features to inform targeted conservation strategies and support sustainable agricultural management is further highlighted by the growing relevance of hedgerow mapping and monitoring for ecosystem service assessment beyond regulatory purposes. Recent studies have pointed out their potential contribution to biomass and carbon storage both aboveground and in soils (Tresise et al., 2021). This interest has encouraged several countries to introduce incentive-based initiatives: for example, France has set up a hedgerow management and certification scheme to increase carbon sequestration (Association Française Arbres Champêtres et Agroforesteries, 2024; ENRD, 2022), while Belgium is actively encouraging the planting of new hedgerows (SPW, 2022). More specifically, the Walloon Region in Belgium implemented the “Yes We Plant” program, which supported large-scale hedgerow and tree planting through

financial incentives and stakeholder participation to improve biodiversity in rural areas (SPW Agriculture, Natural Resources and Environment of Wallonia, 2020–2024). This program was able to achieve its planting targets earlier than expected, after which the first phase of the initiative ended, while other supportive programs continued under the new regional policies.

The case for the integration of hedgerows and other linear woody elements into rural Green and Blue Infrastructure planning is further reinforced by findings from recent empirical and meta-analytic studies. Evidence from multifunctionality assessments has shown that hedgerows, grass strips, and extensive grassland management can simultaneously enhance a wide range of regulating ecosystem services such as soil carbon sequestration, water quality regulation, erosion control, and natural pest suppression, while supporting richer plant and arthropod communities (Van Vooren, 2018). These benefits commonly co-occur with localized trade-offs in provisioning services, such as reduced crop yield in the immediate vicinity of hedgerows, emphasizing the need for carefully designed and context-specific implementation strategies. Complementary research on carbon dynamics reveals that hedgerows are among the most carbon-dense agroforestry features in European farmland, with substantially higher SOC stocks than adjacent fields or grass strips, and that the widespread removal of hedgerows since the 1960s has resulted in significant carbon losses back to the atmosphere (Van Den Berge et al., 2021). These findings provide strong quantitative justification for hedgerow conservation as a climate mitigation measure. At the same time, ecological studies demonstrate that hedgerows can function as reproductive source habitats and dispersal corridors for forest herb species across large spatial scales (Vanneste et al., 2020). This emphasizes their essential role in maintaining landscape permeability and supporting long-term species persistence under environmental change. Together, these studies converge on a consistent conclusion: hedgerows and related semi-natural elements are multifunctional landscape infrastructures whose conservation and strategic restoration can simultaneously address climate, biodiversity, and agricultural sustainability objectives.

2.3 Multi-Source Geospatial Approaches for Vegetation Structure, Connectivity, and Functional Landscape Analysis

Very detailed maps ranging from 1:1000 to 1:10,000 are required to accurately delineate landscape elements, and PICC vector, landcover data can be used in conjunction with LiDAR to provide a comprehensive understanding of landscape elements due to their ability to delineate distinct spatial boundaries and classify vegetation types across broad areas. Optical and microwave remote sensing techniques further enrich this dataset by

offering spectral and structural information that is important to differentiate vegetation characteristics and health (Thompson et al., 2023). High-resolution data such as Lidar often reveal fine-scale landscape features, such as single trees, hedgerows, and tree lines, which are critical for biodiversity but are often overlooked by lower or medium resolution satellite imagery (Pazúr et al., 2021).

LiDAR operates by emitting laser pulses towards the ground and measuring distances and generates highly accurate three-dimensional maps of the earth surface. The returned laser pulses after hitting object are recorded as dense collection of data points that represent 3D structure of the scanned area called as point clouds. The point cloud is processed to classify points into categories like ground, vegetation, and buildings. This processed data is used to create various models like terrain model, height model, etc. LiDAR data provides detailed vertical structure information which is crucial for the quantification of biomass and for an understanding of the complex architecture of field margin elements (Beka et al., 2022). There are studies which have illustrated the utility of LiDAR-derived products in the identification and delineation of individual landscape elements, including hedgerows and isolated trees (Malinowski, 2016). Using LiDAR point cloud data, the study created a normalized Digital Surface Model (nDSM) to map hedgerows and tree vegetation. The technique effectively detected hedgerows, single trees, and tree clusters with an overall classification accuracy of over 98%. The validation was mostly dependent on visual interpretation of orthophotos and LiDAR point cloud rather than comprehensive ground-truth field surveys, which could lower trust in the claimed accuracy values. Such linear vegetation patterns are crucial for lowering wind erosion, preserving soil moisture, and boosting agricultural output, according to similar research by Lackóová and Tárniková (2025), highlighted the usefulness of remote sensing for their monitoring and restoration.

The accurate field margin mapping enables more robust analysis of their ecological functions, for example, their role as ecological corridors or refugia within agricultural landscapes (Mercier, 2021; Wang, 2024). In the same regard, marginal vegetation is a small-scale feature captured by high-resolution imagery that can be effectively mapped using LiDAR (Broughton et al., 2021). In this study, it is evident that information based on LiDAR-derived structure provides better vegetation classification, especially in the riparian and edge regions, compared to spectral information alone. Environmental factors like vegetation canopy overlap, uncertainty at the border between water and vegetation, and variations in vegetation structure due to seasons negatively affect the accuracy of classifications. Also, the authors mention that terrain complexities and varying point densities may influence the consistency of the feature extraction process.

2.3.1 Hedgerows and Woody Linear Feature Mapping

A comparison of recent hedgerow-mapping studies by Muro et al. (2025) and Ahlswede et al. (2021) reveals how different remote sensing strategies, multitemporal high-resolution imagery versus very-high-resolution spatial detail, offer distinct but complementary strengths for detecting small woody landscape features. The PlanetScope-based nationwide assessment in Germany demonstrates the value of multitemporal high-resolution imagery combined with semantic segmentation, showing how seasonal spectral variation enhances the discrimination of narrow vegetation structures and how application-specific models outperform generalized continental products (Muro et al., 2025). By contrast, the IKONOS-based study from south-eastern Germany underlines the strengths of very-high-resolution imagery in association with transfer learning architectures such as Mask R-CNN and DeepLab v3+, showing that fine spatial detail can compensate for limited spectral inputs and geometric augmentations substantially strengthen model generalization (Ahlswede et al., 2021). If the first study underlines temporal diversity as a main driver of benefits for hedgerow detection, the second one points out the power of spatial precision combined with advanced deep learning to simplify mapping workflows and enhance accuracy. Collectively, these findings show that both multitemporal high-resolution data and VHR imagery offer distinct but complementary strengths for characterizing small, structurally complex field margin elements.

Building on complementary insights from multitemporal high-resolution and very-high-resolution (VHR) imagery, these additional studies further demonstrate how the choice of data source and analytical approach—from VHR satellite imagery to UAV-based 3D reconstruction and object-oriented classification on medium-resolution images—affects the accuracy, structural detail, and scalability of hedgerow detection and characterization. The WorldView-2 study demonstrates that VHR multispectral satellite imagery (2 m) combined with advanced spatial features such as texture and local orientation can meaningfully improve hedge discrimination, although high NDVI in non-woody vegetation still leads to false positives (Fauvel et al., 2012). In turn, the UAV-based study underlines the advantages stemming from ultra-high-resolution (centimeter-level) imagery and 3D reconstruction for capturing structural attributes—height, width, and flowering abundance—far beyond what satellite systems can provide, where multispectral UAV data unequivocally outperform RGB-only inputs (Smigaj & Gaulton, 2021). An object-oriented French study shows that medium-resolution imagery (≤ 10 m) may still support large-scale hedgerow inventorying if hierarchical segmentation and fuzzy logic are used, but accuracy is strongly influenced by landscape complexity and hedge density (Vannier & Hubert-Moy, 2008). Together, these papers reveal complementary strengths: VHR satellite imagery supports robust hedge delineation using spectral–spatial features, UAV datasets enable fine-scale structural and phenological assessments unattainable from spaceborne platforms, and

object-oriented methods on coarser imagery remain valuable for broad regional mapping when computational efficiency and scalability are priorities.

Building from these findings, the Bavaria DeepLabV3 study (García et al., 2025) and the EODHaM (Earth Observation Data for Habitat Monitoring) VHR segmentation study (Arias et al., 2013) further emphasize how different mapping strategies are associated with distinct strengths and limitations. The Bavaria approach relies on 20 cm orthophotos and a CNN, achieving a moderate accuracy–F1 ≈ 0.48 and tends to overestimate hedgerows; however, this method captured many narrow linear features that were missing in the Copernicus SWF product, underlining the added value of tailored regional deep learning workflows. In turn, the EODHaM method utilizes VHR optical imagery and object-based segmentation with knowledge-based filtering; while quantitative validation data are lacking, these results are considered robust by expert review. Taken together, the two studies illustrate a clear trade-off: deep learning allows for large-scale automated mapping, whereas OBIA approaches offer more controlled, structurally coherent delineations. This reinforces the broader pattern of findings identified across recent hedgerow research—namely, that method performance depends heavily on the spatial resolution, complexity of the landscapes, and whether a workflow adopted is data-driven or knowledge-driven. Overall, convergence of evidence reinforces the methodological rationale for integrating LiDAR, vector data, and VHR land cover products in Wallonia, where capturing fine-scale landscape heterogeneity is essential for robust ecological assessment.

2.3.2 Grass Margin Mapping

Despite growing research on vegetation mapping, only a limited number of studies have explicitly focused on mapping agricultural grass margins. However, related studies show that remote sensing has an increasing potential to identify low-lying herbaceous vegetation connected to field boundaries. Tansey et al. (2008) effectively identified hedgerows, trees, and low grassy vegetation in an object-based image analysis study utilizing colour infrared imaging and elevation difference models. They also evaluated the existence of required grassy boundary strips using a 2 m hedgerow buffer. According to their findings, 68% of the necessary buffer zones already had green cover, demonstrating how geospatial techniques can help with margin monitoring and agri-environmental compliance. Confidence in the robustness of the mapped outputs is limited, nevertheless, because a thorough assessment of the classification accuracy was not provided.

Additional proof comes from UAV LiDAR studies in grasslands, where dominant grass communities were effectively distinguished with classification accuracy of up to 78.1% using dense point clouds ($\sim 800 \text{ points m}^2$) and structural variables including canopy height (Šrollerů & Potůčková, 2024). Although it was still challenging to distinguish low-abundance species, the study also recorded seasonal variations in vertical vegetation

structure. When taken as a whole, these studies show that combining LiDAR-derived structural metrics with object-based imagery analysis has great potential for mapping the grass margin in the future. This is especially true for evaluating the extent, height, density, and variability of vegetation in agricultural landscape.

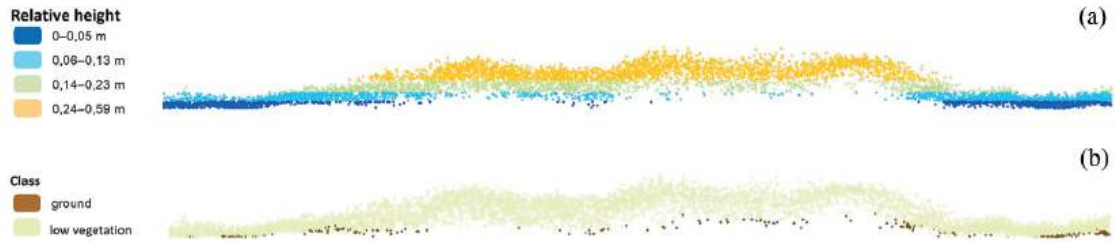


Figure 2.1: Vertical profiles extracted from the relative height (a) and classification point clouds (b); example of Bílá louka meadow grasslands (adapted from Šrollerů and Potůčková (2024))

2.3.3 Ditch and Drainage Network Detection

More recently, peatland ditches have been mapped from aerial photography using CNN-based deep learning techniques. Robb et al. (2023) found approximately 27,900 ditch features over an 802 km² area in the UK's Flow Country with 79% accuracy using a U-Net model. This illustrates how image-based methods are effective and scalable for wide areas. However, unlike LiDAR, which directly captures micro-topography, depending solely on aerial photos can affect accuracy in areas where ditches are covered by vegetation, shadows, seasonal changes, or poor contrast.

For more detailed ditch detection and morphological evaluation, LiDAR-based studies have thus been extensively employed. Rapinel et al. (2013) demonstrated that LiDAR-derived DTMs may be used not only to identify ditch networks but also to estimate ditch morphology through width and depth measurements by automatically defining 54.8% and 63.8% of previously reported ditch lengths in two marsh sites. However, they also draw attention to some significant drawbacks of LiDAR-based ditch mapping: poor ditch boundary delineation can result in mistakes in both width and depth estimates, and standing water and dense vegetation inside ditches can underestimate depth. Also, Malinowski (2016) study found that LiDAR-based ditch detection is highly dependent on landscape visibility since dense herbaceous plants or high-water levels may cover up ditch geometry and lower mapping accuracy.

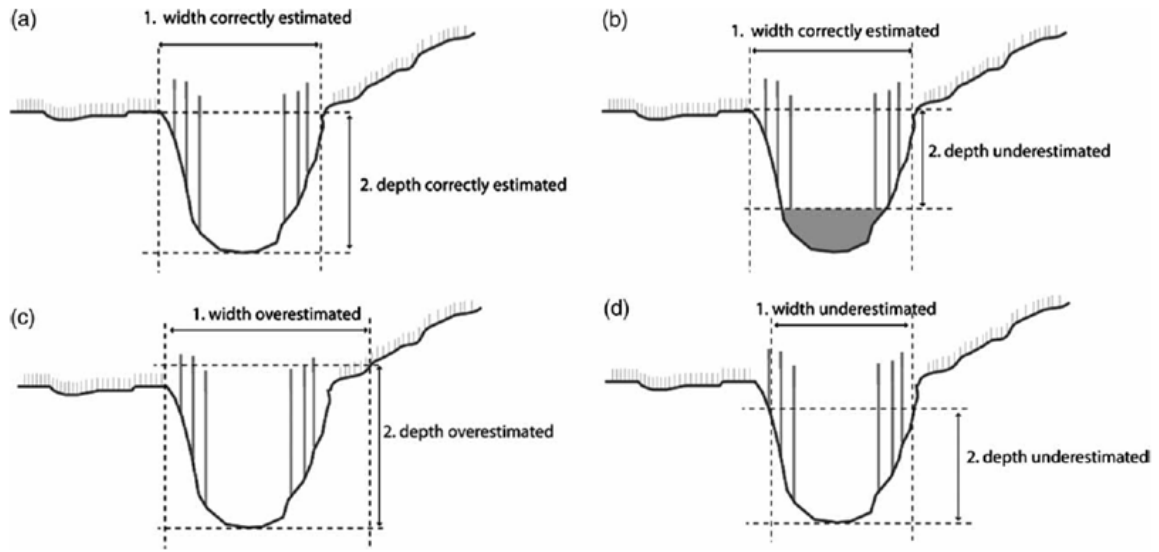


Figure 2.2: Relationship between the width of the ditch and depth estimated from LiDAR data with different configurations: (a) width and depth correctly estimated; (b) width correctly estimated, depth underestimated because of the presence of water; (c) width and depth overestimated; (d) width and depth underestimated (adapted from Rapinel et al. (2013))



Figure 2.3: Examples of ditches seen from LiDAR point cloud (point cloud profile) and orthoimage. (a) a ditch in dry condition (spring dataset), (b) a ditch during high water stage (autumn dataset), (c) a ditch with overgrowing vegetation (adapted from Malinowski, 2016))

2.3.4 Mapping the Trees Outside Forests

Extending the discussion from hedgerow mapping to broader tree-related landscape elements, three recent studies on Trees Outside Forests (ToF) illustrate how methodological choices strongly shape mapping accuracy, transferability, and operational usefulness. The Switzerland study conducted by Malkoç et al. (2021) shows that a fully automated threshold-based workflow, combining a Vegetation Height Model, a national land-cover model, and a forest mask, is effective for mapping ToF by UNFAO-FRA definitions with very high overall accuracy of 95%, but exhibits sensitivity to elevation driven VHM uncertainty. In contrast, the study by Bolyn et al. (2019) integrates orthophotos and LiDAR-derived CHM in a classification of ToF into seven inventory relevant structural classes; results indicate that object geometry and neighborhood context can be operationalized reliably (78% accuracy) and that detailed morphological differentiation beyond simple presence/absence can be automated at local scales. In contrast, the Minnesota study (Meneguzzo et al., 2012) tests two contrasting NAIP-based approaches, an unsupervised Independent Component Analysis (ICA) per-pixel classifier, a statistical technique that separates mixed spectral signals into independent components, and an Object based Image analysis (OBIA) workflow. ICA is particularly useful in remote sensing because it reduces spectral redundancy and enhances separability between land-cover types by isolating underlying information sources that are not directly observable in the original bands. The study finds that while both approaches are suitable for broad-scale TOF estimation, ICA better approximates total tree-covered area, while OBIA captures spatial realism and patch structure. Together, the research again underlines the recurring pattern: height models underpin definitional rigour, OBIA enhances structural interpretability, and high-resolution aerial imagery widens scalability, while the best ToF mapping methods will be matched to landscape complexity and management objectives.

A further contrast arises in comparing object-based methods for the extraction of woody elements in agricultural landscapes. Tansey et al. (2008) conducted their study entirely within eCognition, applying a multi-scale object-based classification workflow that integrated spectral, textural, height, and shape features to map hedgerows and small woody landscape elements with high thematic detail. Tuning segmentation parameters, for example, scale values optimized for narrow linear features, applying hierarchical object relationships, and using fuzzy membership functions, the eCognition rule set embeds expert knowledge directly into the classification process. This allows for refined separation of hedgerows, tree groups, and hedge-height vegetation but also makes the workflow sensitive to segmentation errors and challenging to transfer across heterogeneous sites. By contrast, Sheeren et al. (2009) uses a hybrid pixel-based and object-based approach first leveraging pixel-level texture and spectral cues to identify wooded patches, then employing object-level morphological and contextual descriptors to separate scattered trees, copses

(small group of trees), and linear woody structures. This design reduces dependence on segmentation quality and improves robustness in mixed agricultural mosaics, hence offering a more flexible alternative where small or adjacent ToF elements frequently complicate purely object-based methods.

2.4 Validation and Accuracy Assessment of Field Margin Mapping

Validation of field margin mapping is crucial for quantifying the reliability of multi-source geospatial approaches. Several techniques have been used to quantify performance in classification and detection across studies. Sheeran et al. (2009) presented the visual interpretation of digital photography to validate both pixel and object-based classifications, after which the overall accuracy and Kappa coefficient were derived from confusion matrices. Meneguzzo et al. (2012) implemented site-specific accuracy assessments by comparing ICA and OBIA classifications against reference imagery using stratified random sampling, producing producer’s accuracy, user’s accuracy, and overall accuracy while highlighting locational correctness. Muro et al.(2025)implemented both overlap- and distance-based metrics, such as precision, recall, F1 score, Hausdorff distance, and Average Spatial Distance, to account for spatial performance in narrow hedgerows where small lateral shifts are particularly impactful. Hausdorff Distance is a measure based on boundary similarity that computes the maximum distance from any point on one hedgerow to the nearest point on another hedgerow, thereby capturing the worst-case spatial deviation between predicted and reference features. The methodology of Ahlswede et al. (2021) further extended object-based evaluation to apply multiple thresholds in defining true positives and false positives/false negatives to evaluate object-level precision, recall, and F1-score together with pixel-wise accuracy restricted to areas containing features of interest that address biases due to class imbalance. Taken collectively, these studies represent a progression from broad accuracy assessment toward more spatially explicit, object-focused, and threshold-sensitive metrics for the validation of the detection and characterization of field margins.

Building on these validation methods, field margin mapping and characterization require a combination of pixel-, object-, and distance-based metrics to capture both the classification correctness and spatial accuracy. Narrow linear features, such as hedgerows, have specific challenges, with small positional errors having a huge impact on metrics of overlap, while standard confusion matrix measures may overestimate performance in the case of class imbalance. Similarly, in more recent times, multi-threshold object-based evaluations, per-pixel accuracy restricted to a feature of interest, and further distance-based metrics, such as Hausdorff or average spatial distance, complement the more common approaches to ensure

robust performance assessment. These insights suggests that it is necessary to supplement with rigorous, multi-level validation strategies. By doing so, improvement in the reliability of field margin detection will be achieved, together with providing quantitative confidence in the derived structural attributes, which in turn are critical in assessing ecosystem services, informing policy compliance, and guiding conservation or restoration interventions.

3. Research Objectives

In many regions, field margins are still not adequately mapped and characterized primarily due to the constraints of traditional two-dimensional land cover data, which often lack the spatial and structural detail required to represent fine-scale landscape features. Wallonia has access to several high resolution geospatial datasets, although none were specifically designed to systematically delineate field margins. The *Projet de Cartographie Continue* (PICC) is a vector database at 1:1,000 scale, which contains mainly built-up features, along with some natural features, which provides very accurate geometric boundaries. The SIGEC (*Système d’Identification des Parcelles Agricoles*), or the LPIS (*Land Parcel Identification System*) for Wallonia, identifies the agricultural parcels declared yearly by farmers according to the CAP (*Common Agricultural Policy*). Moreover, WALOUS provides highly detailed land cover information, and LiDAR data collected using aircrafts provide 3D structural information about the vegetation and topography. The integration of these complementary datasets like precise vector boundaries (PICC), agricultural parcel delineation (SIGEC), detailed land cover (WALOUS), and 3D structural information from LiDAR offers a promising approach to improve the detection and characterization of field margins.

The primary objective of this study is the development of a spatial approach based on LiDAR, PICC vector, and Very High-Resolution land cover data that allows the estimation of the extent and characterization of natural elements present in the field margins across 30 sites in Wallonia. These sites are located outside of urban areas and represent landscapes that are predominantly agricultural and semi-natural. This study aims evaluate the compatibility and complementarity of the three current Very High Resolution (VHR) databases for Wallonia concerning the depiction of very small-scale landscape features, such as field margins. In addition, appropriate spatial metrics are identified and applied to quantify the extent, configuration, and spatial patterns of natural elements, including vegetation, ditches, and grass margins. Particular emphasis is placed on assessing connectivity and fragmentation characteristics using selected landscape metrics. Furthermore, the study evaluates the extent to which these metrics support a robust interpretation of the ecological structure and functional significance of field margins. This, in turn, will enhance ecological planning efforts and conservation policies within Wallonia.

4. Materials And Methods

This chapter describes the materials employed and the methodology adopted in this research to create a precise depiction of the field margins in Wallonia. This includes the description of the study area and the sources of data used.

4.1 Study Area: Field Margins in Pollinator Landscapes

This study has been conducted in the Wallonia region of Belgium, located in the southern part of the country and covering approximately 16,901 km². The study has involved 30 sites distributed across Wallonia (Figure 4.2). These sites comprised a number of different land use classes, such as agricultural lands, grasslands, forests, and hedgerows, allowing study to capture heterogeneity within the landscapes studied in Wallonia. The study sites have been equally distributed among the three main agro-biogeographical zones of Wallonia, having 10 sites in each zone.

The three agro-biogeographical zones covered in this study are Hesbaye (Loamy zone), the Mosan zone, and the Ardenne. The Hesbaye or Loamy zone is known for its fertile soils that support intensive farming. The Mosan zone serves as a transitional area between the northern plains and the Ardenne region, characterized by its rugged landscapes filled with ridges and valleys. Meanwhile, Ardenne is primarily a rural area, largely made up of forests, pastures, and less intensive agricultural practices. Together, these regions reflect the diversity of agricultural landscapes and land-use patterns present across Wallonia.

These sites have been reused from the sampling design created by Jeannerod (2025) and investigated within the NUTRIBEE research project supported by UCLouvain. This research framework aimed to improve the understanding of how the distribution, quality, and accessibility of floral resources influence wild bee foraging behaviors and interactions between pollinators and plants in agricultural landscapes. As a result, the chosen sites specifically represent agricultural and semi-natural environments that are ideal for examining the dynamics of floral resources and pollinator activity.

The study areas have been chosen to avoid urbanized regions by creating a 500 m buffer, allowing us to concentrate solely on the floral resources found in agricultural landscapes.

Using agricultural land parcels, orthophotographs, and field surveys, a 500 m walkable transect has been mapped within each study zone, crossing a wide variety of biotopes. The boundaries of each study zone have been defined using a 500 m buffer around the transect, leading to an average site area of about 1.5 km². This distance has been selected based on the typical foraging range of *Bombus* species when they gather resources (Redhead et al., 2016). Each study zone effectively represents an average foraging area for wild bees within an agricultural landscape.

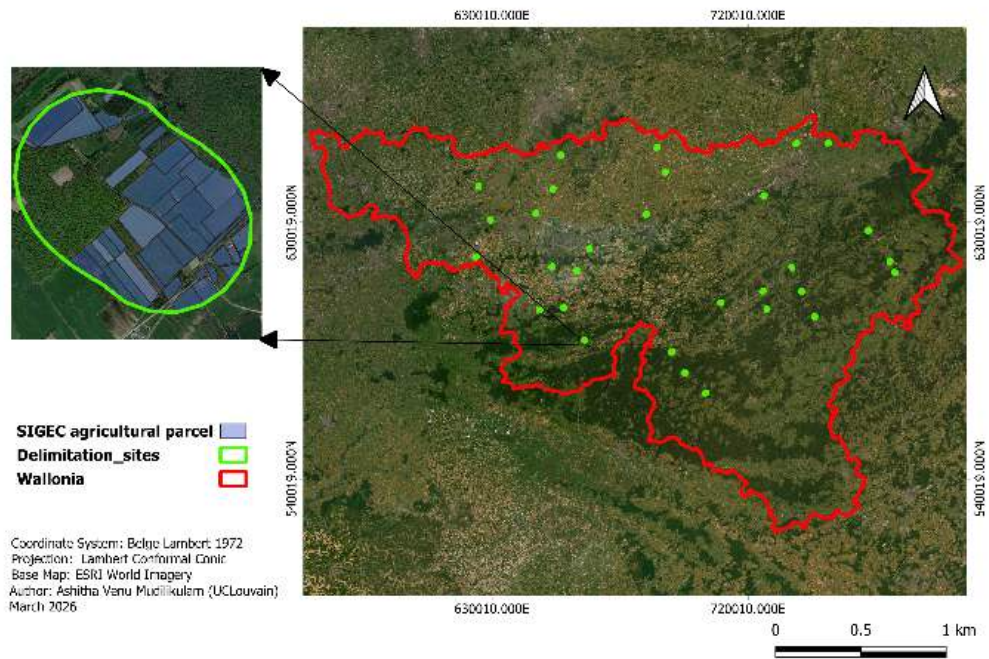


Figure 4.1: Map of study area showing the 30 sampling sites across Wallonia, with site 21 presented in a zoomed in view.

These selected study sites are considered suitable for this study because they contain diverse landscape elements, including hedgerows, grasslands, forest edges, and agricultural fields, which are particularly relevant for the delineation and characterization of field margins. The landscape heterogeneity within the study zones is appropriate for analyzing field margin structures across different agricultural contexts in Wallonia.

4.2 Data Sources

Several data sets have been used for this research, such as SIGEC data, LiDAR point clouds and derived data sets, WALOUS Land Cover, PICC vector data, and UAV data. Each of these datasets are explained in the following sections.

4.2.1 SIGEC Agricultural Parcels

The Système Intégré de Gestion et de Contrôle (SIGEC) database for 2021 serves as the basis for the management of agricultural subsidies according to the Common Agricultural Policy (CAP) and the monitoring of land use in Wallonia. The database, known as Parcellaire agricole issu du SIGEC 2021, is based on the declarations of agricultural parcels by farmers that were then verified and compiled by the authorities using official reference data.

The SIGEC system consists of various databases such as the Land Parcel Identification System (LPIS) and the Geospatial Aid Application System (GSA). These databases are handled within the context of implementing CAP by the Paying Agency of Wallonia (Organisme Payeur de Wallonie - OPW). The SIGEC 2021 data set is available publicly on WalOnMap or Waloon geoportal.

The agricultural parcel delineations are created by farmers or farm advisors using 25 cm resolution natural-color aerial photographs. Although the calculated parcel area is critical for the subsidy computation, no specific positional accuracy is required for the delineation of parcel boundaries, except with respect to neighboring parcels. In this study, only the agricultural parcel boundaries from the SIGEC 2021 dataset are utilized, while crop-specific information contained within the database was not considered.

4.2.2 LiDAR Point Cloud & Derived Products

4.2.2.1 LiDAR data Acquisition & point cloud Classification

The LiDAR dataset used in this research has been acquired with two LMSQ780 and two VQ780II-S scanners at the rate of 900 kHz. All measurements have been taken recorded in the Lambert Belgian 2008 coordinate reference system.

The raw LiDAR point clouds have been automatically classified, followed by manual quality control and correction of classification error. A Triangulated Irregular Network (TIN) model has been created to help in the fast detection of any incorrectly classified points.

Points classified as classes 0, 1, 9, 10, and 15 have been used for over-soil classification purposes. This automated filtration method has enabled detection of most of the buildings that belong to Class 1 and has supported the segmentation of aboveground objects. Moreover, Class 4 (vegetation) elements have been separated from elements belonging to Class 0 (unclassified), Class 10 (bridges), and Class 15 (high voltage lines).

Classification of water bodies has been performed using surface water identification based on bank evaluation in the Digital Elevation Model (DEM). The LiDAR point cloud dataset contains seven classes in total (Table 4.1)

Table 4.1: LiDAR point cloud classification scheme

Classes	Name
Class 0	Unclassified elements
Class 1	Buildings
Class 2	Ground
Class 4	Vegetation
Class 9	Water
Class 10	Bridges
Class 15	High-voltage lines

In this study, only class 4 has been considered, as it represents vegetation-related information within the LiDAR point cloud dataset.

4.2.2.2 LiDAR Derived Products

Besides the point clouds, there are some raster-based products created through LiDAR which have been considered for this research project.

The Digital Surface Model (DSM) stands for the model that covers the height of the terrain, including all the elements like vegetation, buildings, and any other structures present on the surface of the Earth. The DSM has been generated using the highest elevation points, whether corresponding to bare ground or aboveground objects. Its spatial resolution is 50 cm, while the projection system is Lambert Belgian 2008.

The Digital Terrain Model (DTM) refers to the computer model that covers the height of bare soil surface in the study area. In creating it, LiDAR elevation points have been used while excluding the vegetation and man-made structures. DTM has been available at a spatial resolution of 50 cm.

The Digital Height Model (DHM) also referred as nDSM represents the elevation of objects above the ground surface. It indicates the interaction between the terrain and objects on its surface. This model can be generated by subtracting the DTM from the DSM as shown below:

$$DHM = DSM - DTM \quad (4.1)$$

The minimum value of the DHM has been zero meters, representing the ground surface, while the maximum value corresponds to the tallest object in the DHM. In this study, the DHM has been used for vegetation structure analysis.



Figure 4.2: Schematic representation of the derivation of the DHM from the DSM and DTM (source: GeoSun Tech (n.d.))

4.2.3 Plan Informatique de Cartographie Continue (PICC) Vector Dataset

The Plan Informatique de Cartographie Continue (PICC) is the official three-dimensional vector reference data base for Wallonia in Belgium. It is the digital cartography of Walloon territory with identification of different elements on the map according to x, y, and z coordinates, produced at a 1:1,000 scale with a positional accuracy of less than 25 cm. The dataset includes multiple thematic layers such as buildings and engineering structures, public equipment (e.g., poles and pylons), railway networks, hydrographic features, land-use elements (e.g., isolated trees, field edges, sports grounds), relief features (e.g., embankments) and road infrastructure (e.g., road axes, edges, and sidewalks).

To conduct the analysis in this study, various vector layers derived from the PICC dataset have been used as supporting geographic data. The dataset has included polygon, line, and point vector features representing different landscape elements. These layers have included forest patches, water bodies (both natural and artificial), parking spaces, residential areas, road edges, sidewalks, wind turbines, and path edges. The dataset has been acquired from the official Wallonia Geoportal site.

4.2.4 WALOUS Land Cover

The WALOUS Land Cover is a very high resolution land cover map specifically designed for the Wallonia region in Belgium. This dataset has been created to offer harmonized and contemporary land cover spatial data that can be used in the development of territorial policies and monitoring environmental changes in the region. Some of the land cover categories include built-up surfaces, vegetation, agricultural land, transportation networks, bare soil, and water bodies. Its spatial resolution is 1m, while the projection system is

Lambert Belgian 2008.

The WALOUS Land Cover dataset has been developed within the WALOUS programme to ensure the consistent production of regional land cover maps. The dataset has been made publicly available through the SPW Geoportail and provides important spatial reference data at both regional and local scales. In this study, the WALOUS Land Cover 2021 dataset has been used as a supporting data source alongside PICC vector datasets.

4.2.5 Orthophoto

The orthophoto dataset used in this study includes an orthorectified and mosaicked aerial imagery covering the region of Wallonia. The dataset has been acquired in 2021 and has a spatial resolution of 25 cm. The data has been produced by the Walloon Public Service (SPW) within the frame of the regional aerial photography surveys implemented by SPW periodically.

Collection of imagery occurred by means of vertical aerial photography during the period from 6 March 2021 to 25 April 2021. The dataset includes four spectral bands: red, green, blue (RGB), and near-infrared (NIR).

For comprehensive region mapping and maintaining the image consistency, the process adhered to the overlap specifications in the photogrammetry process. A minimum longitudinal overlap of 60% between consecutive images and a minimum lateral overlap of 30% between adjacent flight lines have been maintained, with tolerances of $\pm 5\%$. The final orthophoto products have been generated as tile output with a spatial extent of $2 \text{ km} \times 2 \text{ km}$.

The orthophotos in this study have been mainly applied in interpreting the features and validating the field margins.

4.2.6 Unmanned Aerial Vehicle (UAV) data

UAV imagery was collected by Maxime Buron at 15 out of the total 30 experimental plots in July 2023 and was used for the validation of this study. DJI Mavic Pro 2 drones fitted with RGB cameras were used for data acquisition. The UAV surveys were designed to capture high-resolution images that capture the diversity of habitats of the local landscape in the study areas.

For each site, imagery was collected along three transects. Drone flights were performed over zones of approximately $200 \text{ m} \times 50 \text{ m}$, selected to best represent the diversity of habitats present within the surrounding landscape. During the data collection, the drones followed set pre-defined flight paths to systematically cover the target zones. The flights were conducted between 10:00 and 17:00 in suitable weather and illumination conditions.

The drones flew at an altitude of 10 m above ground level, with the cameras oriented straight down (nadir view) to guaranty consistent image capture and reduce any geometric distortions yielding an approximate pixel size of 5 cm on the ground. In this study, UAV data have been used for the validation of field margin width.



Figure 4.3: UAV orthomosaic (pixel size of ~ 5 cm on the ground, nadir RGB imagery) from one of the site, July 2023.

4.2.7 Summary of dataset

A summary of the datasets used in this study, including their acquisition dates, spatial resolution/geometric accuracy, thematic focus, and respective roles within the analysis, is presented in Table 4.2.

4.3 Methodology Development

An overview of the overall workflow is presented in Figure 4.4. The subsequent sections describe in detail the methodological approaches used for field margin extraction, landscape metric computation, correlation analysis, ditch extraction and characterization, grass margin delineation, and validation.

Table 4.2: Spatial datasets used in this study

Dataset	Data Type	Acquisition Date(s)	Spatial Resolution / Geometric Accuracy	Thematic focus	Expected role
SIGEC agricultural parcels	Vector (polygons)	2021	25 cm ortho photograph-based parcel delineation	Agricultural parcel boundaries and land-use units	Field margin delineation
LiDAR Point Cloud	Point cloud (LAS/LAZ)	2020-2022	6.8 pulses/m ² ; vertical accuracy ± 10 cm	3D structure, classified points	Primary source for DSM/DTM/DHM generation; vegetation structure analysis
DSM	Raster	Derived 2020-2022	50 cm	Top of all surface features	DHM input
DTM	Raster	Derived 2020-2022	50 cm	Bare-earth terrain	DHM input, Ditch extraction
DHM	Raster	Derived 2020-2022	50 cm	Object height above ground	Vegetation height and structural heterogeneity analysis
PICC	Vector (points or lines or polygons)	2021	$\sim 1:1,000$ scale accuracy	Buildings, roads, hydrography, infrastructure	Field margin delineation
WALOUS land cover	Raster	2021	1 m	Land cover classification including vegetation, artificial surfaces, agricultural land, and water bodies	Field margin delineation
Orthophoto	Raster	2021	25 cm	High-resolution aerial imagery providing detailed visual representation of landscape features	Validation and visual interpretation
UAV data	Raster (4 bands - RGB + NIR)	July, 2023	~ 5 cm GSD	High-resolution spectral reflectance and vegetation signatures	Validation of field margin width

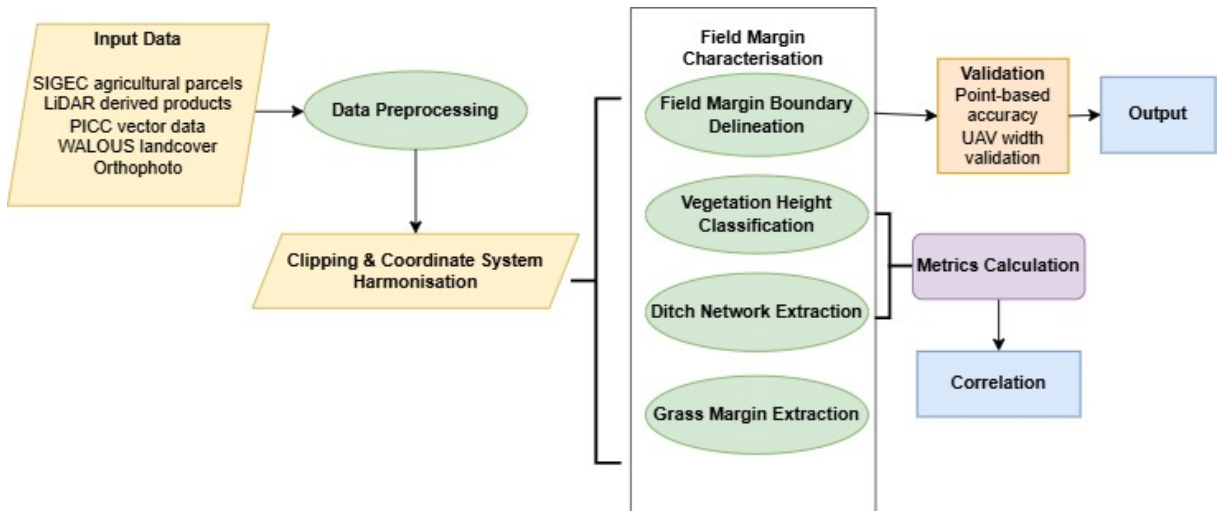


Figure 4.4: Overall methodology workflow.

4.4 Data Processing

4.4.1 Compatibility Analysis

A compatibility analysis is conducted to ensure harmonious integration of various types of spatial information, such as SIGEC agricultural parcels, LiDAR point clouds, WALOUS land cover, PICC reference data, orthophotographs, and UAV imagery. Compatibility analysis considered potential inconsistencies due to different reference systems, acquisition dates, geometric characteristics, and different spatial resolutions. All datasets are reprojected into a common coordinate reference system (EPSG:31370, Belgian Lambert 2008) to ensure spatial alignment across vector and raster layers. In addition, datasets are clipped to the extent of the 30 study sites to ensure spatial consistency.

For non-habitat artificial layers derived from the PICC dataset, a dedicated exclusion layer is constructed. The elements included are roads, parking lots, residential areas, side walk, wind turbines, path edges, and water bodies that have been extracted from the vector dataset of PICC. These layers are merged and subsequently rasterized to match the spatial resolution and spatial extent of the vegetation raster, ensuring consistency across analytical layers.

The spatial resolution varied significantly (Table 4.2), ranging from centimetric UAV imagery to coarser land cover products, which required attention when analyzing the data to address any potential scale issues.

4.5 Software and computational environment

The spatial and geospatial analysis has been conducted primarily using python with key libraries like rasterio for raster analysis, numpy for numeric computation, and geopandas and shapely for spatial vector analysis. The LiDAR data processing and reading are carried out using PDAL and laspy, which made it easy to handle point cloud data and extract vegetation heights from the LiDAR data.

Furthermore, ArcGIS Pro software is utilized for visualization, creation of maps and quality control of the spatial output, especially for the final map layout and checking spatial consistency.

4.6 Field Margin Delineation

The field margin delineation approach follows an established three-part methodological process of ((i) compatibility analysis, (ii) complementarity assessment, and (iii) field

margin mapping. The first two stages serve to provide solid reasoning for the choice of data and spatial processing techniques used for the field margins delineation.

4.6.1 Compatibility Analysis

The SIGEC parcels contain information about the spatial configuration of the agricultural field parcels that farmers have grown. SIGEC agricultural parcels provide very accurate demarcation of fields and serve as the geometrical basis for further buffer analyses and field analysis.

The PICC database acts as a highly accurate source of data regarding infrastructure and some specific elements of land cover. However, it should be mentioned that the description of road networks offered by the PICC database is incomplete in an agricultural setting since private roads, paths, and agricultural roads are not mapped. It happens due to the fact that the PICC database describes only those infrastructure features that are formally registered.

To address this limitation, road information is complemented by WALOUS land cover information, allowing for an enhanced depiction of transport surfaces, including small road categories. The trade-off of this approach is the decrease in geometrical accuracy since WALOUS land cover data is less accurate due to higher generalization and spatial resolutions. The combination of the two data sets thus becomes imperative to reach a compromise between completeness and geometrical precision.

The merging of raster (WALOUS) and vector-based (PICC) data sources causes geometrical inaccuracies due to different modes of representation. When vector data are rasterized or directly overlaid with raster layers, a pixel-based discretization effect may occur, producing staircase-like or jagged boundaries known as the pixel-shape effect. Furthermore, differences in resolution between the data sources might result in breaks along narrow landscape elements such as field margins and linear infrastructures. These effects are addressed through harmonization and filtering strategies embedded in the subsequent methodological steps.

4.6.2 Complementarity assessment

Complementarity analysis identifies the strength and weaknesses of each data set to assign their appropriate functions in field margins delineation. In this way, selection of the most appropriate data set will be based on clear spatial thinking.

Vector-based data sets like SIGEC polygons and PICC dataset have high level of positional accuracy and well-defined boundaries; therefore, can effectively define the polygon geometry and formal infrastructures. Nevertheless, the thematic content of vector data sets is limited in terms of fine scale landscape elements, especially semi-natural features and

small infrastructures.

Raster data sources like the WALOUS land cover database and orthophoto offer continuous coverage and greater thematic detail. However, they are affected by resolution-dependent generalization, which reduces geometric precision along boundaries and narrow features.

There is also some degree of partial redundancy among the databases. The road network, for instance, appears in both the PICC and WALOUS databases, but in varying degrees of completeness and abstraction. PICC primarily includes formal infrastructure, whereas WALOUS extends coverage to additional road classes but with less geometric accuracy.

A composite spatial mask is constructed to delineate non-target anthropogenic and environmental features within the study area, based primarily on the PICC dataset. This mask is used to exclude anthropogenic surfaces such as residential zones, parking areas, sidewalks, and water bodies, which are explicitly identified within the PICC reference layers. These exclusions ensure that only relevant agricultural and semi-natural environments remain available for subsequent field margin analysis.

Road networks are characterized by specific treatment since they have an under-representation in the PICC dataset because of such elements like private roads, unpaved roads, and other small road connections that are absent within the dataset. To address this limitation, PICC road segments are complemented with WALOUS land cover road classes to achieve more complete spatial coverage of transport infrastructure. Before integrating the roads, WALOUS roads are subjected to symmetrical morphological filtering to smooth their boundaries and improve spatial continuity. This ensures that the road layers are free from any geometric noises and minimizes the impact of fragmentation due to raster resolution. The processed WALOUS road layer is then integrated with PICC road segments to produce a unified road mask, which is subsequently used to remove transport surfaces from the field margin zones during the final delineation step.

4.6.3 Field margin mapping method

The field margins have been determined by a rule-based buffering process applied to the SIGEC agricultural parcels. An internal buffer of 1m and external buffer of 3m have been applied over each parcel to represent the field margin areas for each field edge. In the case of isolated field edges, the field margin has been defined by the combination of the internal buffer (1m) and external buffer (3m), making the margin area about 4 meters long along the external field boundary. Field margins in the case of a field margin being shared by adjacent parcels have been determined by creating buffers of 3 meters on neighboring parcels and their overlap would create a margin area that is 6 meters wide between two adjacent parcels.

The initial margin polygons have been subsequently clipped against the aggregation of

all parcels found surrounding each agricultural field to prevent extension of the margins outside the agricultural area. Small gaps found at the intersections of neighboring margins have been removed through morphological gap-filling operations.

To eliminate non-margin surfaces, several masking layers have been applied. The forest area is masked using the PICC forest layer buffered by 4 m to ensure that vegetation directly bordering the forest edges is excluded from the margin zones. The road surfaces have been extracted based on the combined road masks that include both PICC and WALOUS road layers, which ensure complete spatial representation of transportation structures. In addition to roads, other anthropogenic surfaces such as residential areas, car parks, sidewalks, and water surfaces from the PICC layer have also been excluded, as stated in Section 4.4.2.

The remaining margin zones have been exported as both vector and raster layers for subsequent vegetation and landscape metric analyses.

4.7 LiDAR - Based Vegetation structure analysis

In this section, the process used to derive the vegetation structure from LiDAR data and subsequently translating it into a spatial unit is explained. The procedure includes vegetation layer generation and object-based image analysis for capturing the vertical and spatial structure of vegetation and the analysis of vegetation vertical complexity.

4.7.1 Vegetation Layer Generation

Vegetation structure was derived based on the Normalized Digital Surface Model (nDSM), whereas LiDAR point cloud was employed for vegetation verification and noise filtering. First, the vegetation classified LiDAR points were extracted from the LiDAR point cloud and then were rasterized at 0.25 meters to produce two raster layers. The raster layers included (i) the binary vegetation raster layer that indicates whether or not there are any points of Class 4 per cell, and (ii) the vegetation points density raster layer.

nDSM has been used to determine vegetation height measurements (equation 4.1). Based on the predefined height thresholds, four vegetation height classes have been defined to show different vegetation structures (Table 4.2). For very low vegetation (with DHM less than 0.5 m), a point density filter is used, which produces high levels of noise because of the presence of ground return echoes. The point density filter removes noise points, which do not meet the minimum threshold of points density, thus retaining the actual low vegetation cover.

Table 4.3: Vegetation classification based on height thresholds

Vegetation Types	Height Threshold
Very small vegetation	> 0 m and < 0.5 m, density filter ≥ 2
Small vegetation	0.5–1.5 m
Medium vegetation	1.5–3.0 m
High vegetation	> 3.0 m

4.7.2 Object-Based Vegetation Segmentation

In addition to classifying the vegetation layer, another layer has been created through an object-based segmentation method based on a watershed algorithm to provide additional information about the vegetation layer’s spatial structure. The objective of this step has been to extract individual vegetation patches from the vegetation mask generated through LiDAR data analysis. The resulting vegetation objects have been used to derive the margin-to-total ratio metric.

For segmentation, the nDSM served as the basis, where vegetation structure was delineated through the detection of local maxima in height values. Local maxima have been used as seeds, which correspond to the centre points of individual vegetation objects. Only vegetation above 0.5 meters has been taken into consideration in the detection of seeds. The local maxima are identified using a moving search window with a minimum separation distance of 2.0 m to ensure that neighbouring peaks within short distances were not treated as separate vegetation objects.

Next, a marker-controlled watershed segmentation technique has been applied. According to this technique, the nDSM surface has been considered as a terrain surface in which pixels with high values correspond to high vegetation and low values represent the ground and low vegetation parts. The detected local maxima are used as seed markers representing the peaks of vegetation objects. The regions have been gradually expanded starting from these seeds along the descending path of the nDSM surface height towards the other side of the pixels like water flows downhill from mountains to valleys. When neighbouring expanding regions have met, boundaries are formed, thereby separating adjacent vegetation objects.

In order to ensure that over-segmentation does not occur and that patches do not expand unrealistically, the segmentation process is restricted to the boundaries of those vegetation classes detected through the vegetation classification using LiDAR data, where the vegetation patches themselves are further restricted to a maximum radius of 1 m. This implies that none of the vegetation features will extend beyond the 1m neighborhood, thus guaranteeing that a vegetation unit is represented by the smallest possible segment and not an enlarged one. Through this process, a set of vegetation patches was generated from the spatial coherence of the vegetation objects.

For each segment, the structural features were extracted based on the nDSM, specifically the mean vegetation height, which was estimated using all the pixels that belonged to that segment. The mean vegetation height was then adopted as the main feature of the segment and served as the starting point for vegetation height classification. This implied that each segment was assigned a certain height class based on the estimated mean vegetation height. These patches become structurally distinct vegetation objects for subsequent spatial fragmentation analysis.

4.7.3 Foliage Height Diversity (FHD) Analysis

Foliage Height Diversity (FHD) originally proposed by MacArthur and MacArthur (1961), the metric was initially developed to describe how foliage is distributed across various height strata and later adapted for LiDAR-based canopy profile analysis (Simonson et al., 2014). FHD has been derived using the Shannon entropy to quantify the diversity of vegetation height distribution across vertical layers. Mathematically, it is given by:

$$H = - \sum_{i=1}^n p_i \ln(p_i) \quad (4.2)$$

where p_i is the proportion of vegetation occurring within height layer i .

Based on the vegetation height categorization and masking process explained in section 4.5.1, the vegetation layers are processed as inputs for FHD calculation. Vegetation classes corresponding to woody and tall vegetation structures (small, medium, and high vegetation classes), have been combined into a single vegetation mask. The extracted vegetation height are then grouped into vertical height bins at every 0.25 m intervals to characterize the distribution of vegetation across different canopy layers. The proportion of vegetation pixels within each height bin is used to calculate of FHD values.

FHD is very logical and well-accepted measure of the diversity of the canopy structure. Here, FHD will be an effective comparative variable that can help distinguish regions that have more diverse vertical canopy structures. Higher values indicate greater heterogeneity in plant height distribution. Lower values indicate lesser heterogeneity in plant height distribution.

4.8 Landscape Metrics of Vegetation Structure

The use of variables of vegetation structure, configuration, and composition is employed to explore the fragmentation patterns in the 30 field sites. In this regard, landscape metrics are computed to measure the spatial patterns and structures of vegetation, especially those that are relevant in terms of their structure. This will be useful in quantifying the manner

in which vegetation is fragmented within field margins and other landscape elements.

To facilitate the computation of landscape metrics, the vegetation classification described in Section 4.5.1 is simplified into structurally meaningful habitat categories. The classes of vegetation that relate to woody/tall vegetation structures are kept, whereas the vegetation classes in table 4.2 are changed to a binary habitat map, which indicates the possibility of habitat occurrence.

For the derivation of landscape metrics, other artificial and non-habitat components are considered as landscape barriers. This includes roads, parking, residential area, sidewalks, wind turbines, path edges, and water bodies derived from the PICC vector datasets. The data derived in section 4.4.1 are used in this step.

The final habitat layer has been generated by removing the rasterized barrier surfaces from the vegetation habitat mask. The remaining connected vegetation areas have been identified as individual habitat patches. These patches have been used as input for the calculation of landscape metrics such as Effective Mesh Size (MESH), Number of patches, and Mean Proximity Index (MPI).

4.8.1 Number of Patches (NP)

The number of patches (NP) has been used to quantify the degree of fragmentation of the study sites. NP represents the total number of discrete vegetation patches identified within the landscape after the removal of barrier layer. NP is considered as basic aggregation metric that describes the subdivision of habitat into isolated patches.

The higher the NP value, more fragmented landscape (composed of numerous smaller and isolated vegetation patches), whereas lower NP value represents the less fragmented and more continuous vegetation structure. However, NP alone does not provide information on the size, shape, or spatial arrangement of patches and has been interpreted with other metrics like Effective mesh size (MESH) and Mean Proximity Index (MPI).

4.8.2 Effective Mesh Size (MESH)

MESH is an indicator of landscape fragmentation that measures the extent of fragmentation and connectivity of patches according to their sizes. It is equal to the probability that two points chosen at random in the landscape belong to the same patch. From a practical point of view, it can be regarded as the mean patch size weighted by area. Patches identified within each study site after the removal of barrier elements have been used for the calculation of MESH. Mathematically, it is defined as follows:

$$MESH = \frac{\sum_{i=1}^n a_i^2}{A_T} \quad (4.3)$$

where a_i is the area of the patch i , and A_T is the total landscape area.

The higher the MESH value, the better (bigger and more connected) the patches. The lower the MESH value, the higher the level of fragmentation.

4.8.3 Mean Proximity Index (MPI)

MPI is a measure of the degree of isolation or connectivity of vegetation patches based on the size of adjacent patches and the distance between patches. It is adapted from the FRAGSTAT Proximity Index (PROX). Assess the neighborhood context of patches within the habitat. For each focal patch,

$$MPI_i = \sum_{j \in N(i)} \frac{a_j}{d_{ij}^2} \quad (4.4)$$

where A_j is the area of the neighboring patch j , d_{ij} is the Euclidean distance between the patches i and j , and $N(i)$ is the set of neighboring patches within the 100m proximity search radius.

Vegetation patches identified within each study site after excluding barrier elements have subsequently been used to calculate the MPI. The final MPI is obtained by averaging across all patches. When the MPI value is high, the adjacent patches are larger, closer, and more clustered, showing higher connectivity and lesser isolation. Whereas when the value of MPI is low, the patches around are smaller, farther away, or absent.

4.8.4 Margin to Total Ratio

This index is based on the comparison of the vegetation cover within the field margin zones with that in the open zones (area excluding the forest). Vegetation objects generated through the object-based segmentation process have been used to calculate the margin to total ratio by quantifying the proportion of segmented vegetation patches occurring within the field margin zones relative to the total vegetation extent within each study site.

$$R = \frac{D_{margin}}{D_{open}} \quad (4.5)$$

where D_{margin} is vegetation density in the margin zone and D_{open} is vegetation density in the open zone.

$R > 1$ indicates greater vegetation cover in marginal zones. And if $R < 1$ indicates greater vegetation cover in open zones

4.9 Correlation Analysis of Landscape Metrics

The Pearson correlation coefficient has been used for assessing linear associations among selected vegetation and landscape metrics, namely Mean Proximity Index (MPI), Effective Mesh Size (MESH), Number of Patches, and Margin to Total Ratio. The Pearson correlation coefficient has been used to evaluate the degree of association between two continuous variables by estimating both its magnitude and direction, which is described with the help of values from -1 to +1. Positive correlation coefficients mean that when one variable increases, the other variable also increases. On the contrary, negative coefficients denote an inverse relationship. Coefficients close to zero correspond to no linear association.

Statistical significance of each correlation has been assessed with p-values obtained by means of the two-tailed statistical test. Correlation coefficients were declared statistically significant if their p-values were less than 0.05, 0.01, and 0.001.

The correlation analysis has helped identify metrics exhibiting strong relationships, which helped in understanding the relationship between vegetation structure connectivity, vegetation structure fragmentation, and vegetation structure edges. In this case, Pearson correlation proved to be instrumental in achieving this objective.

4.10 Ditch Extraction

Ditches are narrow linear depressions commonly found in agricultural landscapes. Ditches serve the purpose of draining water from farmlands. They are usually a component of the field margin and affect both hydrology and fragmentation.

The ditches have been identified from the DTM through a morphological closing filter difference method, which works well in locating thin depressions found in agricultural landscapes.

The initial step involves morphological filtering of the DTM using maximum and minimum filters for performing closing of the DTM data. Dilation is performed prior to erosion. It is done using a neighbourhood sliding window filter, whereby updating of each raster cell is done according to the maximum and then the minimum values within the moving window. The window size is 3.0 m, which corresponds to the number of pixels at the DTM resolution level. The effect of this process is that of smoothening the terrain by removing local minima and filling small-scale depressions.

Subsequently, the filtered surface has been subtracted from the original DTM (Figure 4.5). This process revealed depressions in the topography where the filtered surface remained elevated above the original ground level. The positive values have represented areas where

depressions existed prior to filling and levelling the terrain.

After this, a threshold value of 0.15 meters has been applied to retain the realistic depressions and eliminate any noise in the data. The final step involved filtering out objects that were too small (less than 4 m²) or too large (more than 500 m²). This method produced a raster layer representing the ditch location per each site.

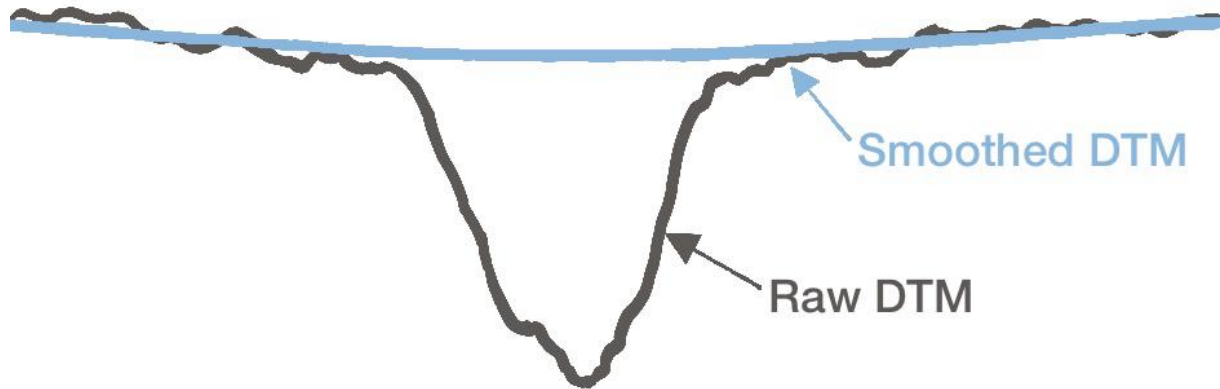


Figure 4.5: Illustration showing raw DTM and smoothed DTM (source: author).

4.11 Ditch Metrics

For the analysis of the ditches, only those that fall within the margins of the sites have been considered. Binary raster maps of the ditches have been subsequently clipped according to the delineated boundaries of the margin zones, whereupon the connected ditch pixels were separated into separate ditch systems. Artifacts have been removed, and small gaps between them have been filled to ensure the continuous segmentation of the ditch networks.

4.11.1 Total Ditch Length

Total ditch length has been defined as the combined centreline lengths of all ditch groups within the sites.

A high total length values have indicated a greater presence and spatial extent of ditch networks within the field margins, while lower value have represented fewer/less extensive ditch systems.

4.11.2 Ditch Area

Ditch area has been calculated by multiplying the number of ditch pixels by the cell size within the raster file. The metric is expressed as:

$$A = N_{\text{pixel}} \cdot r^2 \quad (4.6)$$

where N_{pixel} denotes the number of ditch pixels and r represents the raster resolution (0.5 m).

Larger ditch area values have indicated ditches with wider spatial extents, whereas smaller values have represented narrower ditch features within the study sites.

4.11.3 Ditch Width

The width of the ditch was determined in intervals of 1 meter along the ditch centerline extracted. The width of the ditch was determined as the sum of the perpendicular distances from the centerline to the two edges of the ditch.

In this way, we get a series of values of the width of the ditches along their length. The representative width of each ditch was found as the average value of the widths determined at intervals of 1 meter along the centerline of the ditch.

$$W = d_{\text{left}} + d_{\text{right}} \quad (4.7)$$

where d_{left} number of pixels from centerline to left edge $\times$ resolution (0.5 m), stopping when a non-ditch pixel is hit and d_{right} represents the number of pixels from centerline to right edge $\times$ resolution (0.5 m), stopping when a non-ditch pixel is hit.

Higher ditch width values have indicated wider ditch structures, whereas lower values have represented narrower ditch features within the study sites.

4.11.4 Ditch Depth

The ditch depth is determined using the DTM. In each ditch cluster, the median elevation of the terrain around the ditches at a distance of 5 m from the ditches was considered to be the reference ground level. The difference between this reference level and the elevations inside the ditches gives the ditch depth. This ditch depth was taken to be the average of all positive ditch depths.

$$\text{Depth} = z_{\text{buffer}} - z_{\text{ditch}} \quad (4.8)$$

where z_{buffer} median elevation in surrounding 5 m buffer and z_{ditch} represents ditch pixel elevation.

High depth values indicate deep ditches with high drainage potential, whereas low values represent shallower ditches.

4.12 Grass Margin Extraction

Grass margin raster for all the 30 sites has been created through progressive elimination of non-grass features from the previously delineated margin zone.

Vegetation from the Object-Based Vegetation Segmentation (Section 4.7.2) was used to mask out the vegetation from the field margins. Initially, vegetation pixels of object-based vegetation segmentation have been removed from the margin zone, and then ditch features derived from the DTM analysis (Section 4.10) have also been excluded from the raster.

To improve on the grass margin layer, more land cover objects have been selected from the PICC data set and converted into rasters and later clipped from the residual margin layer. The land cover objects include forests, hedgerows, isolated trees, waterbodies, roads, residential land surfaces, car parks, embankments, and other mapped infrastructures.

Finally, a connected component filter has been implemented to eliminate very tiny, isolated patches under 10 pixels (or 2.5m^2 at a 0.5m scale). The final raster data is the remaining open herbaceous strip of the field margin and is referred to as the grass margin layer.

4.13 Validation of Field Margin Delineation

4.13.1 Manual Orthophoto Interpretation

Sample points were randomly generated for each site, with 15 points inside the margin zone and 15 points in the remaining areas outside the margin zone. All validation points have been manually classified by examining them on 2021 orthophoto maps using ArcGIS Pro software. Each point has then been assigned a reference classification value, where 1 has indicated the margin zone and 0 has represented the interior (non-margin) area.

Validation of the margin zone identification process has been performed by using a confusion matrix made up of four components: true positives (TP), which indicated correct identification of margin zones; true negatives (TN), which indicated proper identification of interior (non-margin) areas; false positives (FP), meaning interior regions mislabelled as margin zones (overestimation); and false negatives (FN), indicating actual margin zones incorrectly categorized as non-margin (underestimation). Based on this confusion matrix, several accuracy metrics have been derived, including overall accuracy (OA), precision, and recall.

In addition, the F1-score has been calculated as a harmonic mean of precision and recall, thereby balancing these two metrics, taking into consideration both omission and commission of errors. Finally, the Kappa coefficient has been computed to assess the level of agreement beyond chance between the classified and reference data. Summary of all

metrics and calculations is presented in Table 4.3.

Table 4.4: Performance metrics used in this study (adapted from Ahlswede et al., 2021)

Performance Indicator	Formula
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 Score	$\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$
Overall Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Kappa	$\frac{p_o - p_e}{1 - p_e}$

4.13.2 UAV Based Margin Width Validation

The UAV jpeg images are processed through Agisoft Metashape Professional software to produce high-resolution georeferenced outputs for validation of the field margins. These UAV images already have GPS data embedded within them, which will be used for setting the camera positions and the photogrammetric reconstruction process.

First, the images are imported into the software, and camera calibration is done by feature matching among overlapping images by taking advantage of GPS data for initialization. This makes the bundle adjustment process more stable and accurate. Once the cameras have been aligned, a dense point cloud is created to reconstruct the 3D surfaces.

From the dense point cloud, a Digital Elevation Model (DEM) is derived to represent terrain and surface elevation characteristics. Using both the DEM and the aligned imagery, an orthomosaic is generated. The georeferenced orthomosaic is then used for the validation of the field margin width.

This emphasizes the validation of the geometry of the predicted margin zones, particularly its width, rather than the classification accuracy at certain locations.

For this purpose, one point per transect has been generated at the intersection between the transect line and the predicted margin zone boundary, resulting in a total of 46 validation points. At each point, margin width has been measured both from the modelled margin zone and from the UAV- derived ortho mosaic using ArcGIS Pro.

Comparison between predicted and observed margin widths has been used to evaluate potential model bias, including overestimation or underestimation of margin extent. The results have been analysed by plotting predicted margin width (m) against observed (UAV-derived) margin width (m). In addition, the coefficient of determination (R^2) and Root

Mean Square Error (RMSE) have been calculated to quantify the strength of agreement and the magnitude of prediction error, respectively. This approach has provided a quantitative assessment of the geometric accuracy of the margin delineation model.

4.14 Overview of derived spatial layers and analytical metrics

The table 4.5 summarizes the derived spatial layers and quantitative metrics extracted from the input datasets, together with their corresponding attributes and roles in the analysis workflow.

Table 4.5: Derived spatial layers and analytical outputs used in the study

Derived Layer / Metric	Derived From	Key Attributes / Metrics	Expected Role
Field margin delineation layer	SiGEC parcel boundaries, PICC	Field margin extent	Base layer for all vegetation and landscape analyses
LiDAR vegetation structure model	LiDAR nDSM, LiDAR point cloud	Vegetation height, structural heterogeneity, canopy variation	Input for vegetation segmentation and structural analysis
Foliage Height Diversity (FHD) layer	nDSM, LiDAR point cloud (LiDAR-derived vegetation layer)	FHD	Quantification of vertical vegetation diversity
Landscape metrics	Habitat patch layer	Number of Patches (NP), Effective Mesh Size (MESH), Mean Proximity Index (MPI), Margin to Total Ratio	Landscape configuration and fragmentation analysis
Ditch extraction layer	DTM	Ditch geometry	Hydrological feature delineation
Ditch metrics	Ditch extraction layer	Total ditch length, ditch area, ditch width, ditch depth	Quantification of drainage structure
Orthophoto Interpretation	Orthophoto	Visual interpretation of margins and land cover	Manual validation and quality control
UAV-based validation	UAV imagery	Field margin width	Validation of automated field margin delineation

5. Results & Discussion

This chapter describes the findings and discussion of study and is organized into eight main sections. The first section covers the analysis of field margin delineation, whereas the second one explores the vegetation structure analysis and foliage height diversity analysis. In addition, fragmentation impact assessment and correlation analysis of landscape metrics to better understand the spatial organization and connectivity of field margins. Ditch metrics and grass margin extraction are also examined to determine the characteristics of the hydrological and vegetational aspects of field margins.

5.1 Field Margin Delineation

Field margin delineation has played vital role in explaining the spatial structure and ecological connectivity of agricultural landscapes, especially in heterogeneous landscapes where margins occur between fields, road, semi-natural elements. Figure 5.1 shows the delineated field margins of site 21 and it is evident that the method has been quite effective in determining field margins within various landscape features. Field margins around roads have generally been accurately delineated due to the presence of clear and well defined PICC road boundaries within the landscape.

The figure above also shows several issues of this field margin delineation approach. Firstly, SIGEC agricultural parcels have been used to determine field margins, which include some inaccuracy issues. Not all fields have been completely mapped (Fig. 5.1). In addition, areas that contain vegetation within the field can be incorrectly considered as field margins. Moreover, the boundaries of the fields with uneven distribution of vegetation cause too much of field margins to be delineated, because of which the boundaries of the field cannot be delineated more accurately than the boundaries between agricultural and non-agricultural land use. SIGEC database is based on parcels, and thus the field margin boundaries are defined according to the declaration of farmers. Inaccuracies of this kind related to parcels, such as LPIS and cadastral data, have been previously described, where the lack of complete field surveys had affected the analysis of the ecological landscape (Zimmermann & Stout, 2012).

The importance of field margins delineation for landscape analysis has been increasingly recognized, particularly in studies focusing on landscape heterogeneity, ecological connectivity and biodiversity in agricultural systems. The role that field margins can play as ecological corridors for the movement of pollinating insects, small mammals, plants, among other organisms, thus making them part of the provision of ecosystem services within agricultural lands, has been established (Baudry et al., 2000). Accurate field margin delineation remains a difficult task in fragmented agricultural landscapes (Watkins & Van Niekerk, 2019).

Moreover, instances where there is an overestimation of the margin have been noted, especially in the case of adjacent agricultural fields. In such instances, some vegetated strips will mistakenly be defined as field margins whereas part of the field itself may be disregarded. This problem arises from the fact that boundaries in nature have always been fuzzy and cannot necessarily be represented as clear cut, a problem that has long been identified in the boundary detection literature (Fortin et al., 2000). There was also lack of precision in the delineation between agricultural lands, as the vegetation on the land was unevenly distributed and there were other transitional landscape features that could not be completely captured by the SIGEC parcel-based data set.

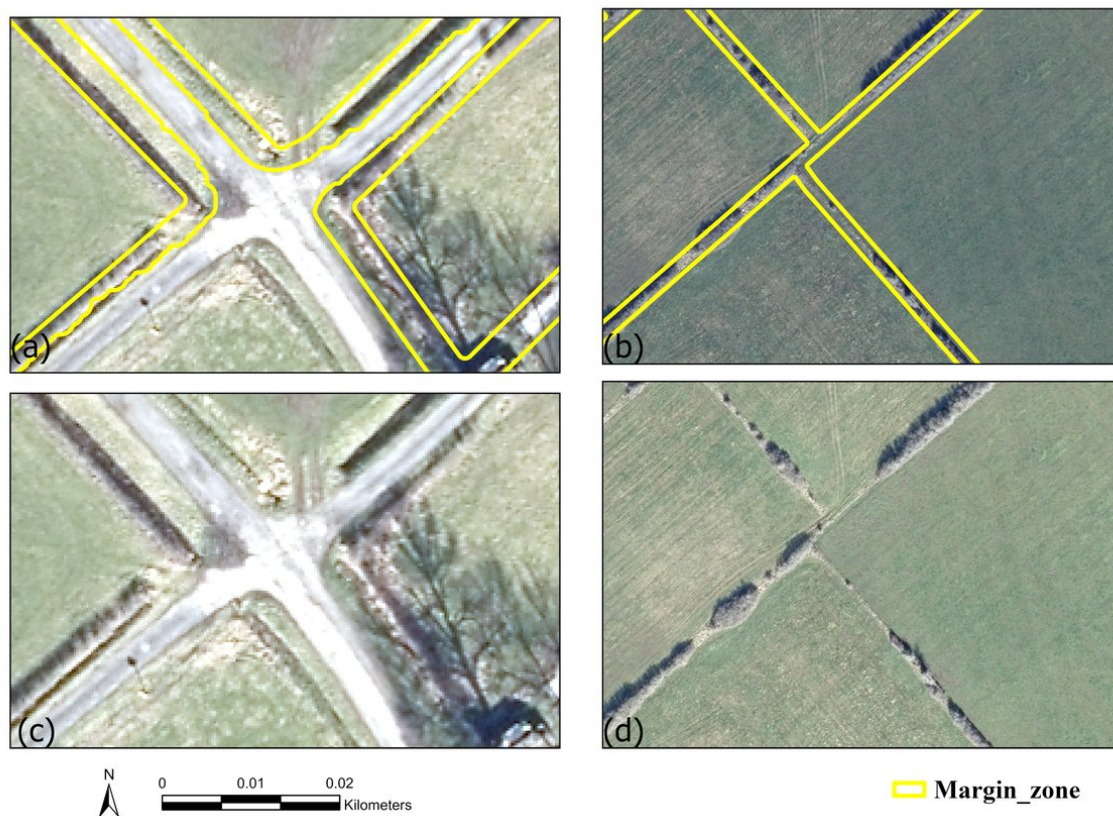


Figure 5.1: Field margin delineation (yellow outline) for site 21(a-b) Examples of margin delineation, and (c-d) corresponding orthophoto

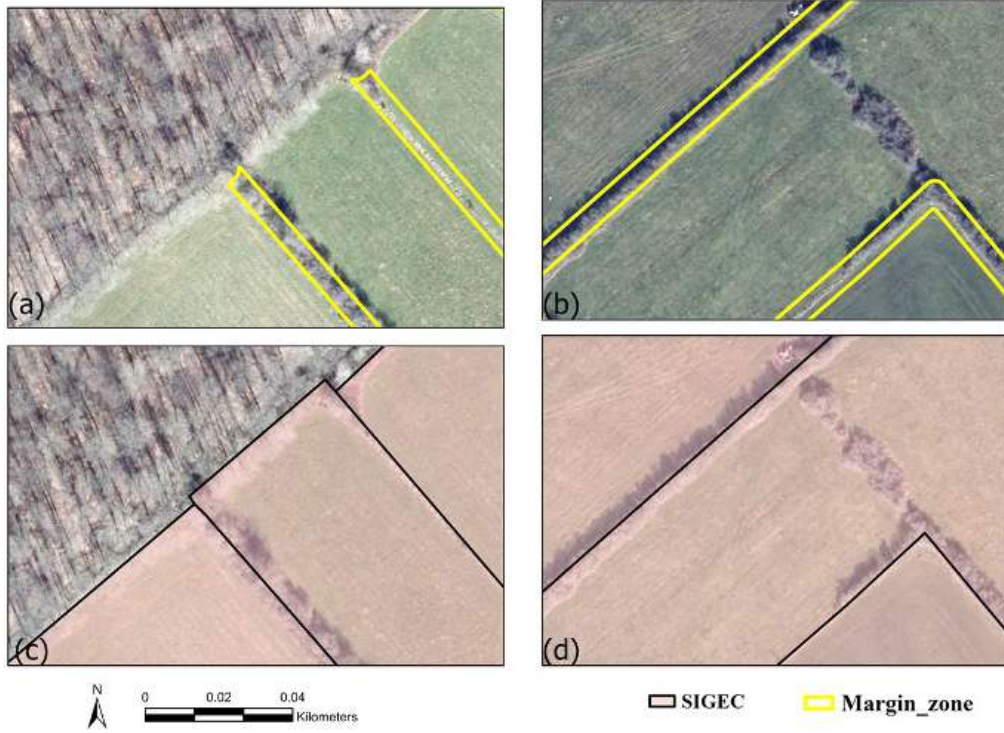


Figure 5.2: Field margin delineation (yellow outline) for site 21 compared with SIGEC field boundaries (black). (a–b) Examples of margin delineation, and (c–d) corresponding SIGEC boundaries highlighting areas of agreement and discrepancy.

5.2 LiDAR Vegetation Structure Analysis

The vegetation segments obtained through the object-based vegetation segmentation approach described in section 4.5.2 have been used to assess the unit height distribution of the combined units in the margin zones of all 30 sites (Figure 5.3). The assessment has provided information on the vertical structure of the vegetation in terms of the average height of all segmented units based on LiDAR vegetation.

A total of 516,390 vegetation units have been detected among all the sites with a mean vegetation height of 11.25m. The result shows a strong dominance of high vegetation fragments within the field margins. Vegetation above 3 meters tall accounts for 85% of the total vegetation, with an average height of 12.88 meters. This shows that there is a dominance of high vegetation, including mature trees, hedgerows, and vertical woody vegetation, in the field margins.

The plot distribution indicates three separate layers of vegetation cover: small, medium, and high vegetation. Clustering of vegetation units within the lower height range implies that there is dense vegetation cover consisting of herbaceous or small shrubs growing close to the ground surface. Nevertheless, this layer appears less developed compared to other vegetation layers. Small vegetation units from 0.5 to 1.5 m make up just 6% of the total

vegetation units, with an average height of 1.15 m. Although relatively less abundant than other groups, small units of vegetation have a narrow and very uniform height range, showing that there is some homogeneity within this group of low vegetation. Units of medium vegetation from 1.5 m to 3 m consist of approximately 8% of the units, with an average height of 2.16 m.

The dominance of tall vegetation suggests that most field margins in the study area have developed complex vertical canopy structures. This structurally diverse field margin is likely to contribute significantly to ecological processes such as habitat connectivity, providing refuge for different species of fauna, nesting places, and climatic control.

The decrease in the density of vegetation objects from 15 meters onward is also caused by the occurrence of a smaller number of very high vegetation structures, which are probably related to individual mature trees or thick forest clusters present at the border of farmlands. In general, the field margins in the study sites are heterogeneous and dominated by tall vegetations.

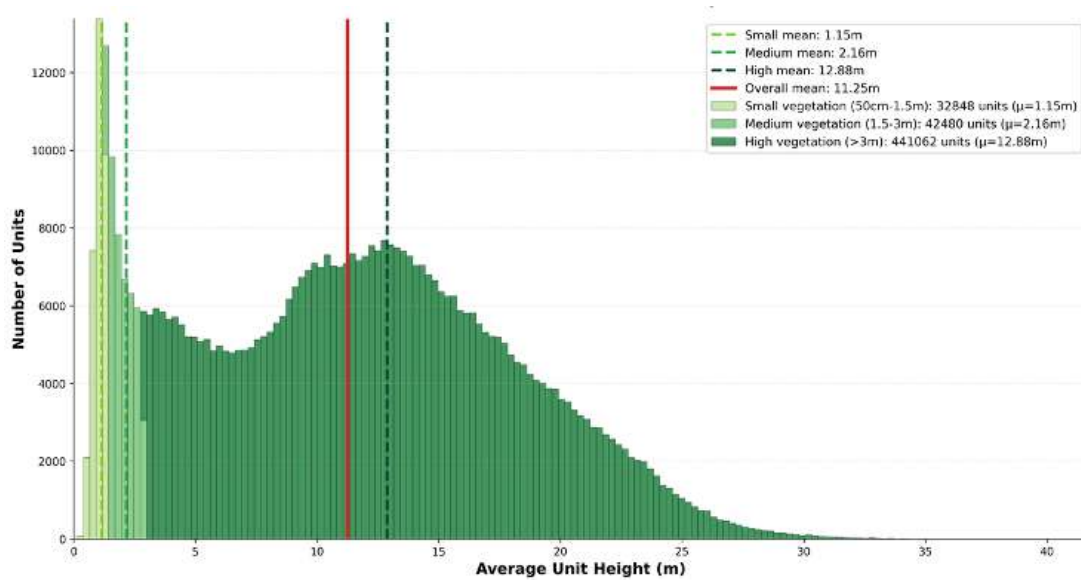


Figure 5.3: Combined unit height distribution of vegetation segments in margin zones across all 30 polygons ($n = 516,390$), showing class-specific means for small (0.5–1.5 m: 1.15 m), medium (1.5–3 m: 2.16 m), and high (>3 m: 12.88 m) vegetation

The object-based segments derived from the watershed segmentation approach have been further analysed to quantify the extent of vegetation patches in the field margin (Figure 5.4). The findings showed considerable variations in the sizes of vegetation patches between the three groups of vegetation heights.

High vegetation units (>3m) have produced the largest vegetation segments with a median area of 16 m^2 , and an average area of 18.9 m^2 . On the other hand, vegetation units between 50 cm and 1.5 m have median area of 2.8 m^2 and an average area of 3.3 m^2 . This implies that vegetation units above 3 m are six times larger on average compared to

vegetation units between 0.5 m and 1.5 m.

High vegetation has also been found to be spatially dominant based on vegetation patch size results. It may be that the relatively high patch size of high vegetation represents continuous woody features, including trees, and canopies present along agriculture edges. This finding complements previous vegetation height distribution results where high vegetation has been seen to make up most of the vegetation patches found at each site.

On the other hand, small vegetation (1,914 units) and medium vegetation (5,226 units) units have been found to have relatively tighter distributions with less pronounced outliers. As shown by the box plots, their inter-quartile ranges are quite tight and they have much lower outliers, which suggests that low and medium vegetation are likely to form small and compact patches. This kind of vegetation could include scattered strips of herbaceous vegetation or low vegetation patches.

The vegetation class (>3 m), too, has exhibited an extensive distribution range and many outliers, as some of the vegetation classes have exceeded 100 m^2 in their area. This is indicative of the high connectivity of the vegetation class and woody components in certain study plots. The variability in this vegetation class clearly indicates a significant variation in the arrangement of tall vegetation in agricultural landscapes in Wallonia.

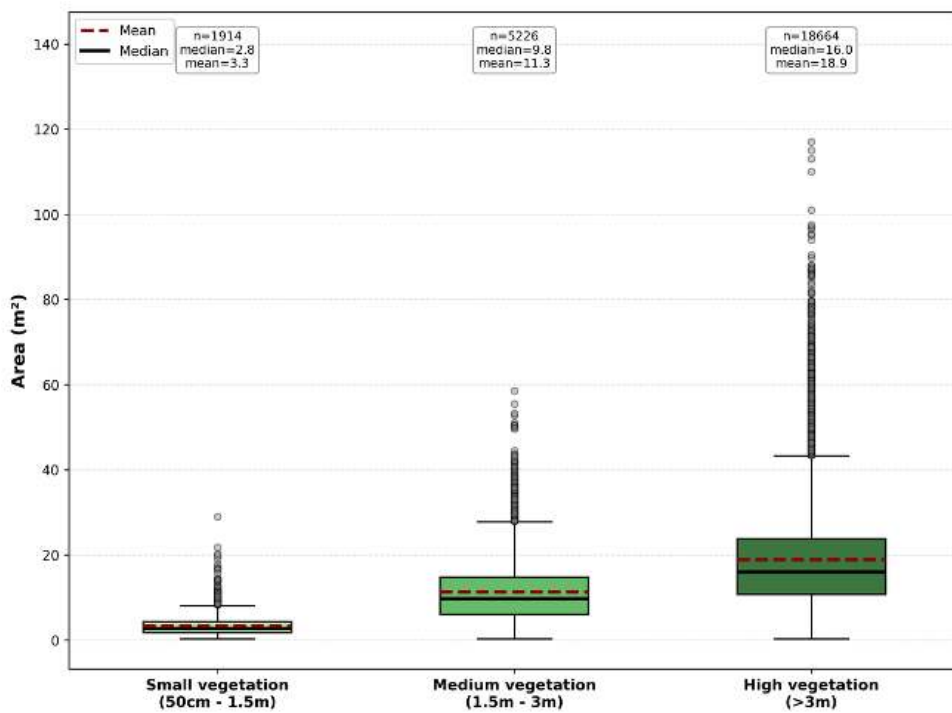


Figure 5.4: Boxplot of vegetation unit area (m^2) by height class in the margin zone, watershed segmentation across all polygons ($n = 25,804$ units).

5.3 Foliage Height Diversity (FHD) Analysis

Further assessment of vertical vegetation structure diversity within field margins has also been carried out by calculation of Foliage Height Diversity (FHD), which is determined based on the height distribution of the vegetation from the LiDAR data (see Figure 5.5). Foliage Height Diversity has been estimated for all study sites as an indicator of structural diversity of vegetation at different heights within the field margins.

The findings have revealed that the FHD values in the 30 study locations fall somewhere between 3.15 and 4.56, with the average FHD value of 4.096. Many locations have shown rather high FHD values near the overall mean value, meaning that vegetation with high structural diversity is found at many places within the study site. However, few locations have recorded lower FHD values. For instance, the FHD levels observed at locations P8 (Site 8), P17 (Site 17), P22 (Site 22), and P2 (Site 2) have been among the highest in the whole database. This high level may be an indication of the existence of several vegetation height levels at the margins. These characteristics are found where there exists structurally heterogeneous vegetation like multiple-layered hedgerows made up of ground-cover herbs, shrubs, and trees. Vertical vegetation is known to increase habitat opportunities for diverse species due to niche differentiation, a phenomenon observed in the habitat heterogeneity-biodiversity link examined by Tews et al. (2003).

On the other hand, sites like P1 (Site 1) have displayed lower FHD values, indicating simple vegetative structure characterized by lower diversity of canopy height distribution. The occurrence of such lower values is associated with field margins characterized by less complex vegetation and those that lack development of woody vegetation.

The small range of FHD values for most of the study locations suggests that a vertical structure of the vegetation is an invariable property for the edge areas of Wallonia. Indeed, this conclusion can be confirmed by the results of the previous analysis of the vegetation height and vegetation unit area, during which a strong prevalence of tall vegetation was proven. It may be supposed that such a dominance of high vegetation and large vegetation units has led to high FHD values at some sites.

Overall, the analysis performed based on vegetation height distribution, area of vegetation units, and Foliage Height Diversity showed that the field margins are comprised of highly variable vertical structures of woody vegetation. The vegetation at high levels predominated among heights and vegetation unit areas, while the FHD index provided additional confirmation of the heterogeneity of vertical canopy structure in most study sites. From an ecological perspective, structural diversity is essential in increasing the number of microhabitats and thus promoting biodiversity in intensively used areas, like agroecosystems (Benton et al., 2003; Tews et al., 2003). Thus, the data suggest that the field margins in study sites have become structurally diverse vegetation complexes that

play an important role in ecological connectivity and biodiversity maintenance.

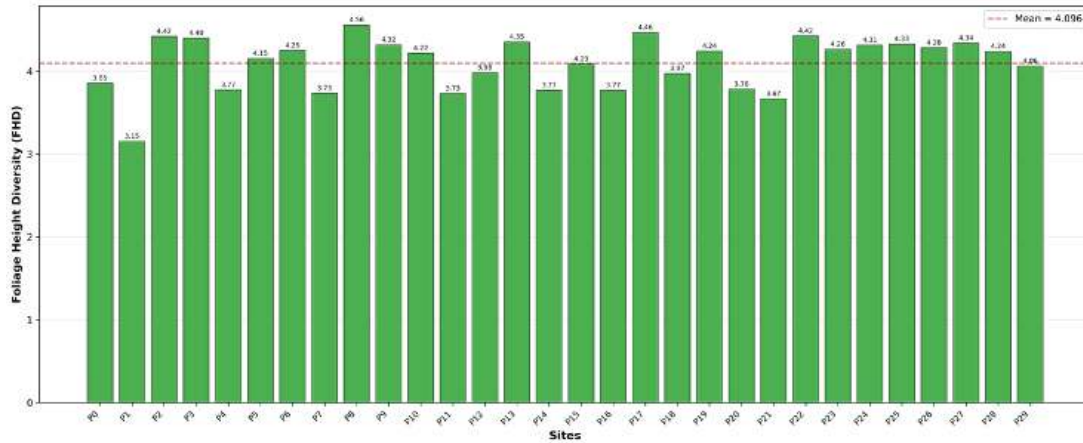


Figure 5.5: Foliage Height Diversity (FHD) across all 30 study sites in the margin zone. The dashed red line indicates the overall mean (4.096).

5.4 Fragmentation Impact Assessment

The fragmentation impact heat map (Figure 5.6) presents comparison of four landscape metrics such as MESH (Effective Mesh Size), MPI (Mean Proximity Index), Margin to total ratio, and NP (Number of patches). The figure shows five selected sites of the total of 30 sites used for this study. These five sites have been chosen to show observed fragmentation conditions in the study area, ranging from well-connected margin zones to severely fragmented landscapes. The location of these five selected study sites are shown in Figure 5.7. The complete heat map for all 30 sites is included in Figure 8.2.

The heatmap employs the colour gradient with a range that extends from dark green (highly connected) via yellow (moderately connected) to dark red (fragmented) based on the normalization direction according to ecological significance of each index. The indices MESH, MPI, and Margin to total ratio have high numbers for good connectivity, hence these numbers are normalized towards dark green. In NP, the case is opposite, since the higher values mean fragmentation; therefore, the values tend to be normalized to red.

Site 9 has emerged as the best-balanced sites across all metrics. The MESH value of 415.3 m² demonstrates that the margin zone has sufficiently large and interconnected vegetation patches. The MPI of 3.40, which is significantly higher than the values in all other sites, shows that there is high connectivity between vegetation patches because they are close to each other. Margin to total ratio of 1.24 proves that vegetation coverage is higher in the margin zone than in the open area, while an NP of 261 is quite appropriate without indicating excessive fragmentation.

site 21 possess highest MESH (459.0 m²) among all five sites, implying the presence of

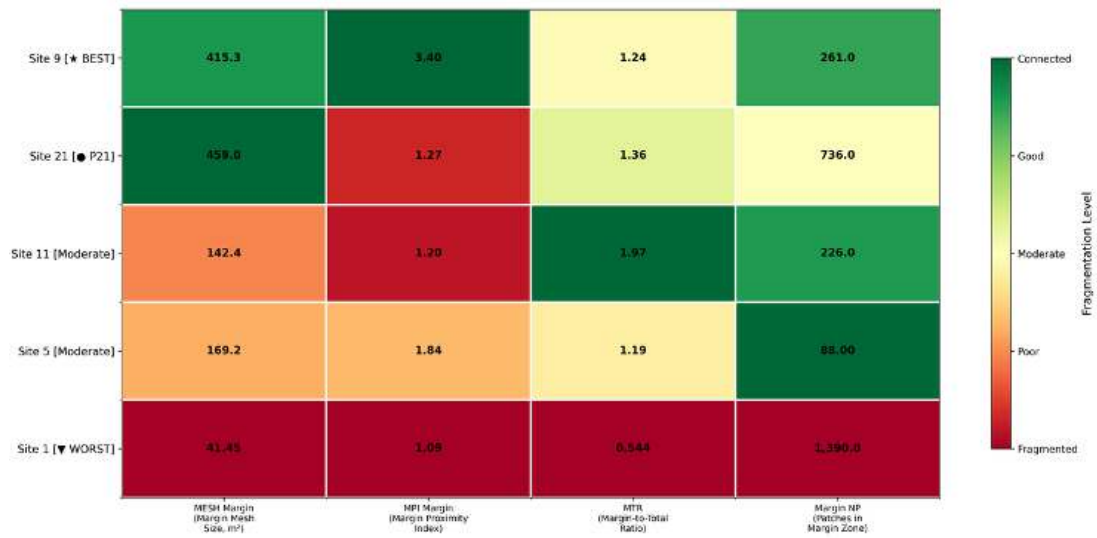


Figure 5.6: Fragmentation impact map comparing four landscape metrics (MESH, MPI, Margin to total ratio, NP) across five representative sites ranging from best-connected (site 9) to most fragmented (site 1). Colour intensity indicates fragmentation level from connected (green) to fragmented (red).

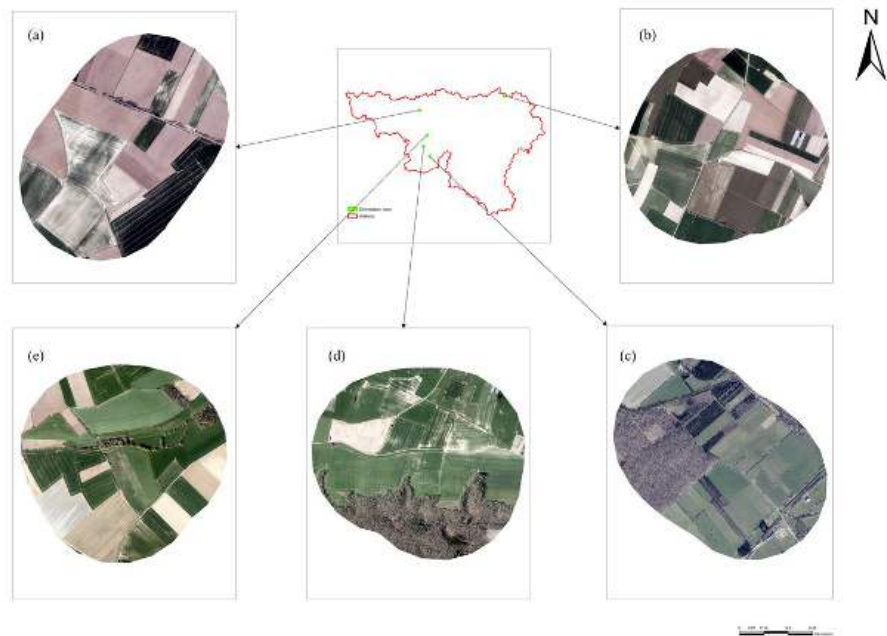


Figure 5.7: Location of five selected study sites in Wallonia, Belgium showed in the fragmentation impact heatmap: (a) Site 5, (b) Site 1, (c) Site 21, (d) Site 11, and (e) Site 9. The central map shows the regional context with site locations marked in green. Orthophoto basemaps illustrate contrasting landscape configurations across the study area.

very large patches are spatially dispersed rather than clustered. In addition, the NP (736), nearly three times the number recorded for site 9, suggests that there have been more fragmented patches of vegetation along with the dominating ones; hence a mosaic of patches. Finally, the Margin to total ratio (1.36) indicates that margin zones manage to hold onto vegetation effectively, except for the low MPI. This implies that site 21 has an adequate vegetation structure but lacks effective patch aggregation.

The three sites like site 11, site 15, site 21 are considered moderately performing sites. For instance, site 11 shows the highest Margin to total ratio value (1.97), which implies that the margin zones within it have almost double vegetation cover than open zones, implying the presence of buffer strips or hedgerows, although its MESH value is still relatively low at 142.4 m², and its MPI value of 1.20 represents a mediocre level of patch clustering. On the other hand, the lowest NP value (88) is found in site 5, indicating that it has the least fragmented landscape among all five selected areas, with Margin to total ratio of 1.19 indicating the predominance of margin vegetation and MESH and MPI values of 169.2 m² and 1.84, respectively, being at the moderate level. Collectively, all these sites illustrate how various combinations of responses to metrics produce different degrees of fragmentation; in site 11, there is high concentration of margin vegetation but no patch area and connectivity, while site 5 exhibits a low number of patches without attaining the same level of connectivity observed in the most successful site.

Site 1 has shown high level of fragmentation across all metrics. With a MESH of 41.45 m² (about one tenth of the MESH in site 9), site 1 shows the occurrence of extremely small and fragmented patches. Similarly, the MPI figure of 1.09 is the smallest among all five sites, confirming that patches are scattered and far apart. The Margin to total ratio of 0.54 represents the only value below 1 across all five sites, demonstrating vegetation is in open areas rather than in marginal zones. Finally, the NP value of 1,390 is by far the highest for all sites. These results imply that intensive farming practices have severely affected the connectivity of the margin zones in site 1. This is in keeping with the observation that intensively farmed land tends to be characterized by botanically poor field margins containing only negative indicators, with a high edge-to-area ratio (Larkin et al., 2022).

5.4.1 Ecological implications

Some of the trends that have emerged from comparing these five sites include the following. First, the degree of fragmentation has not been the same throughout the region. The chosen sites represent the full range of fragmentation from none to maximum fragmentation, indicating that land management plays a significant role in shaping the landscape. Second, from the analysis using Margin to total ratio, four out of the five regions still have Margin to total ratio levels greater than 1, which means that margins serve the purpose of vegetation corridors. Site 1 alone has fallen below this threshold, implying that the practice of

intensive cultivation may be instrumental in reversing the trend of vegetation growth on the margin. This is in line with research showing that intensification of agricultural land use is linked to a decrease in plant species diversity and biodiversity on farmlands (Kleijn et al., 2008). Lastly, MPI has become increasingly effective at capturing connectivity information, as evidenced by polygons with relatively high MESH values (Polygon 21 and Polygon 11) having relatively low MPI values, highlighting connectivity challenges not captured by simple calculations of patch size. The spatial sensitivity of proximity indices has been extensively studied using FRAGSTATS analysis, where MPI was developed to capture patterns of patch isolation, patch clustering, and patch fragmentation that cannot otherwise be calculated through metrics based on area (McGarigal & Marks, 1995; McGarigal, 2002).

5.5 Correlation Analysis of Landscape Metrics

The correlation analysis of the four margin zone landscape metrics noted that there are several interesting correlations between four margin-zone landscape metrics identified based on the correlation coefficient. This coefficient can be interpreted using existing concepts of fragmentation theory, despite weak to moderate nature of relations. The number of patches in the margin (`num_patches_margin`) and the effective mesh size (`mesh_margin_m2`) have shown a positive correlation of 0.25, which suggests that as the margin becomes dissected into a greater number of patches, the effective mesh size tends to increase slightly. The reason behind this correlation lies in equation used in calculating Effective Mesh Size (MESH), which is equal to the ratio of the sum of squared patches' areas to the total landscape area. Due to disproportionate impact of bigger patches on the calculation result, there are cases when several similar patches yield higher MESH values than one big patch with a lot of tiny fragments around (Jaeger, 2000; Wang et al., 2014). The effective mesh size (MESH) is indicative of the level of landscape fragmentation, and its values depend on the size distributions of the patches but not only on their abundance. The slight positive correlation between `mpi_margin` and MESH could be attributed to the partial overlaps among landscape metrics because the relationship between interdependence and redundancy in fragmentation metrics has been extensively studied in landscape ecology research (Kerr & Remmel, 2024).

The mean patch index (MPI) in the margin too has shown a weak positive correlation of 0.17 with margin to total ratio (`margin_to_total_ratio`), indicating that as the percentage of the area categorized under the margin zone increases, the mean size of the patches in that zone is slightly larger. This finding suggests that when the margin occupies a greater share of the landscape, it is configured as fewer, more extensive patches rather than as numerous tiny fragments. In farming and semi-natural habitats, such an arrangement might lead to wider transition zones that might have different ecological roles from narrow,

highly fragmented borders. Such uniformity in weak positive relationships between metrics related to the size component (MPI & MESH) shows that there is some relationship between landscape structure and composition, but the low values of their correlations suggest that they have unique roles, just like it was proposed when choosing non-redundant metrics for fragmentation analysis.

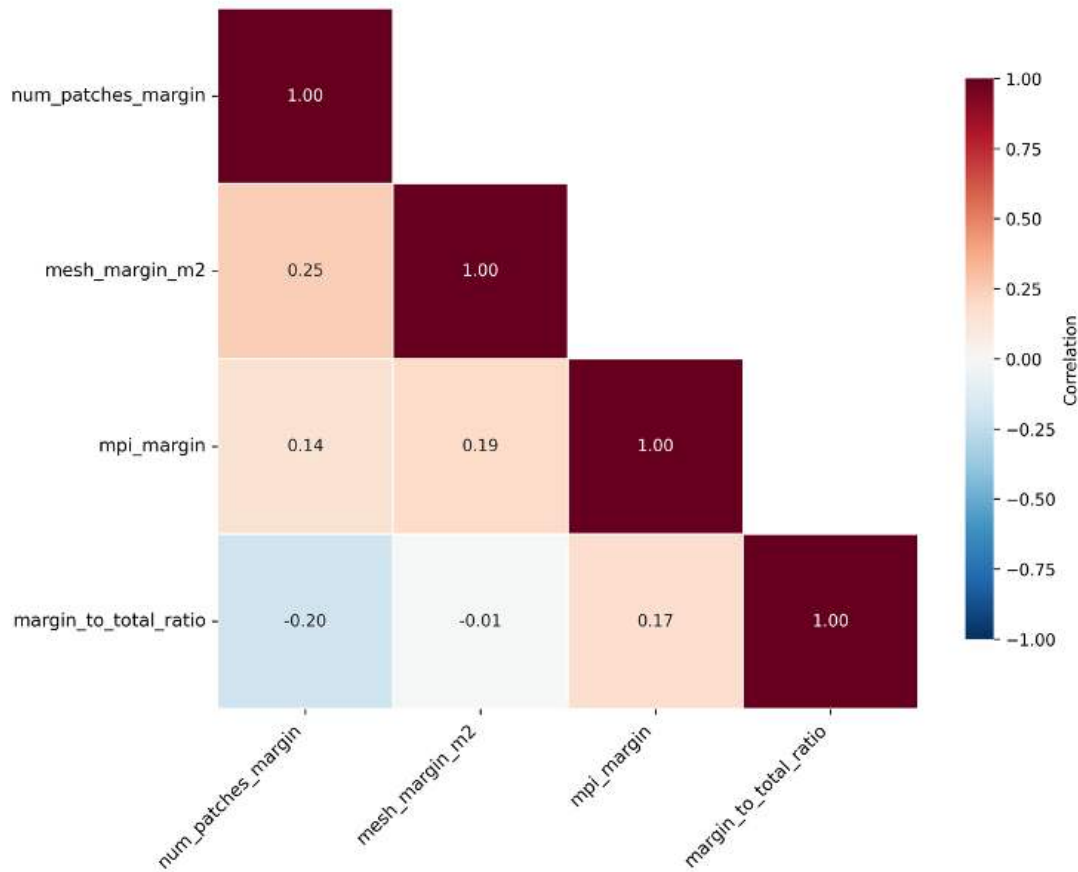


Figure 5.8: Pearson correlation matrix between margin zone landscape metrics (NP = number of patches; MESH = effective mesh size; MPI = mean proximity index; margin-to-total ratio). Lower triangle shows correlation coefficients; diagonal shows perfect autocorrelation ($r = 1.00$).

On the other hand, the margin-to-total ratio has been found to have a relatively low and negative correlation (-0.20) with the number of margin patches. This indicates that site areas with more margin zones within the entire area will be accompanied by a lower number of margin patches. The negative correlation suggests that large margins will mostly remain non-fragmented; indeed, according to landscape ecology, an increase in the size of habitats may lead to patch aggregation (Rutledge, 2003). At the management level, this correlation would mean that an increase in the proportion of margin zones will not cause fragmentation, but may help to create larger margin zones that can improve structural connectivity. Overall, from all the above-mentioned correlations, margin zones work as per theoretical expectations, but generally weak correlation values for all pair-wise

comparisons indicate that margin zone indices add distinct value in determining landscape fragmentation.

5.6 Ditch Metrics

The ditch extraction using the Digital Terrain Model (DTM) has proved far more informative than the PICC ditch bottom vector dataset available. Whereas the PICC line vector indicate merely the extent of ditch bottom channels, the extraction using the Digital Terrain Model has allowed the analysis of other morphometric parameters such as ditch width, depth, length, and area covered by ditch groups. Moreover, the comparison also reveals that ditch features identified through the Digital Terrain Model have also been able to identify several ditch elements not captured in the PICC ditch bottom data (Figure 5.7). This highlights the benefit of using high-resolution terrain models derived from LiDAR for detecting small-scale drainage microtopography (Jones et al., 2007; Tarolli, 2014).

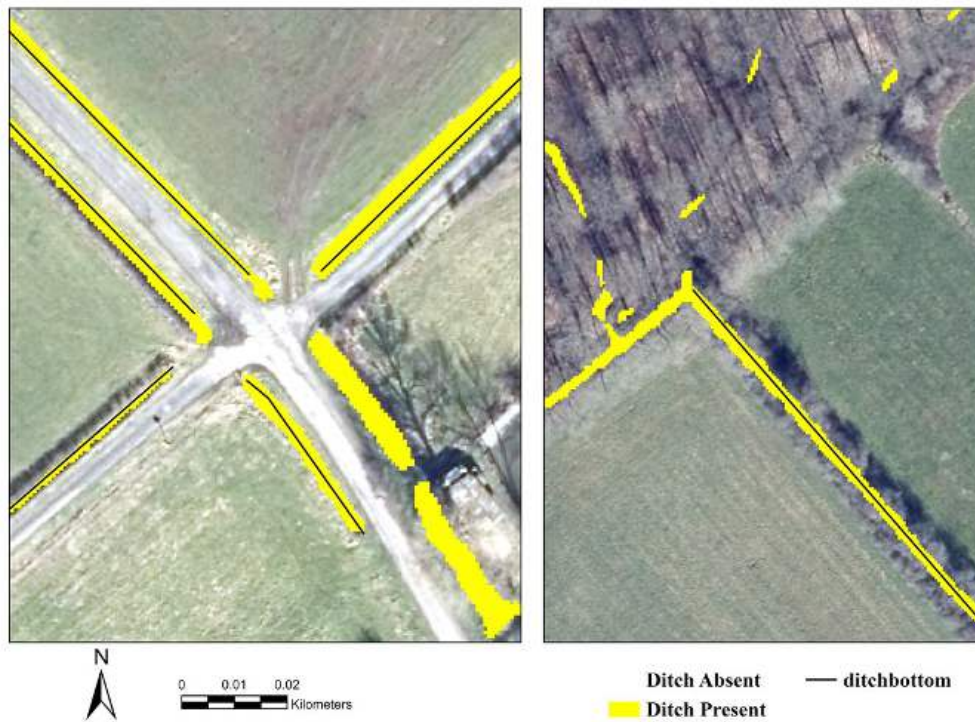


Figure 5.9: DTM-derived ditch features (yellow) overlaid on ortho imagery, compared against PICC ditch bottom lines (black).

A total of 455 ditch groups distributed across 30 sites have been found within the margin zones. It can be observed from the analysis of ditch depth and width distribution that most ditches are comparatively shallow and narrow (Figures 5.9, 5.10). The depth distribution reveals that the mean depths for most ditch groups are spread between 0.2 to 0.6 m, with an average mean depth of 0.51 m. Similarly, the width distribution also shows that most

ditch groups are spread between 1.4 and 2.4 m in width, with a mean width of 2.02 m.

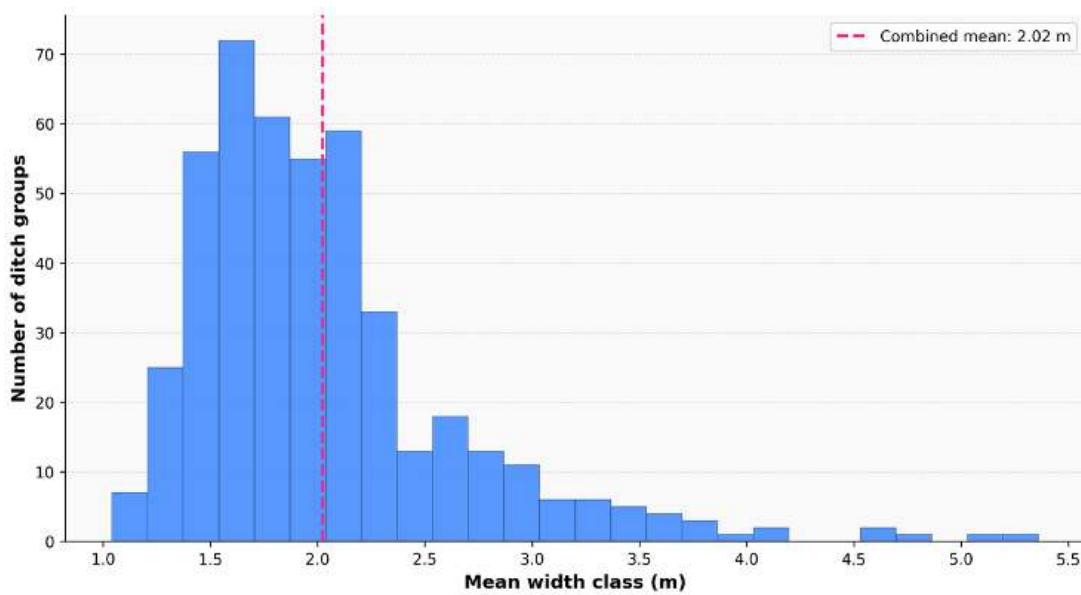


Figure 5.10: Distribution of mean widths across 455 ditch groups in margin zones of 30 polygons. Unimodal, mildly right-skewed with peak at 1.6 m. Combined mean: 2.02 m (dashed line). Majority of ditches are narrow (1.5–2.5 m)

From the histogram, there is a positive skewness in the distribution of the depth and width. There are a smaller number of ditch groups that have higher values and are considered outliers. For the depth distribution, there are ditch groups that have more than 1.5 m depths and even reach up to 3 m. Similarly, there are ditch groups with widths exceeding 4 m. Given that the ditches are mostly shallow and narrow, it can be concluded that the ditch network mainly serves as a surface drainage system aimed at facilitating water transport rather than water storage. It should be noted that similar morphological features can be observed in the case of agricultural drainage networks (Sofia & Tarolli, 2017).

The ditch morphology which was derived using the DTM-based approach, has revealed the variability in ditch morphology within the study sites. The variability in ditch morphology may be attributed to different land management techniques, ditch maintenance, vegetation growth, sedimentation, and hydrological conditions. According to Passalacqua et al. (2015), ‘high-resolution topographic data enable small-scale features and perturbations, natural and anthropogenic, to act in concert in exhibiting significant control over mass and energy fluxes’.

Certain uncertainties can be noted in the extreme values, mainly those in the depth distribution. Such extremes could be attributed to certain limitations of LiDAR data analysis and terrain interpolation. Although LiDAR data set has high accuracy vertically (standard deviation of approximately ± 4 cm), minor inconsistencies in ground classification, interpolation under dense vegetation, or surface roughness could affect depth calculation, especially in ditches with steep slopes. There have been several publications concerning

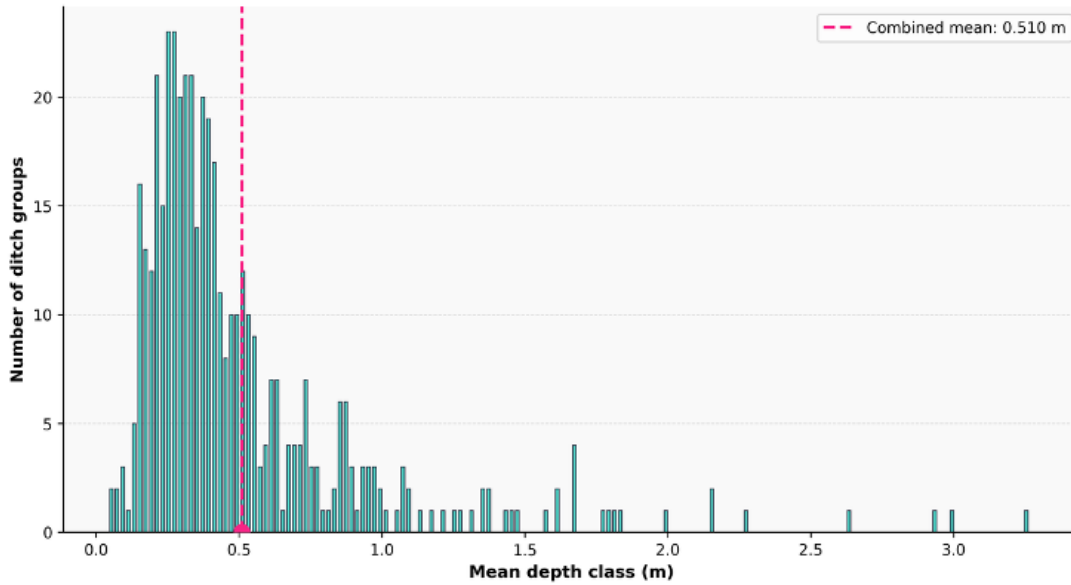


Figure 5.11: Distribution of mean depths across 455 ditch groups in margin zones of 30 polygons. Strongly right-skewed with peak at 0.3–0.4 m. Combined mean: 0.51 m (dashed line). Most ditches are shallow (<0.5 m), with few exceeding 1.0 m.

the problem of artificial depressions in LiDAR-based digital elevation models and their influence on terrain modelling. It was found by Lindsay & Creed (2005) that the technique of depression removal could dramatically affect terrain characteristics, and flat regions are the most vulnerable to such changes. However, ditch morphometry can be considered correct because ditch sizes greatly exceed vertical accuracy of the data set.

The dense pulse acquisition rate of the LiDAR data set (6.8 pulses/m²) could have been instrumental in the successful mapping of the small drainage features not present in the vector map. Previous studies have shown that highly detailed DTM maps generated from LiDAR technology are very efficient in mapping small-scale depression, drainage ditches, and microtopography that cannot be easily captured through conventional mapping techniques (James et al., 2006; Tarolli, 2014). Analysis of the length and area frequency distribution for ditch groups also confirms the spatial variation found in the ditch network.

5.7 Grass Margin Extraction

The grass margin extraction process successfully classifies the grass areas around the field margin. In other words, the grass margin layer created by the procedure gives the overall distribution pattern of grass edges surrounding the farming land parcels and drainages. By continuously stripping off the unwanted features from the field margin layer, we have successfully created an overall continuous layer of the open grass surfaces.

The extraction results shows that the method works well when it comes to extracting

the large portions of herbaceous field margins; however, some overestimation of grass margin extent is also evident. At various points, especially between adjacent agricultural fields, the extracted grass margins extend beyond the actual grass cover based on the orthophotos. Sometimes, classified margins cross original field boundaries to include the cultivated surface that no longer represent the grass margin (Figure 5.11)



Figure 5.12: Examples of grass margin classification (orange) overlaid on ortho imagery, illustrating the spatial distribution of grass margins surrounding agricultural parcels and drainage features.

The observed overclassification suggests that the current extraction technique needs to be improved further to enhance its accuracy. In this case, the over-classification may be because of the threshold employed in delineation. Moreover, seasonal crop conditions, mowing frequency, and plant heterogeneity may further hinder the automated extraction process (James et al., 2006).

Despite the overestimation, the derived grass margin network does offer considerable insight into spatial distribution and connectivity of field margin. In terms of identification of grass margins, this process has proven to be successful at locating most margins at a larger scale. However, refinement of classification thresholds, addition of object-based image segmentation techniques, may improve the accuracy of the grass margin extraction.

The map of grass margin shows the spatial inconsistency between the extracted margins and the actual grass margin boundaries. This is the reason that there has been no further analysis done in this regard in this study for grass margin. These comparisons show

areas where the extraction performs well, while other regions show overlapping of the field boundaries. Such findings are important for analysing the accuracy of the grass margin extraction methodology.

5.8 Validation

5.8.1 Manual Orthophoto Interpretation

The confusion matrix (Figure 5.12) shows the following classification results: there were 440 TN for the correctly classified interior areas, 318 TP for the correctly classified margin zones, 132 FP for the misclassified interior areas into the margin zones, and 10 FN for the misclassified margin zones into interior areas. In this context, interior zones imply those zones that are found within the study site which do not belong to field margin zones. Based on the above results, the overall accuracy (OA) has been estimated as 84.2%, which means that 84.2% of all points used during the validation process were correctly classified. Precision is equal to 70.7%, i.e., the 70.7% of points classified as margin zones belong to these areas. Recall is 97.0%, which means that 97.0% of all points belonging to margin zones were correctly classified by the method. F1-score equals 81.7% and represents the harmonic mean of precision and recall. Thus, F1-score considers both omission and commission errors at the same time. Also, the Cohen's kappa value has been found to be 0.684, which represents substantial agreement between the classified and reference values.

It can be observed that the overall accuracy rate of 84.2% achieved by the margin zone identification method indicates that the method works satisfactorily when it comes to discriminating between margin zones and interiors. In previous land cover classification research, the range of overall accuracy rate is typically between 80 and 90%, which is sufficient to create maps for landscape mapping purposes (Sim et al., 2024). The high recall rate of 97.0% suggests that the margin zone identification method has excellent sensitivity, effectively identifying most of the existing margin zones while minimizing omission errors (Foody, 2002). Sensitivity is an essential feature of the method for ecological studies since omission of field margin zones could cause underestimation of the biological significance of the landscape.

However, the moderate precision of 70.7% suggests that around 30% of the points classified as margin zones have been part of interior zones, causing commission error of 29.3%. The tendency to overestimate the margin zones has pointed out that margin zone detection algorithm may have extended margin classifications into interior zones that share visual or topographic similarities with edge areas. Commission errors have been common in the buffer-based delineation methods, where transition zone between the margin and interior areas indefinite characteristics (Congalton, 1991). The substantial difference between

recall and precision has highlighted a skewed error distribution, with a high number of false positives ($n=132$) compared to false negatives ($n=10$), showing that method has bias toward overestimation. The error is consistent with issues noted in previous studies on riparian zone delineations, which used buffer methods and encountered problems with unclear boundaries, especially for flat landscapes and transitional lands (Salo et al., 2016).

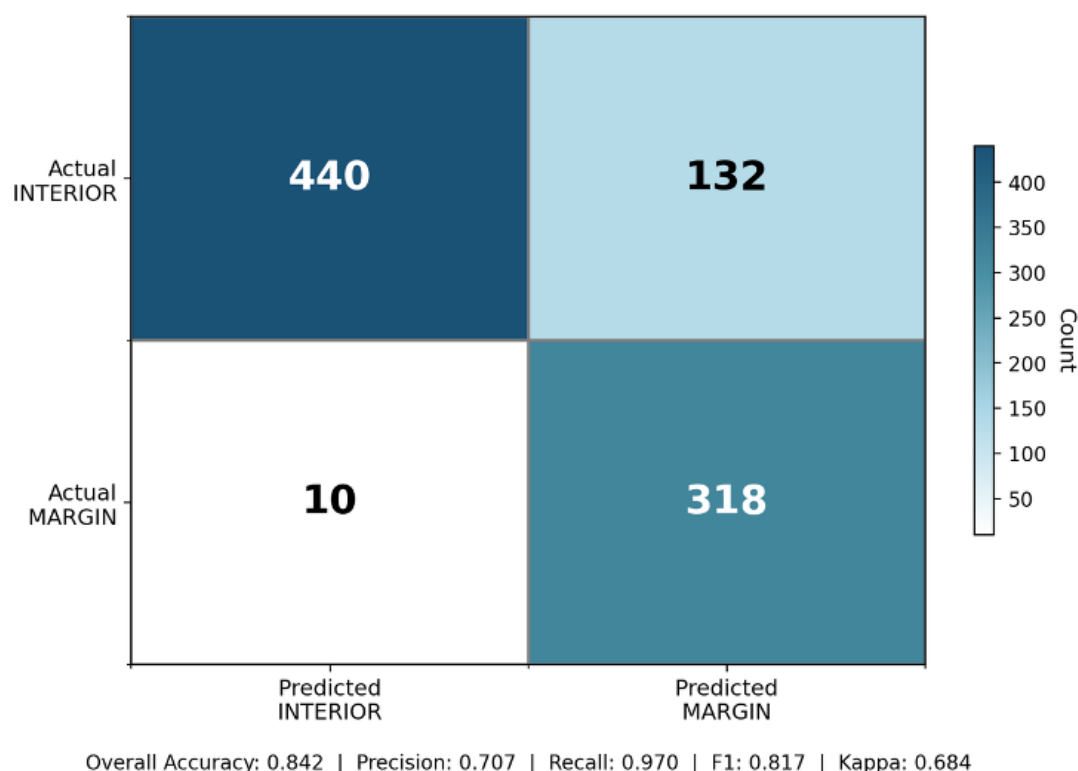


Figure 5.13: Confusion matrix comparing predicted and reference classifications of margin zone and interior areas based on 900 validation points. Metrics: OA = 84.2%, Precision = 70.7%, Recall = 97.0%, F1 = 81.7%, Kappa = 0.684.

Compared with other methods used in land cover validation, the results of accuracy measures received in this study fall in the interval of accuracy values for comparable binary classifications. In the literature, when orthophoto was applied as a validation tool, overall accuracies of 85-95% were noted for clearly identifiable land cover types, while the value of the kappa coefficient varied between 0.70 and 0.90 (Malinowski, 2016). The somewhat lower precision value was explained by the problem of determining boundaries of the margin zone, which has less spectral contrast than the classification based on satellite imagery and requires interpretation through topography and context. The tendency to overestimate the area of the margin zone near fields is a typical issue encountered in landscape mapping research, as the transition zone between forest vegetation and agricultural areas is not easily identifiable because of its gradual change (Pu et al., 2021).

The validation methodology adopted in this study is in line with existing methods of measuring accuracy in remote sensing techniques, whereby the use of confusion matrices

obtained through stratified sampling is a typical method (Congalton, 1991). Manual classification of high-resolution orthophotos is a common technique to use as a source of reference data since visual analysis is still considered an effective means of detecting features with ambiguous or complicated edges (Pu et al., 2021). The stratified sampling strategy that included a similar representation of both classes (margin and interior) was essential in evaluating classification accuracy consistently in both classes. The balanced sample design, where each point is equally distributed between margin and interior strata, has contributed to the elimination of any possible bias resulting from unequal representation in the margin stratum because of its spatially confined nature (Stehman, 1997).

In conclusion, the method used to identify the margin zone can be said to be successful in achieving acceptable levels of accuracy when applied in landscape ecological studies, especially in identifying real margin zones. The only disadvantage of this technique is that it suffers from low precision due to errors caused by commission. Further improvements on this technique should consider ways of minimizing over-classification errors in the transition of interior areas. The use of measures such as overall accuracy, precision, recall, F1-score, and kappa statistic has made it possible to evaluate this method effectively, thereby validating it as appropriate for landscape ecological studies.

5.8.2 UAV based Margin Width Validation

The validation of the predicted margin zone geometry has been validated by comparing the model derived margin zone width with UAV ortho mosaic image based measured widths at 46 locations where the transects intersect (Figure 5.13). The analysis of scatterplot showing model-predicted and UAV-measured margin widths indicated a moderate correspondence between the two, characterized by $R^2 = 0.5015$ and $RMSE = 1.732$ m. The best-fitted regression line has consistently appeared below the 1:1 ideal agreement line within the margin width range, with the gap becoming especially significant beyond the predicted width threshold of 3 m. Narrow margin widths (below 2 m) have been reasonably well predicted by the model, evidenced by their proximity to the 1:1 line; however, with the increasing predicted widths, the dispersion of data points has significantly grown, with UAV-measured margin widths corresponding to 6 m predicted values ranging from 3 m to 6m. This shows that even though the trend regarding the variation in the size of the margin has been captured by the model, significant differences still exist in individual predictions.

The coefficient of determination value of 0.5015 suggests that nearly half of the variability in margin widths derived from UAV data has been captured in the model predictions, indicating moderate prediction capacity but much room for improvement. Such level of correlation is consistent with the results obtained from other studies involving geometric extraction of elevation or image data, wherein geometric extraction of complex vegetation

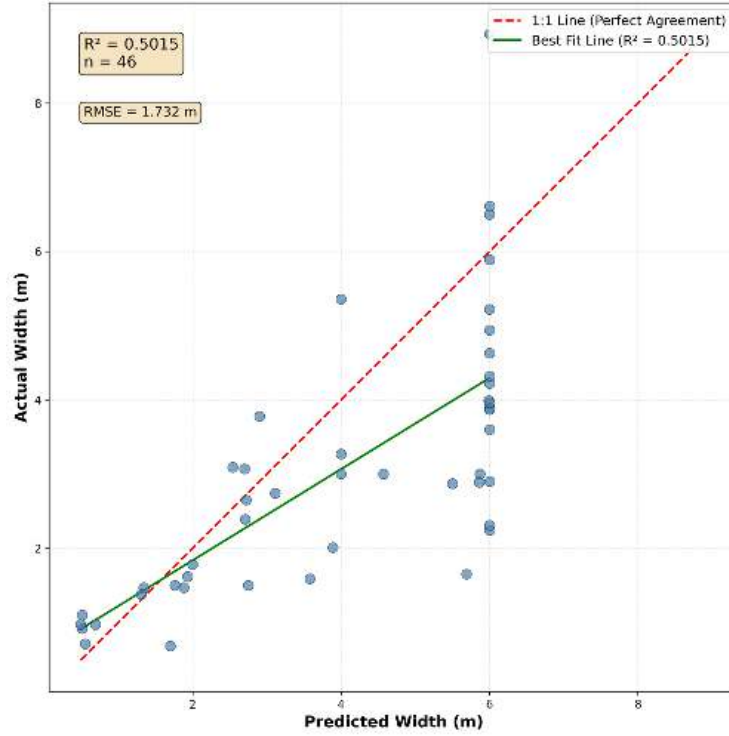


Figure 5.14: Scatter plot of predicted margin width versus UAV-derived margin width ($n = 46$). The dashed red line indicates 1:1 perfect agreement, while the solid green line represents the best-fit linear regression ($R^2 = 0.5015$). $RMSE = 1.732$ m.

boundaries has been found to be relatively challenging to accomplish with great accuracy. In LiDAR-assisted studies, the agreement between predicted and actual values has been high regarding the mapping of the length of woody linear features; however, estimating their height has proven to be relatively more challenging (Broughton et al., 2025). Hedgerow mapping studies have similarly observed similar difficulties with mapping narrow landscape boundaries despite the utilization of very high-resolution remote sensing data (Gardossi et al., 2025). Overall, the obtained R^2 value has been found to fall within the ranges reported in previous literature regarding mapping of complex vegetative boundaries using remote sensing technologies.

The $RMSE$ of 1.732 m, although still relatively large when compared to the range of widths of the margin zone (0 - 6 m) that has been identified in this dataset, is indicative of the fact that, on average, the prediction errors are significant in terms of being large percentages of the width variance. On the other hand, according to the research findings, very high levels of geometric accuracy have been demonstrated for UAV-LiDAR validation tests for surfaces with well-defined shapes after implementing the necessary correction procedures (Abdel-Maksoud et al., 2025). However, such findings are usually associated with stable geometric features instead of the more complicated irregular vegetation margin edges under investigation in the current study. Consequently, the high $RMSE$ values may be attributed to the fact that, in this case, it is challenging to delineate margin boundaries

based on the vegetation mask and UAV ortho mosaics due to their blurry nature as the transition between the margin and the other areas (field or other landscape features) takes place gradually rather than abruptly. As a result, the RMSE value should be seen as an aggregation of the errors in both the UAV ortho mosaics and SIGEC datasets. This problem has also been observed in field boundary mapping, where the complexity of the landscape and the uncertainty of the reference data can limit the accuracy of mapping despite using high-resolution images (Hu et al., 2021).

The clear systematic underestimation, as seen in the placement of the best-fit line below the 1:1 line, seems to be the most prevalent bias for this validation effort. This may have been caused by several different reasons. Firstly, the systematic nature of the measurements done through transects could have meant that the measurement point occurred precisely when the width of the margin zone was atypical, not matching the average value represented in the model. Finally, it could be possible that variations in the spatial resolution and edge detection methods used by the SIGEC data based delineation and visual interpretation of UAV ortho images could cause a consistent shift, where the ortho mosaics with their high spatial resolution and true colour contrast allowed for extending the boundary of the margins beyond what the vegetation threshold algorithm has allowed. Earlier studies have demonstrated that both spatial resolution and boundary-delineation technique affect the precision of maps of linear landscape elements, especially at transitional or intricate borders (Gardossi et al., 2025b). The current findings imply that variations in boundary-delineation techniques could induce systematic error, despite the availability of high-resolution data.

Overall, it has been possible to establish an adequate correlation between predicted and UAV-measured margins in terms of their width, though with an imperfect $R^2 = 0.5015$ and $RMSE = 1.732$ m. It was demonstrated that this model has worked acceptably enough when narrow margins were analyzed, while its weaknesses became evident when estimating wide margins. As both modelling and validation steps were based on remote sensing data, the presented figures of inaccuracy are indicative of total errors in this combined approach. In turn, for general landscape-scale monitoring and policy assessment purposes, they could be considered acceptable. On the other hand, for practical decision-making and regulatory evaluations, further improvement could be required. According to existing studies of the geometry of field boundaries from field surveys using GIS technologies, spatial resolution of imagery and methodology could significantly affect results. It has become evident that UAV margin width extraction requires further refining as well.

5.9 Discussion & Recommendations

Even though the research has demonstrated the potential of integrating SIGEC data, WALOUS land cover, LiDAR-derived terrain analysis, and UAV validation for field margin

assessment, several methodological limitations remain.

The extraction process has performed effectively for field margins located next to the road than those that were situated between agricultural fields. Field margins between agricultural fields tend to be narrow, fragmented and consist of a gentle transition zone between cultivated and herbaceous vegetation, which makes it hard to extract with the existing rule-based method.

The grass margin extraction has also shown noticeable overestimation in some locations. As the process of grass margin extraction mainly focuses on the removal of non-grass elements from the field margin layer instead of classification of herbaceous vegetation, some agricultural areas and transitional zones have also been included in the grass margin layer. This problem is particularly visible in areas where field boundaries are diffuse or poorly defined.

Another significant limitation is the difficulty in interpreting UAV images during the validation process. In some cases, it is difficult to differentiate between field boundaries and the surrounding crop fields because of their similar spectral signatures and vegetation (Figure 5.13). The gradual transition between the cultivated areas and the grassy borders makes it even more difficult to identify boundaries even when conducting visual validation using UAV images.

The temporal mismatch in datasets could have affected some of the validation outcomes as well. In this case, although the orthophotos used in validation represent the same timeframe as the SIGEC dataset from 2021 and thus provide a more coherent temporal basis for validation, the UAV imagery has been collected in July 2023. Some changes in the vegetation cover, agricultural practices, mowing, or minor changes in boundaries that occurred between 2021 and 2023 could thus affect some of the differences noted in the validation based on the UAV imagery. Nonetheless, the UAV imagery proved to be very useful in terms of assessing field margin geometry.

Despite these constraints, the study contributes to the methodology of field margin delineation and fragmentation assessment in agricultural landscape. The use of several spatial layers shows that it is possible to analyse narrow landscape elements in relatively high spatial resolution.

Future studies, could improve extraction process using methods such as Object-Based Image Analysis (OBIA), machine learning, or deep learning. In addition, the use of spectral vegetation indices, multitemporal satellite images, and higher frequency UAV flights will help to discriminate better herbaceous field margins from cropped areas. A potential improvement would be to use orthophotos from different years or VHR imagery acquired during periods when agricultural fields are bare soil, as this would provide a stronger contrast between cultivated fields and field margins, thus improving the accuracy

of margin delineation. Further research can evaluate additional fragmentation metrics and investigate their ecological relevance across different agricultural landscapes.



Figure 5.15: UAV-based ortho mosaic illustrating the difficulty in distinguishing field margins from adjacent crop fields due to similar vegetation characteristics.

6. Conclusion

This study demonstrates that integrating the SIGEC dataset with vegetation structure from LiDAR, PICC vector layers, and very high-resolution land cover map is an effective method to analyze agricultural field margins in Wallonia.

The field margin detection and estimation of its width resulted in a good predictive performance, with the best-fit linear regression model providing an $R^2 = 0.5015$ and $RMSE = 1.732$ m, implying a moderate degree of match between predicted and actual field margin widths, yet revealing uncertainties inherent to boundary delineation. The validation through orthophoto interpretation and UAV observations demonstrated the overall adequacy of the algorithm with a high accuracy rate (84.2%), precision (70.7%), recall (97.0%), F1-score (81.7%), and kappa coefficient (0.684). This means that the method can be considered rather effective at detecting the presence of field margins, with a high recall, while there is overestimation due to transitional vegetation zones and inclusion of adjacent parcel vegetation. Across the 30 study sites, field margin density showed strong spatial variability, reflecting differences in agricultural intensity and landscape configuration. Most sites exhibited a Margin to Total Ratio greater than one, indicating that field margins remain dominant linear ecological elements within the agricultural matrix, while a smaller number of sites with lower ratios suggest simplified and more intensively managed landscapes with reduced connectivity.

Using several landscape metrics including Margin-to-Total Ratio, Number of Patches, Mean Patch Index and Effective Mesh Size it was found that the landscapes studied included a diverse spectrum ranging from highly connected landscapes with corridors to strongly fragmented agricultural landscapes. However, the weak correlations observed between metrics confirm that each indicator captures a different aspect of landscape structure, reinforcing the necessity of a multi-metric approach to properly describe fragmentation and connectivity patterns.

The analysis of LiDAR vegetation showed the prevalence of high vegetation, which means the presence of woody elements like hedges and tree rows, whereas the presence of low and middle vegetation means the presence of herbaceous strips and intermediate zones. The Foliage Height Diversity also proved the presence of great vertical diversity of field

margin elements, thus proving the ecologic function of those elements.

The ditch network derived through the use of DTM extractions was highly advantageous in characterizing hydrological features, as opposed to PICC vector data that only provided for the detection of 455 ditches, which were mostly shallow and narrow and providing improved estimates of their spatial extent and morphology.

Despite these strengths, limitations remain related to boundary uncertainty, transitional vegetation zones, and overestimation of margin extents, largely due to parcel delineation constraints and heterogeneous vegetation structure.

In conclusion, the findings reveal the importance of field margins from an ecological point of view as elements of agricultural landscapes of Wallonia. The spatial layers and metrics produced serve as important analytical tools in environmental monitoring, landscape planning, and agri-environmental policies, especially with regards to implementing biodiversity conservation programs and analyzing landscape connectivity.

7. References

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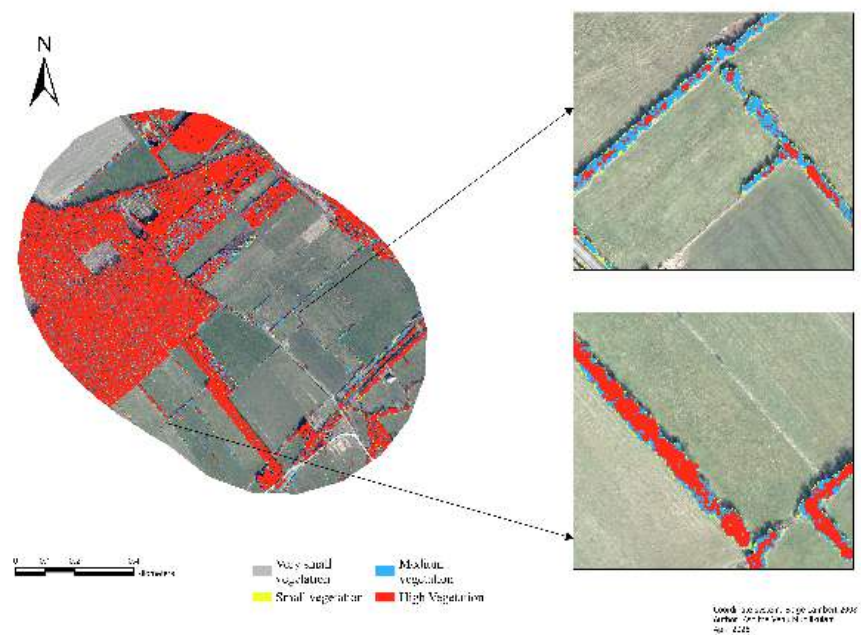
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8. Appendix

A. Result & Discussion



Figure 8.1: Field margin zone of site 21



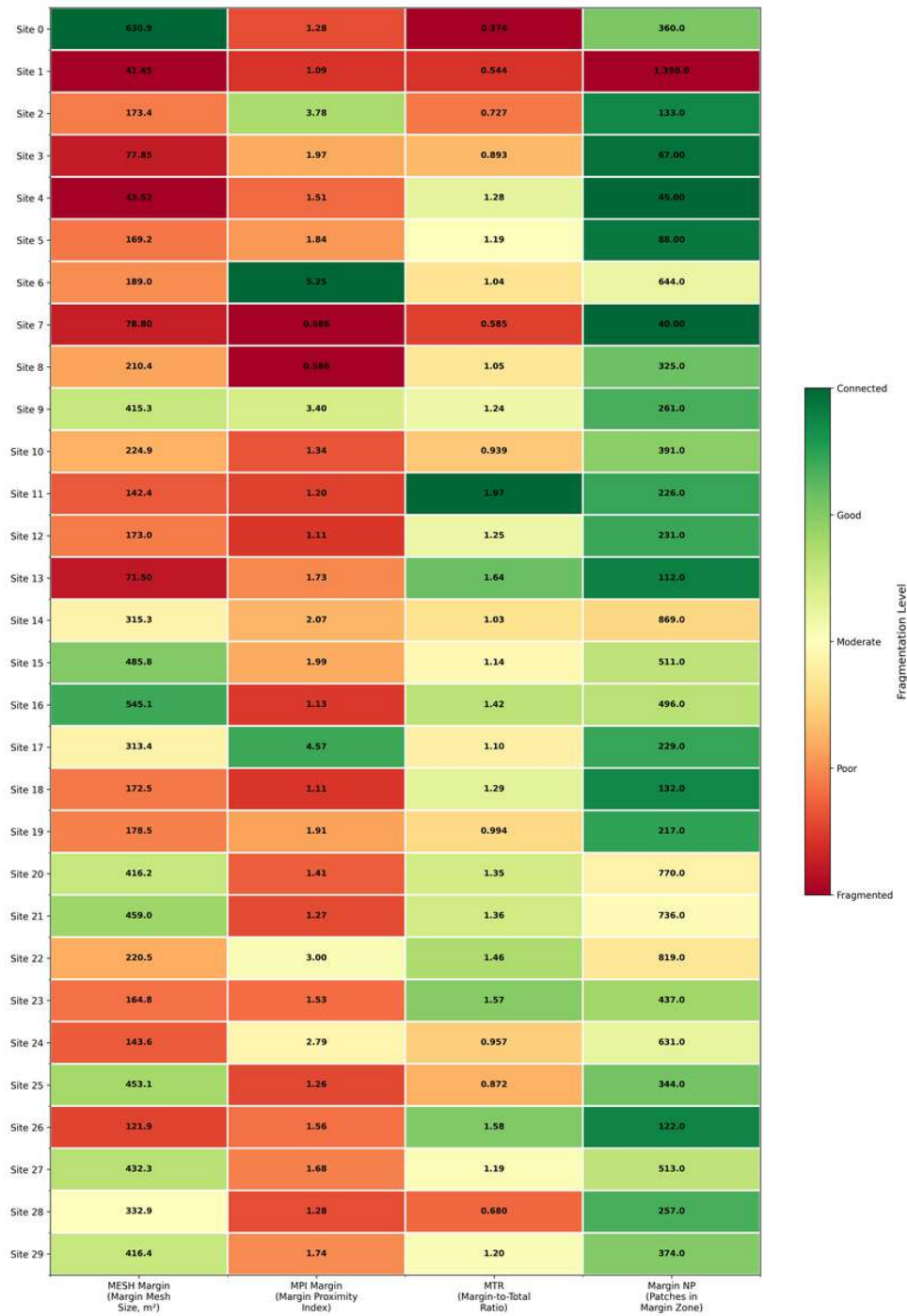


Figure 8.3: Fragmentation impact heatmap across all 30 study sites based on four landscape metrics: MESH Margin (Mesh Size of margin zone), MPI Margin (Mean Proximity Index of margin zone), Margin-to-Total Ratio, and Margin NP (Number of Patches in Margin Zone). Color gradient indicates fragmentation level from Connected (dark green) to Fragmented (dark red).

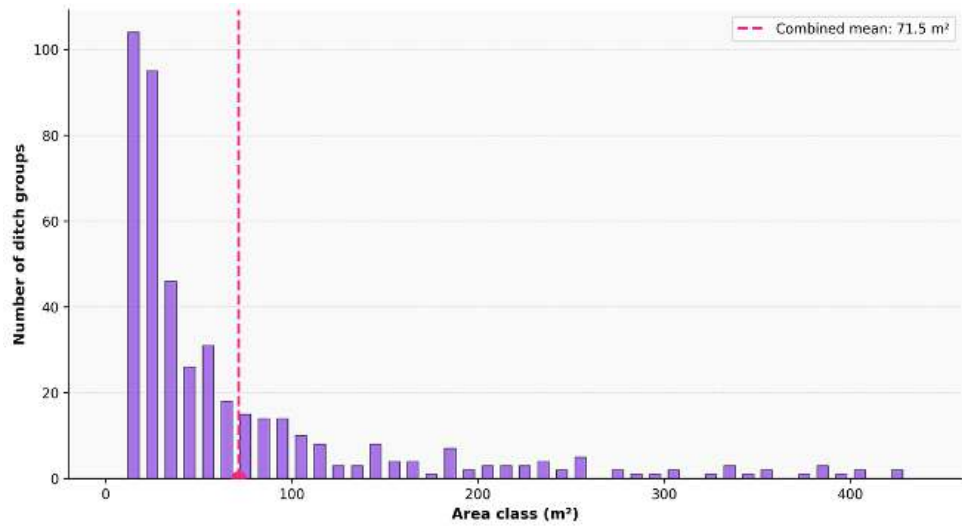


Figure 8.4: Distribution of ditch group areas within the margin zone across all 30 study polygons ($n = 455$ ditch groups). The histogram shows the number of ditch groups per area class, with the combined mean area indicated at 71.5 m^2 (dashed line).

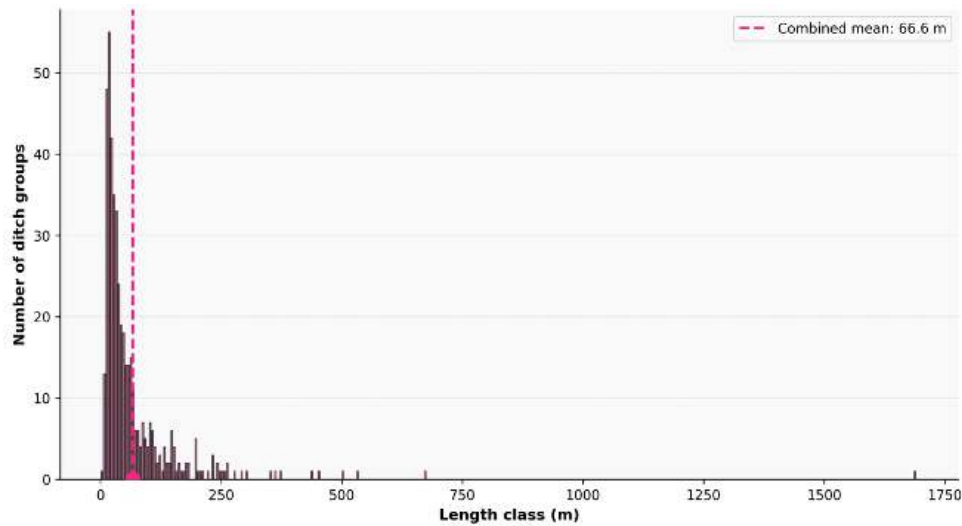


Figure 8.5: Distribution of ditch group lengths within the margin zone across all 30 study polygons ($n = 455$ ditch groups). The histogram shows the number of ditch groups per length class, with the combined mean length indicated at 66.6 m (dashed line).

Field Margin Quantification and Characterization Using Very High Resolution Multisource Geospatial Data in Wallonia, Belgium

Ashitha Venu Mudilikulam

Field margins are important structural and ecological components of the agroecosystem. The primary objective of this study is to develop a spatial approach that integrates LiDAR, PICC vector data, and very high-resolution land cover information to accurately delineate field margins across 30 sites in Wallonia. This approach specifically aims to detect and characterize the natural elements present within these field margins, including vegetation, ditches, and grass margins, while evaluating the compatibility and complementarity of these three datasets for representing very small-scale landscape features. Furthermore, the study identifies and applies appropriate spatial metrics to quantify the extent, configuration, connectivity, and fragmentation patterns of these margin elements. This study shows that integrating SIGEC data, LiDAR-derived vegetation structure, PICC vector layer, and land cover maps provides an effective methodology for delineating and characterising the field margins across 30 sites in Wallonia. The margin detection algorithm achieved strong validation performance, while width estimation yielded a moderate predictive fit with some overestimation attributable to transitional vegetation zones. Landscape metric analysis revealed high spatial variability across sites, with most exhibiting Margin to total ratios exceeding one, indicating that field margins remain dominant linear ecological features, though a subset of intensively managed landscapes showed reduced connectivity and greater fragmentation. The weak correlations between individual landscape metrics reinforcing the necessity of a multi-indicator approach. Foliage Height Diversity analysis confirmed substantial vertical structural complexity across the study sites. DTM-based extraction identified a more extensive ditch network than PICC, including 455 predominantly shallow and narrow ditches, thereby providing improved hydrological characterization. Despite some limitations in field margin extraction, this study offers a foundational framework for more detailed characterization of field margin ecosystems in future research. Overall, the findings underscore the ecological significance of field margins within Wallonia's agricultural landscapes, and the derived spatial metrics provide a useful basis for assessing margin connectivity and vegetation structure at the site level.