AGROFORESTRY EXTENT AROUND THE LAKE STATES REGION: NOVEL SPATIAL METHODS COMBINED WITH SURVEY EVIDENCE TO ANALYZE AGROFORESTRY ADOPTION ACROSS MICHIGAN, OHIO, AND WISCONSIN, USA

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ABSTRACT

This thesis examines the extent of agroforestry in Michigan, Ohio, and Wisconsin by combining high-resolution spatial analysis of linear woody features with landowner survey data. The primary aim is to document the prevalence of practices such as windbreaks and riparian forest buffers and to investigate the management intentions explaining their genesis. Convolutional neural networks (CNNs) were employed to create a sub-meter land cover product using US Department of Agriculture (USDA) National Agricultural Imagery Program (NAIP) imagery, and shape-based metrics were then used to detect the presence of linear small woody features. Validation and case studies in 35 counties indicate that this approach accurately pinpoints narrow tree lines in agricultural landscapes.

Parallel survey work engaged landowners through a multi-wave mailing strategy. Participants described their use of woody features, offering details on motivations, management intensity, and plans for future tree establishment or maintenance. Results demonstrated alignment between survey-reported windbreaks and riparian forest buffers and the automated mapping outputs in many cases, though some discrepancies arose in parcels with fragmented ownership or minimal maintenance.

The findings emphasize the significance of precise, high-resolution classification methods for quantifying agroforestry practices at scale. They also highlight how social and economic factors shape whether landowners consider these woody features essential to farm and forested systems. By integrating spatial and survey-based evidence, this thesis provides a fuller perspective on agroforestry extent and adoption in the Lake States and presents strategies to refine classification thresholds. The multi-layered methodology can inform regional policymakers, resource managers, and extension services seeking to recognize and support these beneficial tree-based practices.

This work is dedicated to the strongest person I know, to the person I love most, Kayla, and to the memory of her mother, Sally. Kayla, my dear partner, best roommate ever, and sounding board for many of my zany ideas, has the best of her mother. In a list that could be very long, we will miss Sally's supportive nature, always-friendly smile, and adventurous curiosity. She was the source for the best parts of her daughter's personality.

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LIST OF ABBREVIATIONS

AF:	Agroforestry
AI:	Artificial Intelligence
CDP:	Census Designated Place
CNN:	Convolutional Neural Network
EDDM:	Every Door Direct Mail
FIA:	Forest Inventory and Analysis
FctImp:	Fractional Impervious Surface NLCD layer
GEOBIA:	Geographic Object-Based Image Analysis
GIS:	Geographic Information System
gNATSGO:	A national soil dataset used for deriving the Soil K-factor
LiDAR:	Light Detection and Ranging
LndCov:	NLCD Land Cover layer
LULC:	Land Use/Land Cover
LSWF:	Linear Small Woody Feature(s)
NAC:	National Agroforestry Center
NAIP:	National Agriculture Imagery Program
NIR:	Near-Infrared
NLCD:	National Land Cover Database
NREL:	National Renewable Energy Laboratory
OBIA:	Object-Based Image Analysis
PCA:	Principal Component Analysis
RF:	Random Forest
RBI:	Riparian Buffer Index
RGB:	Red, Green, Blue
SAR:	Synthetic Aperture Radar

Sentinel: Sentinel Satellite Imagery (10 m resolution)

SNFI: Straight and Narrow Feature Index

ToF: Trees Outside Forests

U-Net: U-Net Convolutional Neural Network Architecture

UTM: Universal Transverse Mercator

USDA: United States Department of Agriculture

USFS: United States Forest Service, an agency in the United States Department of Agriculture

USPS: United States Postal Service

VHR: Very High Resolution

WSI: Windbreak Sinuosity Index

Chapter 1: Advancing the Automation of Linear Small Woody Feature (LSWF) Detection: Machine Learning Land Cover Applications and LSWF Feature Segmentation in the Great Lakes Region of the United States

Objectives:

- Develop a scalable, automated method to map linear small woody features (LSWFs) using high-resolution remote sensing and machine learning.
- Leverage convolutional neural networks (CNNs) and shape-based filtering to detect windbreaks and riparian buffers with sub-meter precision.
- Enhance agroforestry mapping accuracy to support targeted conservation, soil management, and land-use planning in the Great Lakes region.
- Establish a robust workflow adaptable to diverse landscapes and transferable to broader applications.

1.0 Abstract

Linear small woody features (LSWFs), including agroforestry practices known as windbreaks and riparian forest buffers, serve key ecological and practical roles in the Great Lakes region. This paper presents a scalable approach for detecting LSWFs using publicly available high-resolution imagery and image classification through convolutional neural networks (CNNs) to develop a sub-meter resolution land cover product. A shrink-expand technique isolates Trees Outside Forests (ToFs), followed by shape-based filtering and segmentation methods to identify and refine linear tree canopy structures. Many different methods of censusing LSWFs have been presented in literature across world contexts, at increasingly precise spatial resolutions. However, metrics to create aggregate metrics on LSWF presence or the processes to filter, validate, and scale findings in LSWF studies have not been adequately standardized. We propose a robust method that improves accuracy using band-limited, very-high-resolution NAIP imagery provided throughout the continental US, and can therefore be leveraged for scaled precision conservation and provide a more reliable aggregate censusing of LSWFs. We applied the method to 35 counties in Michigan, Wisconsin, and Ohio, revealing varying densities of LSWFs and demonstrating the feasibility of sub-meter resolution workflows. These results

contribute practical insights for stakeholders interested in censusing LSWF features for use in precision land management and providing technical assistance to landowners interested in agroforestry-associated practices. The framework underscores the potential of emerging geospatial tools for mapping ToFs and informing broader conservation efforts.

1.1 Introduction and Literature Review

Linear small woody features (LSWFs) on agricultural landscapes, including riparian woody areas, windbreaks, hedgerows, and shelterbelts, are widely recognized for their positive economic, ecological, and social benefits. Despite their global significance, the United States lacks a comprehensive nationwide survey documenting these features (Smith et al., 2022). LSWFs play a critical role in both ecological and socioeconomic contexts, mediating environmental processes and enhancing agricultural resilience. Ecologically, they connect habitats, enhance biodiversity, control soil erosion, and regulate microclimates, making them vital for sustainable and resilient agricultural systems (Jose, 2009). Additionally, they provide ecosystem services such as carbon sequestration and support for local flora and fauna (Rubio-Delgado et al., 2024, Garrett et al., 2022). Socioeconomically, LSWFs improve agricultural productivity by mitigating wind damage, retaining soil moisture, and buffering against climate variability and extreme weather events (Schoeneberger et al. 2017). Integrated into agroforestry (AF) systems, LSWFs are foundational to achieving biodiversity conservation and sustainable agricultural productivity goals (Jose, 2009; Rubio-Delgado et al., 2024). As interest in AF continues to grow globally, understanding the distribution and structural characteristics of LSWFs is essential for advancing sustainable land management practices.

Field surveys and remote sensing are two common approaches to mapping LSWFs. Historically, manual field surveys, while rich in detail, are resource-intensive and, therefore, are impractical for large-scale or nationwide assessments (Pippuri et al., 2016; Li et al., 2018). Conversely, remote sensing (RS) presents a scalable, efficient alternative, capturing spatial and temporal data across expansive landscapes—a critical advantage for mapping complex AF structures and LSWFs across regions (Aksoy et al. 2010; Rizvi et al., 2020; Sharma et al., 2023; Patriarca et al., 2024).

Recent advances in RS, incorporating machine learning approaches, have significantly expanded the potential for automated LSWF detection. High-resolution satellite and airborne imagery now provide the sub-meter spatial detail necessary to identify even the smallest LSWFs precisely (Burke et al., 2019; Sarti et al 2021; Luscombe et al., 2023). For instance, as Liknes et al. (2017) demonstrated, shape-based classification methods leverage specific indexes like the Straight and Narrow Feature Index (SNFI) to detect linear features semi-automatically and the Windbreak Sinuosity Index (WSI) to measure the sinuosity, or bendiness, of small tree canopy features. The SNFI, developed to identify elongated, narrow landscape elements such as hedgerows and windbreaks, quantifies the linearity of features within imagery by calculating shape-based metrics similar to length-to-width ratios. By assigning higher scores to features that conform to expected geometric properties of LSWFs, the SNFI enables the prioritization of likely LSWF candidates for further analysis or validation. This index significantly enhances the efficiency of semi-automated detection by reducing false positives and narrowing down regions of interest for more detailed study (Liknes et al., 2017). However, such approaches often require refinement to handle the varied morphologies of LSWFs in heterogeneous landscapes. Additionally, technologies such as Line Intersect Sampling (LIS) and LiDAR, such as those employed by Pasher et al. (2016) and Penner et al. (2024), provide enhanced vertical structure differentiation, making them invaluable for detailed feature detection in AF contexts. When integrated with machine learning methods, these tools also offer a path for automatically extracting LSWFs across diverse agricultural and forested environments.

Traditional RS methods, such as pixel-based analysis (Aksoy et al., 2010; Liu et al., 2018) and object-based approaches (e.g., OBIA/GEOBIA), provide foundational insights on singular objects in a focused study area but often struggle to scale, for accuracy assessments and computational costs for larger study areas, with issues of feature fragmentation and discontinuity, especially in regions with variable land management practices and tree canopy patterns (Blashke, 2010). Most recently, Deng et al. (2023) explored methods to extract individual linear woody features (LWF) using a shape-oriented method, which allowed for identifying networks of LWFs and fixing partial connectivity issues between otherwise continuous belts of woody barriers.

Advancements in RS technology, like high-resolution imaging and machine learning approaches like CNNs, increase the capability to identify LSWFs, which is crucial to understanding agroforestry's ecological and economic impact (Deng et al., 2023; Xing et al., 2016). For example, Deng et al. (2017) mapped windbreaks using SPOT5 data through human-machine interpretation, while Yang et al. (2017) and Amichev et al. (2015) showed that machine learning and SPOT5 data could be used for broader landscape mapping—although limitations with image resolution and the connectivity of features remained.

Efforts have been made to help automate the process and leverage emergent data and techniques to improve the census of small woody features associated with AF systems (Liknes et al., 2017). However, mapping LSWFs presents several challenges that have constrained traditional and automated approaches. More scalable, automated techniques using existing land cover products such as the NLCD or Sentinel 10m LULC Level 3 product encounter difficulties in accurately distinguishing LSWFs from other land cover types due to their narrow, linear forms, often smaller than the resolution of the land cover and the spectral similarity of their tree canopy vegetation to surrounding agricultural or wetland areas. Furthermore, shape-based detection methods using indices like SNFI and WSI (Liknes et al. 2017) have demonstrated potential. However, they often face limitations in non-homogenous agricultural landscapes with woodlots and forests directly connected to LSWFs, or when dealing with the diverse anisotropic morphologies of LSWFs that are not aligned with cardinal directions or are occasionally curved, as seen in bends in rivers, railroads, or roadways. These challenges underscore the need for refined methodologies to address the complexity and variability inherent in LSWF structures.

Trustworthy measures of LSWF extent could help augment national estimates of AF adoption within the US, supporting practices for sustainable land use associated with AF (Smith et al., 2022). Despite the growing recognition of agroforestry's importance, national datasets, such as those produced by the USDA (e.g., county-level analysis based on the 2017 and 2022 Census of Agriculture (Kellerman et al., 2025)), remain too coarse to capture smaller LSWFs or their spatial distribution adequately. Smith et al. (2022) point out that current classification schemes often underestimate AF adoption due to aggregating diverse AF elements into broad spatial categories (e.g., counties, states), which can obscure finer-scale features. This sentiment has been echoed in non-U.S. contexts (Rubio-Delgado et al., 2024); a general lack of precision has left critical gaps in our understanding of agroforestry's true extent and has limited the ability to assess ecological and socioeconomic contributions effectively. Addressing this issue requires the development of consistent, high-resolution mapping methodologies that can accurately detect smaller AF elements, such as LSWFs. Such data would close existing data gaps and directly inform policy or conservation programs, including those aimed at incentivizing AF adoption and improving land-use sustainability.

Recent advancements in convolutional neural networks (CNNs) have significantly enhanced the capability to produce very high-resolution land cover products with less comparative supplemental band context than traditional LULC products, particularly for applications in precision conservation. Efforts by the Chesapeake Conservancy Conservation Innovation Center (CIC) and the University of Vermont Spatial Analysis Lab (UVM SAL) to develop 1-meter and 0.5-meter land cover products, respectively, for their regions of interest exemplify the increasing granularity now achievable in mapping land features, although these developments are relatively new. Robinson et al. (2019) demonstrated an ability to scale CNN machine learning methods, integrate multi-resolution data for high-resolution land cover mapping, and achieve detailed classification of diverse land cover types. Further, Robinson (2020) highlighted many broader applications of machine learning in computational sustainability, emphasizing its potential to support conservation practices by accurately and precisely identifying and monitoring small-scale, ecologically significant features. Extensions of CNN use cases, particularly closer to research of woody features on agricultural landscapes, have identified hedgerows and hedgerow gaps in study areas in the UK (Wolstenholme et al., 2025).

1.1.1 Objectives

The primary objective of this chapter is to develop a scalable, automated method for mapping LSWFs using machine learning and high-resolution remote sensing. By focusing on the unique landscape characteristics of the Great Lakes Region, this study aims to create a widely applicable methodology that captures even the smallest features. Such an approach has important implications for land management, as it provides precise, actionable data to inform conservation policies and sustainable land-use practices. Accurate LSWF mapping can empower policymakers and landowners with insights needed to design biodiversity-friendly landscapes, implement soil conservation measures, and encourage AF practices in places that maximize both ecological and economic goals.

This novel approach leverages the strengths of CNN-based ML for detecting LSWFs with great precision, which is crucial in landscapes with a mixture of contiguous forested spaces (or woodlots) and agriculturally productive areas. The unique feature set derived from sub-meter resolution aerial imagery (USDA 2022 NAIP) allows for increased accuracy in tabulating linear AF features and examining their characteristics. These innovations, alongside developing high-resolution, landscape-specific filtering and segmentation methods, aim to provide a reliable and robust assessment of AF patterns within the Great Lakes region. Additionally, the procedures here were developed to be applied further outside our study area with a high-resolution tree canopy dataset. Finally, our work emphasizes the practical utility of these outputs for policymakers and land managers, aligning model findings with regional AF support needs and conservation strategies that support sustainable land use and ecosystem and agrarian resilience.

1.2 Methods

This study develops a multistep process for extracting LSWFs, using convolutional neural networks (CNNs) to develop land cover classifications from USDA 2022 NAIP aerial imagery at fine scales (0.3 m and 0.6 m), as has been approached previously at much coarser spatial scales (Basu et. al., 2015). The use of CNNs in generating a very high-resolution land cover has been implemented using the same methods (Robinson et al. 2020; Zhang et al., 2024). Still, the extraction of LSWF information with enhanced edge detection methods associated with CNNs has not been described or published. This tailored approach focuses on capturing even the smallest LSWFs to 1) evaluate effective linear small woody features, which would have continuity at sub-meter scales, and 2) refine and extend regional mapping accuracy. The potential for further integration of machine learning into these processes suggests a path forward wherein continuous LSWF networks and improved feature connectivity can better support sustainable AF practices and inform ecological management policies in the Great Lakes region.

1.2.1 Study Area

The study area encompasses 35 counties across Michigan, Wisconsin, and Ohio, representing a diverse mosaic of land cover types. The total area evaluated directly from imagery for the study is roughly 60,187 km^2 or 23,238 mi^2. Together, this is approximately the size of the US state of West Virginia, the country of Ireland, or the water surface area of Lake Michigan. These counties were selected to investigate LSWFs due to their AF prevalence and varying land-use patterns. The study area includes at least four contiguous counties in each state, creating a representative sample of the transition zones between agricultural and forested landscapes as indicated by the 2019 National Land Cover Database (NLCD). This strategic selection captures a range of predominant land uses, including row-crop agriculture, forage production, urban agroforestry, and tree crops, facilitating the identification and analysis of LSWFs in different ecological and socio-economic contexts.

This region is particularly relevant for studying LSWFs due to its blend of intensive agricultural activity and significant woodland areas. The counties were further considered for inclusion as study counties using Cropscape 2022 data to gather a diversity of dominant farm outputs—from counties with predominant presences of field crops like corn and soybeans to counties focused on forage (hay/alfalfa) or specialty tree crops like cherries (Han et al., 2012). Other data that were used for initial county selection and validation include results from the 2017 Census of Agriculture, which identified counties where agroforestry practices like windbreaks and riparian first buffers were more or less common, such that a diversity of both 'hotspot' and 'non-hotspot' counties in agrarian-forestland transition zones were chosen. This categorization ensures that the analysis can account for the regional variability in land-use practices and their influence on LSWF formation and persistence. The selected counties also include urban and urban-fringe areas, where AF practices, such as windbreaks and riparian buffer zones play critical roles in promoting biodiversity and mitigating environmental impacts of both agricultural and urban/suburban pollution. Figure 1 illustrates the geographic extent of the study area, highlighting the counties selected for this research and their respective AF and land-use characteristics.

Figure 1: 35 counties used for LSWF analysis across Michigan, Wisconsin, and Ohio. Each state has four counties analyzed with a predominant woodland-farmland 'transition,' as well as spatially diverse counties with different predominant developmental/ agricultural land uses (e.g. forage/rowcrops) based on USDA Cropscape 2022 (Han et al., 2012).

1.2.2 Data

A single data source is needed to extract exhaustive high-resolution LSWF data within our study counties. High-resolution aerial imagery from the National Agriculture Imagery Program (NAIP), was used to produce a land cover at the NAIP native spatial resolution using CNNs. The imagery was sourced from the 2022 4-band NAIP in (R, G, B, and NIR), chosen for its sub-meter resolution, which could precisely capture canopy structure not attempted at such a high resolution before in the US to census LSWFs. Native NAIP imagery resolutions were at 0.6

meters for Michigan and Wisconsin, and 0.3 m for Ohio, as each state was collected at separate resolutions for the 2022 NAIP release.

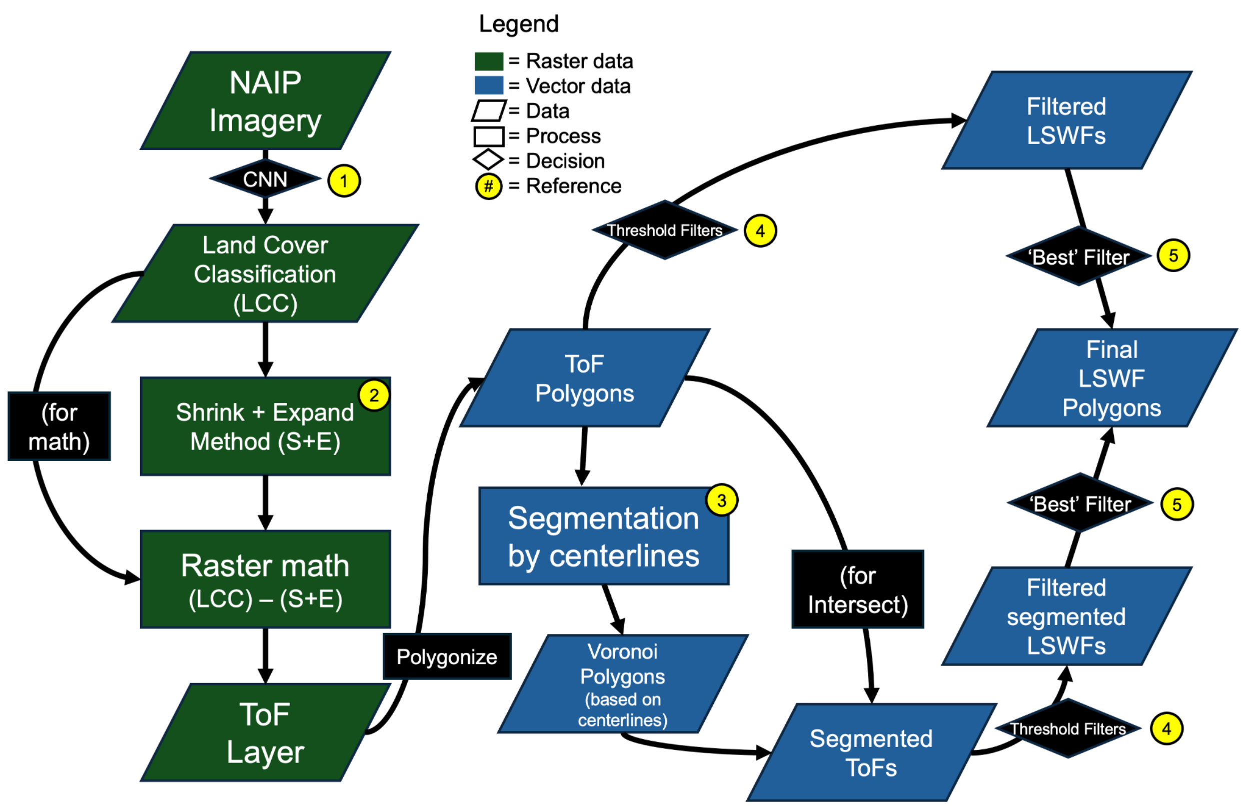

Figure 2: Summarized methods to capture LSWF features as polygons from imagery, for both standalone trees outside forest (ToF) areas and segmented ToF networks.

1.2.3 Preprocessing

Image preprocessing focused on ensuring data consistency across the study area. Georeferencing and image alignment were previously conducted for the NAIP level 2 imagery received for the project, and maintaining the native resolutions for NAIP imagery throughout the methods preserved data integrity. All NAIP input data were maintained on their Universal Transverse Mercator (UTM) zones, which were standardized for each county—UTM 15N, 16N, and 17N—ensuring spatial coherence across state boundaries and facilitating seamless feature delineation.

1.2.4 Sub-meter Land Cover Classification

A CNN model was employed to achieve high-resolution (sub-1.0m) land cover classification across 35 counties (Reference 1, Figure 2). Constructed with a U-Net architecture, the model excelled in semantic segmentation tasks such as vegetation mapping and fine-scale feature extraction. Its encoder-decoder structure extracted discriminative features from high-resolution aerial imagery and accurately projected them onto pixel space for LSWF classification (Ronneberger et al., 2015). A learn rate during training maintained consistent output quality across subtle spectral differences. Compared to conventional methods like Random Forests (RFs), the U-Net model demonstrated superior edge detection and texture handling by capturing context at multiple spatial scales via skip connections (Robinson, 2020). Recent studies further confirm the architecture's strength in delineating fine spatial features, such as vegetation edges and linear elements in high-resolution remote sensing data (Ronneberger et al., 2015; Iglovikov & Shvets, 2018). Although RFs are computationally simple, their pixel-based approach often struggles with spatial coherence and detailed edge representation—issues critical for accurate LSWF detection (Belgiu & Dragut, 2016; Kampffmeyer et al., 2016; Ford, 2020). In contrast, the CNN U-Net model leverages inherent spatial contextual information to differentiate subtle boundaries and textures, making it particularly adept at delineating the irregular, elongated shapes of LSWFs even in datasets with limited band context, such as NAIP (R, G, B, NIR) (Claggett et al., 2022; Robinson et al., 2020).

1.2.4.1: Model Training and Validation Data

The CNN model was developed using the Chesapeake Bay area NAIP high-resolution land cover dataset from 2013/2014. This dataset, produced by the Chesapeake Conservancy in collaboration with the University of Vermont Spatial Analysis Lab (UVM SAL) and Worldview

Solutions, Inc. (WSI), provided a strong foundation for training with its seven-class classification schema. The original dataset's detailed 1m resolution, trained using a method of class selection per objects as identified through OBIA and subsequent parcel-image segments (Clagett et al., 2022), offered a comprehensive basis for model generalization to the study area and North American landscapes, as generalization has been shown to work on other Midwestern landscapes (Robinson et al., 2019). Further, minimal fine-tuning of the pre-trained model to a sample area in Northern Clinton County, MI, tuned spectral bands to an agricultural landscape in the Midwest with a typical combination of mixed forested and agrarian spaces, as is first described in Robinson et al. (2019). An OBIA-based fine-tuning was aimed to adjust the calibration of the model from the Chesapeake Bay region to the Midwest, although there are many noted spectral similarities among classes between the two areas with the spectral-context-limited NAIP imagery bands. As the U-Net model in ArcGIS Pro is also designed to adapt at a user-set rate (in this study, 'learn' is set at a low rate, 0.01), minor changes in spectral qualities across NAIP imagery for each county were corrected across the imagery where the CNN model was run.

Validation of the CNN model was focused on human-driven manual processes, as described in more detail in "1.3 Verification and Validation Measures/Methods". Stratified testing areas were sampled randomly across 1000 points in three counties of the complete 35-county set (one representative county per state), and manual labeling was employed to refine class delineation, particularly in regions where automated classification might falter. In total, 3000 points were evaluated for accuracy in all classes, reflecting similar quality to other published results from similar studies using the same CNN methods (University of Vermont 2019, 2024; Pallai et al., 2016). This approach minimized classification bias and ensured high fidelity in identifying the spatial patterns of LSWFs.

1.2.5 Shrink-Expand Method

The novel shrink-expand method was employed to isolate ToFs by effectively masking continuous forest regions (see Figure 2, Reference 2). This technique enabled the precise identification of small woody features (SWFs) located outside, yet connected to larger forested areas, facilitating a targeted analysis of LSWFs without interference from connected, contiguous forested areas.

1.2.5.1 Filtering Based on FIA Definitions

The nationwide USDA/USFS Forest Inventory and Analysis (FIA) program defines forest land as areas with "at least 10 percent canopy cover, composed of trees of any size, or areas that have previously supported such cover but are not currently developed for non-forest use. Forested areas must be at least 1 acre in size and 120 feet in width to qualify under this definition." (USDA, 2015) This analysis used the 120-foot width threshold to distinguish LSWFs from contiguous forested areas. Notably, an area with 120ft · 120ft (14400 ft^2) of continuous canopy would already account for over 30% of an acre of canopy cover. However, it should be noted that while the FIA's 10 percent canopy cover criterion was not explicitly evaluated, the high resolution (0.6m and 0.3m) of the land cover dataset provided sufficient spatial context to delineate potentially contiguous wooded areas accurately. This resolution, therefore, allowed for a more nuanced interpretation of LSWFs.

To create the continuous forest mask layer, the tree canopy raster was geomorphically shrunk by approximately 60 feet (determined based on raster pixel dimensions). Subsequently, the shrunken layer was expanded by approximately 72 feet (20% more than the initial shrink value) to account for edge sinuosity and irregularities in the tree canopy layer. This shrink-expand process effectively eroded polygons to meet the 120-foot threshold, filtering out contiguous forested areas while retaining ToFs for further analysis.

1.2.6 Further Filtering Based on Size Exclusions

To reduce computational complexity and refine the dataset, isolated ToF areas smaller than 250m² were excluded from subsequent analyses at two steps in the overall methodology. This threshold was determined based on visual inspection and judgment, as it sufficiently filtered out smaller groups of trees or single trees that were unlikely to represent structurally significant LSWFs. The exclusion of polygons smaller than 250m² removed over two-thirds of the ToF areas from a large vector polygon dataset for each county in the study, enabling a more focused and efficient analysis of relevant LSWFs.

1.2.7 Shape-Based Refinement of LSWFs Using Object Splitting

Segmentation is the next critical step in the analysis of individual LSWFs, enabling the differentiation of distinct linear features within complex landscapes. By accurately identifying and isolating these linear structures, segmentation provides the foundation for generating precise metrics and insights essential for modeling their ecological and agricultural functions.

1.2.7.1 Centerline-Based Object Splitting and Voronoi Polygons

Although commercial options exist to achieve Object-Based Imagery Analysis (OBIA) to segment tree canopy classes in imagery (e.g., Trimble eCognition, Overwatch Feature Analyst), the segmentation parameters can be computationally inefficient and inexact (requiring much time for QA/QC) at larger scales (Hossain and Chen, 2019), leading to improper grouping or assessment of woody features. Machine learning methods are developing further to fill these noted gaps (Morgan et al., 2024). Segmentation of LSWF networks was targeted to generate summary statistics to model the presence and characteristics of LSWFs individually on the landscape scale (see Figure 2, Reference 3). This segmentation method only required the single environmental class of tree canopies reduced to ToFs, which was then polygonized in previous steps, as opposed to OBIA methods, which use imagery directly.

The shape refinement process utilized Voronoi polygons to perform centerline-based object splitting, an essential step for distinguishing linear features and managing complex shapes within the dataset. Centerlines were derived via computing the medial axis of ToFs and connecting ends of lines at larger tree canopy sections, and some data cleaning via clipping, trimming, and removal of spurs removed nonsignificant lines. Individual centerlines within polygons were attached where just two lines met at points. This established standalone centerlines for each ‘straight’ section of a ToF polygon, which could later be associated with a filtered LSWF. This could then separate or ‘segment’ sections of LSWF networks, particularly those with T- or X- shaped contiguous woody features.

To handle irregular LSWFs with near 90-degree bends—where no additional linear woody features met at a bend to form a network (for example, L-shaped or Z-shaped LSWFs)—we evaluated a Line-Straightness Index (LSI) using a moving window on lines. This approach specifically targeted the near 90-degree bends. Lines were simplified to differing thresholds of line simplification, and the "retain critical bends" line simplification algorithm was applied to preserve the essential geometry of these features. Points were then placed at the near 90-degree angles or other significant inflection points within the threshold, where the LSI calculated straight sections at least 4 m long before and after a significant near-90-degree bend, and the centerlines from the original file were split along that section. This ensured that Voronoi segmentation captures straight, linear segments of a continuous standalone LSWF that possesses an L- or Z-shapes, while also allowing for segmentation of LSWF networks which have T- or X-shaped continuities.

Finally, equidistant points were placed along the final split lines to segment the centerlines in a ToF layer so that each straight segment of an LSWF network had a separate polygon. Using these points, Thiessen (Voronoi) polygons were generated and subsequently merged based on their respective centerline identifiers. This approach allowed for accurate segmentation and analysis of linear features—such as windbreaks or narrow wooded strips—even when they exhibited contiguous or convoluted shapes.

1.2.7.2 Size and Shape Filtering Criteria

Following the centerline-based segmentation and polygon creation, the resulting polygons underwent a final filtering process, removing features based on the same size threshold of 250m². This criterion was again applied to exclude smaller, less ecologically relevant features created during the process to split polygons as they were associated with centerlines. Smaller LSWFs, such as very narrow LSWFs surrounding a farmstead, or features that fall below the minimum segmented or whole-length threshold of 100 m, are filtered from the final dataset. However, thresholds can be modified to be more inclusive of these features.

1.2.8 Measurement of Shape Indices for LSWF Evaluation

The evaluation of LSWFs incorporated two critical shape indices: the Straight and Narrow Feature Index (SNFI) and the Windbreak Sinuosity Index (WSI). These indices were calculated on both the base and the polygons split through Voronoi analysis to allow comprehensive shape-based assessments and comparisons. The SNFI quantified the elongation and straightness of features relative to the UTM coordinate grid. At the same time, the WSI measured the perimeter-to-area ratio, reflecting the sinuosity of the feature edges.

1.2.8.1 Modified SNFI and WSI Calculations

Adjustments were made to the traditional calculations of SNFI and WSI to accommodate the unique characteristics of anisotropic data and improve computational efficiency. Specifically, modifications included: 1) calculating the SNFI based on both an isotropic grid and an anisotropic, axis-based calculation of how straight and narrow a feature is, 2) polygon boundary simplifications to calculate the longest Euclidean length of a polygon feature and the orientation of an axis along that longest length, and 3) calculating the spatial extent (i.e. erosion) of straight and narrow polygons (as opposed to rasterized LSWFs), which improves the ability to calculate

WSI and the SNFI while accounting for potential anisotropy and reducing the need for high-resolution raster data and more computing resources for each polygon during intermediate steps of an erosional analysis. These adjustments established that the indices remained precise and representative using the vector dataset, even with complex geometries, while minimizing the computational overhead.

1.2.9 Final Filtering and Selection for LSWF Dataset Creation

The final stage of the workflow involved selecting the optimal polygons for inclusion in the LSWF dataset. These scripts prioritized the selection of polygons depending on their SNFI values, WSI values, and maximum Euclidean distance between two vector points in the polygon (see Figure 2, Reference 4). Filtering was based on an SNFI threshold of 0.8, ensuring the inclusion of features that exhibit sufficient elongation and straightness. Sinuosity thresholds, such as a maximum WSI of 3.0, were used to exclude overly irregular features that deviate from typical windbreak structures. A minimum Euclidean distance threshold of 100 m on the longest axis was applied, limiting the dataset to LSWFs with significant length.

1.2.9.1 Final LSWF Dataset Construction and Verification

The final LSWF dataset was constructed by merging the “Default” LSWF filtering process results and the Voronoi-segmented polygons through a best-selection criteria framework (see Figure 2, Reference 5). This merging process prioritized features based on the maximum SNFI value and structural alignment metrics for both the segmented and original, pre-Voronoi-segmentation datasets. For polygons in both datasets, preference was given to features with higher SNFI values and lower sinuosity scores, ensuring the inclusion of polygons that best represented linear, straight, and agroforestry-relevant features.

1.2.10 Measurement of LSWFs for Analysis

To evaluate the distribution of LSWFs across counties, the metric of the average distance of LSWFs per km² was used rather than simply counting individual features or summarizing their total area or length in a study region (see Figure 4). This metric provides a more nuanced understanding of LSWF distribution by capturing their density and spatial arrangement with the land area. Previously published metrics to create summary assessments of LSWFs have noted weaknesses. Counts of individual LSWFs in a study region as studied and reported previously may overemphasize smaller, fragmented features, and summaries of total LSWF area or distance in a region can risk underrepresenting the importance of linear connectivity or having issues related to spatial inequivalence.

1.3 Verification and Validation Measures/Methods

An error matrix was developed using ground-truth data from Jackson County, MI, as it was central in the overall study area and possessed both a high density of identified LSWFs in the final dataset and a diverse set of LSWF morphologies to evaluate. The evaluation framework computed overall accuracy alongside user and producer accuracy rates for the LSWF class. The kappa statistic was calculated to account for chance agreement, thereby reinforcing the reliability of the automated classification. These metrics confirm that the detection algorithm aligns closely with ground observations and provide a robust quantitative basis for performance assessment. The error matrix thus serves as a critical baseline, paving the way for complementary spatial analyses such as length matching and omission rate evaluations. Additionally, two key validation metrics—length matching rate and omission rate—were employed to assess the robustness and consistency of the automated LSWF identification process. These metrics evaluate the model's spatial accuracy, detection completeness, and specificity, providing a comprehensive framework for performance assessment.

- Length Matching Rate: This metric quantifies the proportion of detected windbreak feature length that aligns with ground-truth data. It serves as a direct measure of spatial accuracy, ensuring that identified features correspond closely to their real-world counterparts.
- Omission Rate: The omission rate measures the proportion of true windbreaks missed by the model. High omission rates indicate areas where the model requires refinement to improve detection coverage and minimize false negatives.

1.3.1 Matching Validation Metrics with Previous Studies

The validation methodology incorporates insights from Deng et al. (2023), and projects that validated their CNN machine-learned land cover products (University of Vermont 2019, 2024; Pallai et. al., 2016) by aligning metric definitions and thresholds with those established in prior studies. This alignment establishes methodological rigor and facilitates direct comparison with similar research.

1.3.2 Accuracy Assessment of Land Cover Output

Validation involved both automated and manual processes. Stratified testing areas were sampled randomly across 1000 points in each of the three counties in the complete 35-county set (one representative county per state), and manual labeling was employed to refine class delineation, particularly in regions where automated classification might falter. In total, 3000 points were evaluated for accuracy in all classes, reflecting similar quality to other published results from similar studies using the same CNN methods (University of Vermont 2019, 2024; Pallai et al., 2016). This approach minimized classification bias during manual validation and ensured high fidelity in identifying the spatial patterns of LSWFs. The accuracy of the model output was evaluated using automated accuracy metrics, as well. Metrics such as overall accuracy, precision, recall, and F1-score were calculated for each feature class, comprehensively assessing the model's strengths, limitations, and error distribution. This analysis highlighted the model's ability to generalize well across different landscape types, while also identifying specific feature classes where performance could be improved.

Manual validation results for the Land Cover dataset aligned with those from similar studies, including the Vermont and Chesapeake reports, establishing consistency with previous CNN-derived land cover methods. Overall accuracy was around 92.17% for three reviewed counties (see section 2.3.2 Comparative Accuracy Assessment), which is roughly the same as other CNN-derived accuracy measurements for all classes (Robinson (et al.), 2019, 2020; Vermont

SAL, 2019, 2024). The verification matrix followed the framework applied in these studies, offering a breakdown of metrics for distinct feature types. This approach facilitated a nuanced understanding of the model's accuracy across varying landscape contexts, further reinforcing its reliability for LSWF classification and mapping. Automated validation yielded results similar to the ESRI-published validation metrics, if not slightly lower.

1.3.3 Accuracy Assessment of LSWF Product

Verification of the final LSWF dataset involved a systematic review of the extraction method’s performance over a focused area in the southwest corner of Jackson County, MI. Each feature in a set of n = 2920 model-produced LSWFs was evaluated to identify discrepancies between the automated outputs and expected linear woody features on the landscape. Detailed inspections identified instances where canopy bridging over roads, shadow artifacts, or segmentation challenges resulted in misclassification. Geometric attributes were measured to ensure that each candidate met the prescribed filters for LSWF length, continuity, and width. Furthermore, the same area in southwest Jackson County was visually checked for all ‘missed’ LSWF features that were not identified through the methods. This rigorous verification process, paired with visual inspections of much of the results across all counties studied, confirmed that the filtering criteria effectively minimized false positives and negatives, while also offering valuable insights for refining the methodology in future iterations.

1.3.4 Model Quality Across Imagery and Environmental Factors

The model demonstrated broadly consistent accuracy across diverse landscapes, with minor variations influenced by characteristics such as canopy density, terrain type, and vegetation cover. Accuracy was highest in landscapes with clearly defined contrast between classes, such as open fields of low, bright-colored vegetation mixed with areas of leafy, more textured hardwood forested spaces. This distinction proved particularly significant for tracking LSWFs in open agricultural fields and along tree lines in transitional zones, where spectral clarity between land cover types facilitated more accurate classification. However, notable misclassification occurred in intense, darker green crop fields, which were occasionally misidentified as algae-covered, very deep-green water features due to spectral similarities in the 4-band NAIP imagery, as well as a noted under-classification of wetland areas which, with 4 bands of visible NAIP imagery, spectrally look similar to areas of green low vegetation in the Midwest. Challenges also arose in areas with complex topography or densely forested regions where longer shadow distances below canopies made CNN feature delineation more difficult at edges or in areas where sourced NAIP imagery lacked clarity in the 2022 dataset. Notably, Auglaize County, OH, which had a large smoke/vapor plume overlaying much of the imagery in the center of the county, results for Auglaize County have an asterisk (*) noting this issue. Seasonal variations in vegetation growth and foliage density had a limited impact on model accuracy, as imagery collected between May and September 2022 generally maintained consistent feature detectability during extensive visual inspections, which is consistent with other findings when working with CNNs to generate land cover products. However, the most significant differences were linked to the time of day when NAIP imagery was captured. Variations in lighting conditions and shadowing influenced the visibility of certain features and feature edges, occasionally obscuring smaller LSWFs or causing less certain classification at the edges of the tree canopy class.

1.4 Results and Discussion

The model outputs provide insights into the spatial distribution and characteristics of LSWFs across the Great Lakes Region in the study counties. Outputs highlight various agroforestry-related features, including windbreaks, riparian buffers, and small woody corridors. The spatial patterns revealed in the dataset indicate areas with high densities of LSWFs (see Figure 4), which often align with transitional zones between agricultural fields and natural landscapes.

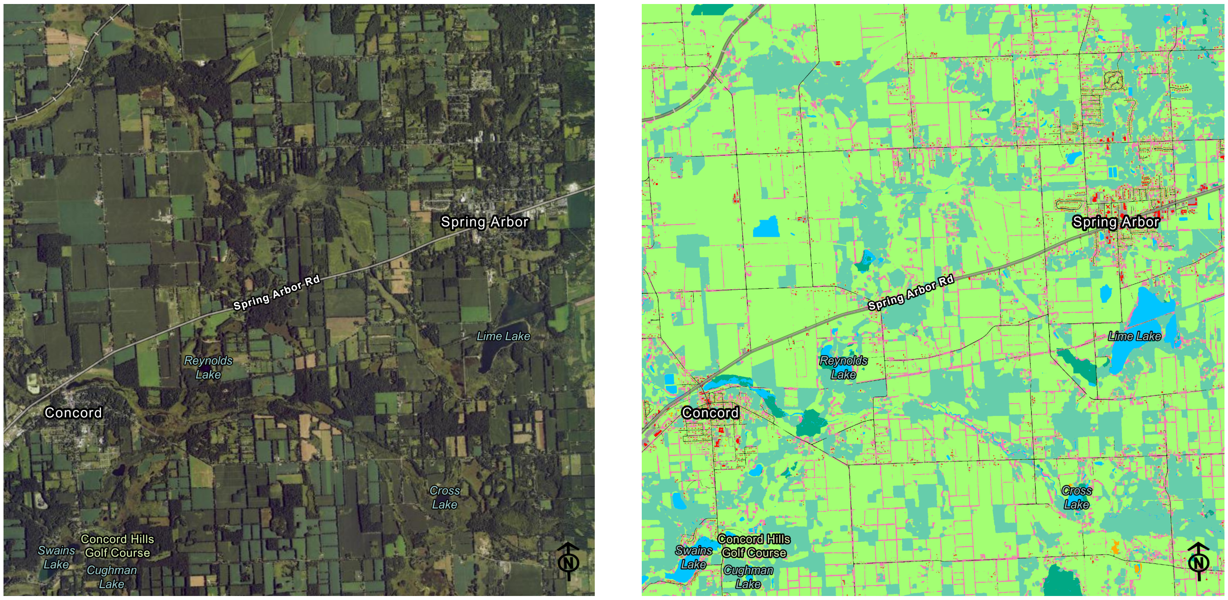

Figure 3: (Left) Source NAIP imagery over a section of southwest Jackson County, Michigan, around the towns of Spring Arbor and Concord. (Right) CNN Land Cover output and shrink-expand isolation of Trees outside Forests (ToFs) for the same area around Spring Arbor and Concord. The Teal and Pink colors were identified as woody canopies from imagery and then separated via shrink-expand ToF isolation.

We addressed limitations in quantifying LSWF networks or assessing detailed individual LSWF characteristics by applying advanced segmentation techniques. This approach distinguishes individual linear features—capturing subtle connectivity and anisotropic canopy forms—through filtering with modified indices such as the Windbreak Sinuosity Index (WSI) and Straight and Narrow Feature Index (SNFI) (see Appendix B), along with segmentation methods using Voronoi polygons and moving-window centerline analysis. This strategy improves feature continuity beyond what traditional summary methods provide.

The aggregated distance metric (Figure 4) highlights the role of LSWFs as spatially distributed, linear ecological corridors per equal spatial unit. This approach consistently compares LSWF patterns across counties with varying land-use intensities and landscape structures, as was seen in previous meta-analyses of hedgerows in North Dakota (Burke et al., 2019). These insights are valuable for understanding these features' ecological and agricultural functions in study regions.

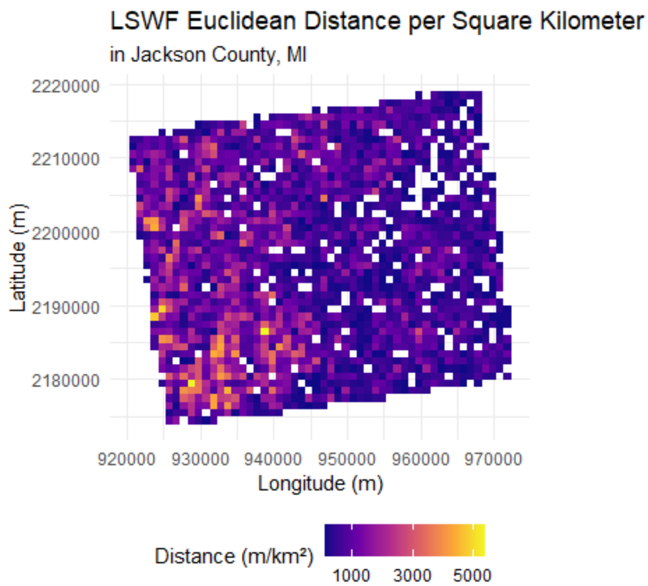

Figure 4: Distribution of Linear Small Woody Features (LSWFs) in Jackson County, MI as measured through aggregated longest-dimension Euclidean distance of LSWFs per km^2.

To further illustrate these findings, we generated a county-level map displaying the average distance of LSWFs per km^2 across the study area (example shown in Figure 4, all counties shown in Chapter 2, Figure 8). This map highlights regions with exceptionally high or low LSWF densities, much like graphics presented in Burke et al. (2019), providing a spatially explicit view of distribution patterns. For example, counties with extensive forested land cover or LSWF presence would directly exhibit lower LSWF densities. However, they would still have higher average densities of LSWFs than a predominantly forested county. In contrast, counties with mixed land use or significant riparian networks display higher densities.

Table 1: Total summary statistics on extracted LSWF datasets for all study counties, with metrics for average LSWF dimensions shown. All units for length and average width are measured in meters.

Count (*n*)	**Mean LSWF Length**	**Median Length**	**Length st. dev.**	**Length IQR**	**Mean Avg Width**	**Median Avg Width**	**Avg Width st. dev.**	**Width IQR**
137055	185.5	154.5	107.4	101.7	16.09	15.36	5.71	7.54

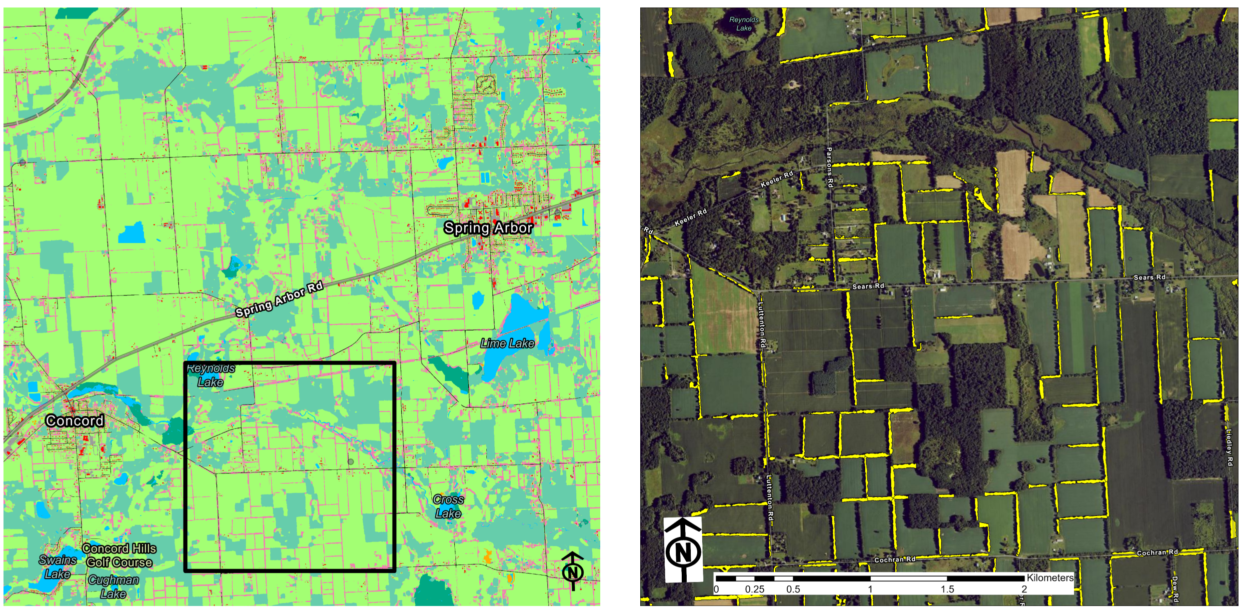

Figure 5: (Left) Same 0.6 m-resolution extracted land cover as shown above, with contiguously forested areas in teal and ToFs in pink. The box represents the inset shown on the (right). The inset details the final extracted segmented LSWF features within Jackson County, MI, as shown in yellow. Note how the separation of LSWF polygons at L, T, and X-shaped vertices allows for enhanced individual and summary assessments of the structure of LSWFs. This also illustrates the effectiveness of the shrink-expand and shape-based refinement methods in isolating forested or woodlot areas from LSWFs, such as windbreaks and narrow riparian buffers.

Identifying and mapping LSWFs at a sub-meter resolution opens opportunities for their targeted integration into land management practices where they are not currently present, including windbreak establishment, erosion control, and wildlife corridors. The results align with findings by Deng et al. (2023), which demonstrated the efficacy of shape-oriented methods in detecting narrow, linear, woody features. However, this study's improved SNFI thresholds and segmentation approaches provide greater precision in mixed agricultural and forested landscapes, addressing a limitation noted in earlier studies. Additionally, the incorporation of moving-window and Voronoi-based splitting methods distinguishes this work by offering enhanced individual feature metrics, which can be summarized, surpassing the capabilities of traditional pixel-based methods (Liknes et al., 2017; Sarti et al., 2021; Deng et al., 2023; Luscombe et al., 2023). By quantifying the spatial extent and structural characteristics of LSWFs, this study provides foundational data to inform AF planning and policy development.

1.4.1 Accuracy Assessment of LSWFs

Table 2: Raw accuracy metrics on model performance in SW Jackson County, MI

Metric	**Value (count)**	%
Total Evaluated Area (LSWFs identified by model)	2,920	–
True Positive Count (Correctly identified LSWFs)	2,609	92.36%
False-Negative Rate (**Omission Rate**, LSWFs missed)	321	10.96%
False-Positives (Non-LSWFs incorrectly classified as LSWF)	311	10.65%
Producer’s Accuracy	2,609 / 2,930	89.0%
User’s Accuracy	2,609 / 2,920	89.2%

Table 2 summarizes the raw accuracy metrics for the automated LSWF (linear small woody features) detection workflow in southwestern Jackson County, MI. Based on the validation dataset, 2,609 LSWFs were correctly identified out of 2,930 total validated (reference) LSWFs—resulting in a producer’s accuracy of 89.0%. Of the 2,920 LSWF features identified by the model, 2,609 were correctly classified—yielding a user’s accuracy of 89.2%. The model missed 321 LSWFs, corresponding to an omission rate of 10.9%. In addition, 311 areas that were not LSWFs were incorrectly classified as LSWFs, which, when estimated as a proportion of the total predicted positives, gives an alternative false-positive “rate” of 10.65%.

In the verification area, the cumulative length of correctly detected LSWFs (true positives) is 523,607.79 m, and when combined with an estimated false-negative length of 60,238.9 m (derived from 311 missed LSWFs at the average LSWF length from the accuracy assessment), the total expected ground-truth length is 583,846.69 m. This results in a LSWF length-matching rate (as used in Deng et al. 2024) of 89.7%.

Table 3: Estimated error matrix for LSWFs in Jackson County, MI, verification area.

	Reference LSWF	Reference Non-LSWF	Total
Mapped as LSWF	2,609	311	2,920
Mapped as Non-LSWF	321	≈2,607	≈2,928
Total	2,930	≈2,918	≈5,848

The model predicted 2,920 positives (of which 2,609 were true positives and 311 were false positives). The reference positive count is 2,930 (2,609 true positives plus 321 false negatives). By assuming that the traditional FP rate (FP divided by FP plus true negatives) is equivalent to the estimated 10.65%, we solve for the true negatives, which yields about ≈2,607. This leads to an estimated reference negative count of ≈2,918 and a total sample size ≈5,848. With these values, the overall model accuracy is approximately 89.2%, and Cohen's kappa is estimated to be around 0.78, indicating robust performance with strong concordance to the ground-truth data.

1.4.2 Automated LSWF Detection for Land Management and Conservation

Automated detection of LSWFs offers substantial advantages for both agroforestry planning and ecological restoration, as discussed further in 1.6.1. Advanced geospatial tools enable a detailed assessment of windbreaks and riparian forest buffers across entire watersheds. Riparian buffers are most effective when implemented across a watershed, as isolated buffers on a few farms have limited potential to enhance water quality. This issue is well documented in regions like the Chesapeake Bay, where fragmented buffer implementation has constrained measurable improvements. The integration of automated LSWF mapping allows for the identification of watersheds that exhibit the greatest need for buffer establishment, thereby guiding more impactful conservation strategies. Windbreaks also benefit from a landscape-scale approach. Widespread deployment across contiguous agricultural areas reinforces protection against wind erosion and creates more reliable microclimatic conditions. This comprehensive perspective enhances both environmental resiliency and agricultural productivity by linking fragmented features into coherent, functional networks.

Automated mapping in the Great Lakes Region, where agricultural and forested landscapes frequently intersect, provides stakeholders with actionable information to support sustainable land-use practices. Specifically, the ability to identify and evaluate AF features such as windbreaks and riparian zones enables more strategic decision-making for:

- **Land Management Practices:** Automated detection assists farmers and land managers in pinpointing areas suited for windbreak installation and in targeting degraded regions for buffer restoration.
- **Policy Development:** Local governments and conservation agencies can leverage detailed LSWF datasets to establish incentive programs for AF adoption and to refine land-use regulations.
- **Ecological Restoration:** Comprehensive LSWF mapping facilitates landscape-scale restoration by identifying corridors and reconnecting fragmented habitats.

In conclusion, the model outputs and methodologies presented in this study illustrate the transformative potential of automated LSWF detection for land management and conservation. Integrating these findings into broader planning frameworks empowers stakeholders to promote sustainable land-use practices while enhancing the ecological integrity of the Great Lakes Region.

1.5 Challenges and Limitations

While this study's results demonstrate the potential of automated methods for mapping linear small woody features (LSWFs), several challenges, limitations, and potential improvements or modifications to methods should be acknowledged.

1.5.1 Computational Constraints

The high-resolution nature of the datasets, with resolutions of 0.6m and 0.3m, demanded significant computational resources for preprocessing, training, and analysis. While effective, the CNN-based land cover product, shrink-expand method, and Voronoi-polygon-based refinement processes are computationally intensive, particularly when applied to large spatial extents at very high resolutions. These constraints can limit the scalability of the methodology for broader applications without access to high-performance computing resources. However, resources may be warranted to produce high-resolution land cover data products for precision conservation.

1.5.2 Landscape-Specific Errors

The model's performance varied across different landscapes, with errors primarily occurring in areas with dense overlapping vegetation or mixed land-use contexts. For instance, clusters of trees in urban or peri-urban areas were sometimes carried through the analysis as LSWFs, as the groups in final datasets usually form a ‘linear’ tree canopy grouping. The most common misclassification in the land cover dataset was in very green or deep green agricultural fields, which were infrequently improperly classified as water surfaces (much like a duckweed- or algae-covered pond). However, this did not impact the tree canopy classification, which was used for LSWF outputs. At the same time, sometimes very narrow, relatively minimal woody features occasionally fail to meet the size, SNFI, or sinuosity thresholds (see 1.5.7).

1.5.3 Improvement in the Shrink-Expand Method

For an additional future analysis to address potential forest gaps and ensure more comprehensive masking of contiguous forested areas, an initial expansion of 10 to 20 linear feet could be applied to the tree canopy raster before the shrink-expand process (feet are used in this filter to align with FIA units). This preliminary step effectively bridges small gaps within forested regions, enhancing the accuracy of delineating contiguous forested polygons. Following this initial expansion, the subsequent shrink and expand process would have a carried over transformation to include the initial 60 feet shrink plus the additional 10 to 20 feet expansion, and the expansion step would incorporate the same initial adjustment, with a final tree canopy class expansion of approximately 72 to 84 feet (20% more than the ‘shrink’).

1.5.4 Constraining Segmentation of Polygons

Most LSWFs are spatially independent of each other unless they were directly connected as part of an LSWF network. Therefore, the centerlines of LSWF features are significantly far apart from any other part of an LSWF. There were a handful of exceptions where a centerline used for the ToF segmentation would pull a small piece (i.e., a ‘sliver’ or ‘shard’) of another adjacent windbreak not directly connected to an LSWF network. Methods to constrain the Voronoi drawing process could be implemented to fix these errors, or methods to reconnect the small, infrequent separated pieces could improve full output quality.

1.5.5 Misidentification of Irrelevant LSWFs

Some LSWFs are not agriculturally or ecologically relevant and can contribute to the misattribution of all LSWFs to have agricultural or ecological significance. Future work should include filtering considerations for LSWFs in urban and suburban areas to better control for misattribution. A simple way to incorporate an urban or suburban filter within the US would be to remove LSWFs within census-designated places, developed commercial or residential areas. Furthermore, future work should have additional filtering considerations for common landscape features with LSWFs. For instance, within the upper Midwest, golf courses and cemeteries have LSWFs that meet the filter criteria to be included as LSWFs in our final dataset, but often do not contribute to agricultural or functional relevance.

1.5.6 Dependence on High-Resolution Data

The dependency on high-resolution NAIP imagery limits the study's ability to replicate similar findings to areas without such datasets. While the resolution of 0.6m and 0.3m imagery enabled the detection of fine-scale features, the availability and cost of acquiring similar high-resolution datasets for other regions may hinder the broader adoption of this methodology. Implementing these methods with satellite imagery and other imagery sources (either at slightly lower resolutions or other high-resolution sources) with global coverage may be feasible.

1.5.7 Incorporation of Belt-oriented Connections

Deng et al. (2024) and Wolstenholme et al. (2025) describe methods to connect disconnected sections of LSWF belts, thereby improving the completeness of a dataset that may contain disconnected linear features or appear as a ‘dashed’ line rather than a continuous one. Incorporation of methods to connect otherwise disconnected features could identify additional LSWFs that may act as partially effective windbreaks, riparian buffers, or other functional AF features. Many partially effective linear woody features in our exhaustive dataset may have been removed due to the filtering constraints, which exclude features with a total length of less than 100 m or a lack of elongation along an axis. While these may not be considered in our final, full dataset, the gaps in canopies from imagery at such a high resolution likely mean they would not be regarded as a significant or fully effective, intensive AF feature by the definition used for this study. However, it would be interesting to evaluate the presence of partially effective or partially filled LSWF features, as they could be LSWFs that were established recently or are in succession.

1.6 Further research

In this study, we mapped LSWFs in diverse agricultural and forested landscapes, where smaller features (though not smaller than 100 m in length) could be captured and tabulated for analysis. This approach builds on prior studies by developing a robust, high-resolution mapping methodology tailored to the specific characteristics of the Great Lakes Region's heterogeneous landscapes, which are typified by fragmented forest patches, diverse land management (both forested and agricultural), and a mix of agricultural and natural land cover configurations. Recognizing the ecological and structural complexity of Linear Woody Canopy Features (LWCFs) such as windbreaks, our study focuses on adapting and enhancing convolutional neural network (CNN) methodologies to handle the region’s distinctive landscape features, filling a critical gap in region-specific automation for LSWF identification.

Running the model across the remaining counties in the Great Lakes Region would allow for a comprehensive estimate of LSWFs across the study area. This broader analysis would offer a more exact quantification of features and provide additional context for understanding regional LSWF presence, and, with additional validation, AF practices. Furthermore, integrating other land cover data sources or machine learning methods into the validation process would generally strengthen LSWF detection.

Future research could benefit from integrating additional datasets, such as LiDAR or hyperspectral imagery, to capture finer details of canopy structure (such as fill) and health. Similarly, incorporating socio-economic data, such as landowner management practices or conservation program participation, would provide a richer context for understanding the drivers of LSWF distribution. These advancements would enhance detection accuracy and facilitate targeted interventions tailored to regional needs.

Expanding this approach to entirely different states or landscapes, such as arid regions, forested mountainous areas, or highly urbanized environments, would test the model's robustness and scalability. These additional trials would provide invaluable insights into its applicability for various ecological and AF challenges. Future research should focus on extending the developed methodology to landscapes beyond the Great Lakes Region to evaluate the model's generalizability. Testing the model in regions with differing vegetation structures, agricultural practices, or environmental conditions would provide critical feedback on its adaptability and reliability.

1.6.1 Implications for Policy and Management

This study's findings and methodologies contribute significantly to the growing body of knowledge surrounding small woody features and land management. By providing a reliable and scalable approach for detecting and analyzing LSWFs, this work supports efforts to advance ecological policymaking at both regional and national levels. With a complete dataset on the presence of LSWFs, policymakers can leverage these findings to develop or refine conservation incentives, land-use regulations, and AF support programs that emphasize the ecological benefits of LSWFs.

The detailed LSWF maps produced by this study could serve as baseline datasets for monitoring AF adoption within programs like the USDA's Conservation Reserve Program or other regional conservation initiatives. Furthermore, such maps could be incorporated into incentive structures, such as payments for ecosystem services, where farmers and landowners are compensated for maintaining or restoring LSWFs that provide critical ecological functions. Moreover, the model demonstrates considerable potential as a tool for sustainable forestry management and AF development. Its integration into state or regional environmental technical support systems could streamline land management operations, enabling decision-makers to identify priority areas for windbreak restoration, riparian buffer establishment, and biodiversity corridor enhancement. With further refinement, this methodology could become a cornerstone of data-driven AF initiatives, fostering more sustainable and resilient landscapes.

1.7 Conclusion

This study demonstrates the potential of automated detection methods for mapping Linear Small Woody Features (LSWFs) in the Great Lakes Region. We developed a scalable methodology capable of identifying LSWFs with exceptional precision by leveraging high-resolution aerial imagery and advanced convolutional neural networks. Incorporating innovative segmentation techniques, such as shape-oriented indices and Voronoi-based feature splitting, enabled a nuanced analysis of LSWF structure and connectivity across diverse landscapes. These advancements address longstanding challenges in AF mapping, including limitations in detecting smaller, fragmented features and achieving consistent classification across variable land-use patterns.

The findings underscore the ecological and agricultural significance of LSWFs, highlighting their role as critical elements of sustainable land-use practices, from erosion control and habitat connectivity to windbreak establishment. Beyond immediate applications, this study's methodology provides a robust framework for scaling automated LSWF detection to broader regions and integrating it into AF planning, conservation policies, and ecological restoration efforts. While data dependency and computational intensity persist, future research incorporating additional datasets and adaptive modeling techniques can enhance the methodology's scalability and applicability. This work lays the foundation for data-driven strategies to support resilient AF systems and sustainable landscapes by bridging technological innovation with actionable insights.

REFERENCES

Aksoy, Selim, et al. "Automatic Mapping of Linear Woody Vegetation Features in Agricultural Landscapes Using Very High Resolution Imagery." *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 1, Jan. 2010, pp. 511–22. *IEEE Xplore*, https://doi.org/10.1109/TGRS.2009.2027702.

Amichev, Beyhan Y., et al. "Mapping and Quantification of Planted Tree and Shrub Shelterbelts in Saskatchewan, Canada." *Agroforestry Systems*, vol. 89, no. 1, Feb. 2015, pp. 49–65. *Springer Link*, https://doi.org/10.1007/s10457-014-9741-2.

Basu, Saikat, et al. "A Semiautomated Probabilistic Framework for Tree-Cover Delineation From 1-m NAIP Imagery Using a High-Performance Computing Architecture." *IEEE Transactions on Geoscience and Remote Sensing*, vol. 53, no. 10, Oct. 2015, pp. 5690–708. *IEEE Xplore*, https://doi.org/10.1109/TGRS.2015.2428197.

Belgiu, Mariana, and Lucian Drăguţ. "Random Forest in Remote Sensing: A Review of Applications and Future Directions." *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 114, Apr. 2016, pp. 24–31. *ScienceDirect*, https://doi.org/10.1016/j.isprsjprs.2016.01.011.

Blaschke, T. "Object Based Image Analysis for Remote Sensing." *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 65, no. 1, Jan. 2010, pp. 2–16. *ScienceDirect*, https://doi.org/10.1016/j.isprsjprs.2009.06.004.

Burke, Morgen W. V., et al. "Detection of Shelterbelt Density Change Using Historic APFO and NAIP Aerial Imagery." *Remote Sensing*, vol. 11, no. 3, 3, Jan. 2019, p. 218. *www.mdpi.com*, https://doi.org/10.3390/rs11030218.

Claggett, Peter, et al. *Chesapeake Bay Program's One-Meter Resolution Land Use/Land Cover Data: Overview and Production*. Sept. 2022.

Copernicus Land Monitoring Service (CLMS) and European Environment Agency (EEA). *Copernicus Land Monitoring Service High Resolution Land Cover Characteristics Small Woody Features 2018 and Small Woody Features Changes 2015-2018*. European Union, 2021, https://land.copernicus.eu/en/technical-library/high-resolution-layer-small-woody-features-2018-product-user-manual/@@download/file.

Czerepowicz, L., et al. "Using Satellite Image Data to Estimate Aboveground Shelterbelt Carbon Stocks across an Agricultural Landscape." *Agriculture, Ecosystems & Environment*, vol. 156, Aug. 2012, pp. 142–50. *ScienceDirect*, https://doi.org/10.1016/j.agee.2012.05.014.

Damjan Strnad, et al. "Detection and Monitoring of Woody Vegetation Landscape Features Using Periodic Aerial Photography." *Remote Sensing*, vol. 15, no. 11, May 2023, pp. 2766–2766. *EBSCOhost*, https://doi.org/10.3390/rs15112766.

Deng, R. X., et al. “Remote Estimation of Shelterbelt Width from SPOT5 Imagery.” *Agroforestry Systems*, vol. 91, no. 1, Feb. 2017, pp. 161–72. *Springer Link*, https://doi.org/10.1007/s10457-016-9915-1.

Deng, Rongxin, et al. “Extraction of Farmland Shelterbelts from Remote Sensing Imagery Based on a Belt-Oriented Method.” *Frontiers in Forests and Global Change*, vol. 6, Sept. 2023. *Frontiers*, https://doi.org/10.3389/ffgc.2023.1247032.

Ford, Derek James. *UAV Imagery for Tree Species Classification in Hawai’i: A Comparison of MLC, RF, and CNN Supervised Classification*. 2020. University of Hawai’i at Manoa, M.A. *ProQuest*, https://www.proquest.com/docview/2492630745/abstract/FF519D213F644FDPQ/1.

Garrett, Harold E., et al., editors. *North American Agroforestry*. 3rd edition, Wiley, 2022. *K10plus ISBN*, https://doi.org/10.1002/9780891183785.

Golicz, Karolina, et al. “The Role of Small Woody Landscape Features and Agroforestry Systems for National Carbon Budgeting in Germany.” *Land*, vol. 10, no. 10, Jan. 2021. *EBSCOhost*, https://doi.org/10.3390/land10101028.

Grabska, Ewa, et al. “Forest Stand Species Mapping Using the Sentinel-2 Time Series.” *Remote Sensing*, vol. 11, no. 10, 10, Jan. 2019, p. 1197. *www.mdpi.com*, https://doi.org/10.3390/rs11101197.

Han, Weiguo, et al. “CropScape: A Web Service Based Application for Exploring and Disseminating US Conterminous Geospatial Cropland Data Products for Decision Support.” *Computers and Electronics in Agriculture*, vol. 84, June 2012, pp. 111–23. *ScienceDirect*, https://doi.org/10.1016/j.compag.2012.03.005.

Hossain, Mohammad, and Dongmei Chen. “Segmentation for Object-Based Image Analysis (OBIA): A Review of Algorithms and Challenges from Remote Sensing Perspective.” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 150, Feb. 2019, pp. 115–34. *ResearchGate*, https://doi.org/10.1016/j.isprsjprs.2019.02.009.

Iglovikov, Vladimir, and Alexey Shvets. *TernausNet: U-Net with VGG11 Encoder Pre-Trained on ImageNet for Image Segmentation*. arXiv:1801.05746, arXiv, 17 Jan. 2018. *arXiv.org*, https://doi.org/10.48550/arXiv.1801.05746.

Jose, Shibu. “Agroforestry for Ecosystem Services and Environmental Benefits: An Overview.” *Agroforestry Systems*, vol. 76, no. 1, May 2009, pp. 1–10. *Springer Link*, https://doi.org/10.1007/s10457-009-9229-7.

Kampffmeyer, Michael, et al. “Semantic Segmentation of Small Objects and Modeling of Uncertainty in Urban Remote Sensing Images Using Deep Convolutional Neural Networks.” *2016 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2016, pp. 680–88. *IEEE Xplore*, https://doi.org/10.1109/CVPRW.2016.90.

Kellerman, Todd, et al. “Agroforestry across the United States: Results of the 2022 Census of Agriculture.” *Agroforestry Systems*, vol. 99, no. 2, Feb. 2025, p. 34. *Springer Link*, https://doi.org/10.1007/s10457-024-01096-2.

Liknes, Greg C., et al. “Shape Indexes for Semi-Automated Detection of Windbreaks in Thematic Tree Cover Maps from the Central United States.” *International Journal of Applied Earth Observation and Geoinformation*, vol. 59, July 2017, pp. 167–74. *DOI.org (Crossref)*, https://doi.org/10.1016/j.jag.2017.03.005.

Lü, Y., et al. “Automatic Recognition of Farmland Shelterbelts in High Spatial Resolution Remote Sensing Data.” *Nongye Jixie Xuebao/Transactions of the Chinese Society for Agricultural Machinery*, vol. 49, no. 1, Jan. 2018, pp. 157–63. *EBSCOhost*, https://doi.org/10.6041/j.issn.1000-1298.2018.01.020.

Luscombe, David J., et al. “Rapid, Repeatable Landscape-scale Mapping of Tree, Hedgerow, and Woodland Habitats (THaW), Using Airborne LiDAR and Spaceborne SAR Data.” *Ecology and Evolution*, vol. 13, no. 5, May 2023, p. e10103. *PubMed Central*, https://doi.org/10.1002/ece3.10103.

Matthew M. Smith, et al. “Agroforestry Extent in the United States: A Review of National Datasets and Inventory Efforts.” *Agriculture*, vol. 12, no. 5, May 2022, pp. 726–726. *EBSCOhost*, https://doi.org/10.3390/agriculture12050726.

Morgan, Grayson R., et al. “Deep Learning for Urban Tree Canopy Coverage Analysis: A Comparison and Case Study.” *Geomatics*, vol. 4, no. 4, 4, Dec. 2024, pp. 412–32. *www.mdpi.com*, https://doi.org/10.3390/geomatics4040022.

Pallai, Cassandra, et al. *Chesapeake Bay Watershed 2013/2014 High-Resolution Land Cover Dataset Lessons Learned and Stakeholder Outreach*. 2016.

Patriarca, Alessio, et al. “Wide-Scale Identification of Small Woody Features of Landscape from Remote Sensing.” *Land*, vol. 13, no. 8, 8, Aug. 2024, p. 1128. *www.mdpi.com*, https://doi.org/10.3390/land13081128.

Pippuri, Inka, et al. “Classification of Forest Land Attributes Using Multi-Source Remotely Sensed Data.” *International Journal of Applied Earth Observation and Geoinformation*, vol. 44, Feb. 2016, pp. 11–22. *EBSCOhost*, https://doi.org/10.1016/j.jag.2015.07.002.

Quackenbush, Lindi J. “A Review of Techniques for Extracting Linear Features from Imagery.” *Photogrammetric Engineering and Remote Sensing*, vol. 70, no. 12, Jan. 2004, pp. 1383–92.

Rizvi, R. H., et al. “Mapping Agroforestry and Trees Outside Forest.” *ICAR-Central Agroforestry Research Institute (CAFRI), Jhansi and World Agroforestry (ICRAF), South Asia Regional Programme*, 2020.

Robinson, Caleb, et al. “Large Scale High-Resolution Land Cover Mapping With Multi-Resolution Data.” *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, 2019, pp. 12718–27. *DOI.org (Crossref)*, https://doi.org/10.1109/CVPR.2019.01301.

---. “LARGE SCALE MACHINE LEARNING FOR GEOSPATIAL PROBLEMS IN COMPUTATIONAL SUSTAINABILITY.” *COMPUTATIONAL SUSTAINABILITY*, Aug. 2020.

Ronneberger, Olaf, et al. *U-Net: Convolutional Networks for Biomedical Image Segmentation*. arXiv:1505.04597, arXiv, 18 May 2015. *arXiv.org*, https://doi.org/10.48550/arXiv.1505.04597.

Rubio-Delgado, Judit, et al. “Small Woody Features in Agricultural Areas: Agroforestry Systems of Overlooked Significance in Europe.” *Agricultural Systems*, vol. 218, Jan. 2024. *EBSCOhost*, https://doi.org/10.1016/j.agsy.2024.103973.

Sarti, Maurizio, et al. “Trees Outside Forest in Italian Agroforestry Landscapes: Detection and Mapping Using Sentinel-2 Imagery.” *European Journal of Remote Sensing*, vol. 54, no. 1, Jan. 2021, pp. 610–24. *Taylor and Francis+NEJM*, https://doi.org/10.1080/22797254.2021.1986678.

Scholefield, P., et al. “A Model of the Extent and Distribution of Woody Linear Features in Rural Great Britain.” *Ecology and Evolution*, vol. 6, no. 24, Dec. 2016, pp. 8893–902. *EBSCOhost*, https://doi.org/10.1002/ece3.2607.

Sharma, Prashant, et al. “Geospatial Technology in Agroforestry: Status, Prospects, and Constraints.” *Environmental Science and Pollution Research*, vol. 30, no. 55, Nov. 2023, pp. 116459–87. *Springer Link*, https://doi.org/10.1007/s11356-022-20305-y.

Ting Liu, et al. “Research on Rapid Extraction of Shelter Forest Using GF-2 Images Based on Vegetation Indices.” *Forest Engineering*, vol. 34, no. 6, Nov. 2018, pp. 13–19.

United States Department of Agriculture, Forest Service. *FIA Database Documentation*. 2015, https://apps.fs.usda.gov/fia/datamart/datamart.html.

Vermont Land Cover 2016 Final Report v3.0. University of Vermont, Spatial Analysis Lab, 19 Aug. 2019, https://vcgi.nyc3.digitaloceanspaces.com/portal-pages/VT-Land-Cover-2016-Final-Report-v3.pdf.

Vermont Land Cover 2021-22 Final Report. University of Vermont, Spatial Analysis Lab, Nov. 2024, https://vcgi.nyc3.cdn.digitaloceanspaces.com/portal-pages/VT-Land%20Cover-2021_22%20Final%20Report.pdf.

Vermont Statewide Base Land Cover, Impervious Surface and Forest Cover Quality Control 2019: QC Report. University of Vermont, Spatial Analysis Lab, 26 Aug. 2019, https://vcgi.nyc3.digitaloceanspaces.com/portal-pages/VT%20High%20Res%20Land%20Cover%20Overview-QAQC_Final_v1.0.pdf.

Xing, Z., et al. "Extracting Farmland Shelterbelt Automatically Based on ZY-3 Remote Sensing Images." *Linye Kexue/Scientia Silvae Sinicae*, vol. 52, no. 4, Apr. 2016, pp. 11–20. *EBSCOhost*, https://doi.org/10.11707/j.1001-7488.20160402.

Yuanxin Jia, et al. "Super-Resolution Rural Road Extraction from Sentinel-2 Imagery Using a Spatial Relationship-Informed Network." *Remote Sensing*, vol. 15, no. 17, Aug. 2023. *EBSCOhost*, https://doi.org/10.3390/rs15174193.

APPENDIX A - Supplemental Data

Table 1.9.A1: Raw counts and summary statistics of LSWFs in each exhaustively surveyed county across the study area. All numerical units are in meters unless otherwise noted.

County	ST	Count (*n*)	Mean LSWF Length	Median Length	Length st. dev.	Length IQR	Mean Avg Width	Median Avg Width	Avg Width st. dev.	Width IQR
Alpena	MI	1833	169.9	144.2	95.4	88.1	15.83	14.78	6.23	8.18
Athens	OH	2999	182.7	149.5	110.4	98.1	16.37	15.52	5.65	7.43
Auglaize*	OH	1997	209.2	166.2	138.9	124.3	14.28	13.27	6.02	8.22
Bayfield	WI	1719	175.6	149.3	98.0	91.1	17.53	16.72	6.50	8.92
Berrien	MI	4962	193.1	156.9	118.7	109.8	16.25	15.62	5.68	7.50
Chippewa	MI	2449	179.1	149.2	115.6	96.2	16.40	15.83	6.02	8.35
Clark	WI	3588	171.9	145.4	91.7	90.3	14.85	13.90	5.75	8.05
Columbiana	OH	4652	180.1	151.8	108.9	95.1	16.14	15.39	5.40	7.15
Crawford	OH	2354	200.8	165.0	121.2	119.9	14.26	13.42	5.52	7.29
Defiance	OH	2862	222.9	178.5	147.3	145.7	14.40	13.18	6.01	7.92
Door	WI	3000	174.3	146.5	89.6	92.6	15.86	14.54	6.11	7.57
Green Lake	WI	2847	184.2	156.8	95.1	104.8	17.08	16.35	5.47	7.22
Hamilton	OH	5556	213.7	165.8	152.1	131.5	17.10	16.19	6.32	8.25
Houghton	MI	1500	168.3	143.2	96.0	84.6	16.08	15.31	5.52	7.56
Holmes	OH	3716	177.7	150.5	92.3	98.1	15.56	14.69	5.77	7.34
Huron	MI	2953	176.9	148.8	98.9	95.3	13.26	12.09	6.00	8.08
Iowa	WI	3619	183.3	152.0	105.1	102.1	16.92	16.14	6.03	8.29
Isabella	MI	3751	177.8	152.2	91.5	93.8	15.41	14.77	5.49	7.50
Jackson	MI	9568	185.7	160.7	95.2	99.7	16.83	16.27	5.00	6.66
Kent	MI	7711	178.5	150.9	95.0	95.7	16.80	16.17	5.41	7.29
Knox	OH	6220	191.5	160.9	107.7	107.8	15.29	14.56	5.44	7.12
Leelanau	MI	1661	171.3	146.8	88.5	90.0	16.00	15.12	5.86	7.97
Licking	OH	8305	193.8	159.6	120.2	107.1	15.40	14.73	5.28	6.90
Marquette	WI	2676	179.1	153.7	92.0	98.6	16.84	16.13	5.83	7.78
Mecosta	MI	3058	166.9	145.1	79.9	80.0	16.40	15.67	5.59	7.56
Montcalm	MI	5572	181.5	154.5	95.4	95.1	16.38	15.65	5.31	6.80
Oceana	MI	2381	176.3	150.8	92.1	91.0	15.89	15.21	5.61	7.57
Oneida	WI	2301	184.8	152.8	109.0	101.5	18.08	17.59	6.28	8.52
Ozaukee	WI	2752	184.0	152.5	101.0	98.6	16.43	15.61	5.71	7.19
Richland	WI	3384	185.1	156.7	99.1	105.0	17.43	16.74	5.61	7.49
Sauk	WI	5165	187.3	158.3	101.1	107.8	16.87	16.10	5.69	7.55
Shawano	WI	3611	168.2	143.5	83.0	86.4	15.63	14.78	5.49	7.22
Vernon	WI	4209	180.6	152.0	98.8	99.4	17.25	16.61	5.43	7.27
Wayne	OH	5314	187.9	154.6	111.7	105.2	15.14	14.48	5.40	6.93
Warren	OH	6810	195.6	159.6	120.2	108.8	15.59	14.92	5.60	7.29
TOTALS		137055	185.5	154.5	107.4	101.7	16.09	15.36	5.71	7.54

APPENDIX B - Measurements used in Methods/Accuracy Assessment

Line Straightness Index (LSI)

Two common formulations capture "straightness" of a line:
(a) *Global Straightness*
A simple measure is the ratio of the straight-line (Euclidean) distance between the endpoints to the actual path length *L*:

$$\mathrm{LSI} = \frac{d_E}{L}$$

A perfectly straight line gives LSI=1; any deviation (for example, a 90° bend) will reduce the value.
(b) *Localized (Moving Window) Straightness*
If one wishes to capture local bends (e.g., detecting near 90° angles), one can use the deviation at each vertex. Let θ_i be the internal angle at vertex *i* (with 180° representing no bend). Then, over *n* vertices the index can be defined as:

$$\mathrm{LSI} = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{|180^\circ - \theta_i|}{90^\circ}\right)$$

In this formulation, a vertex with θ_i = 180° (perfectly straight) contributes 1, while a 90° bend contributes 0.

Original Morphological SNFI (Liknes et al. 2017)
In the original paper the SNFI is calculated using a hit-or-miss morphological erosion applied to a binary tree-cover map. Two different structuring elements are used:

- A horizontal kernel (of size 1×*m*)
- A vertical kernel (of size *m*×1)
- Let $S_h = \sum z_{f,s(1\times m)}$ be the zonal sum (i.e. count of remaining foreground pixels) after horizontal erosion, and
- $S_v = \sum z_{f,s(m\times 1)}$ be the zonal sum after vertical erosion.

Then the index is defined as:

$$\mathrm{SNFI} = \frac{S_h - S_v}{S_h + S_v}$$

Interpretation:

- For a zone that is narrow in the east–west direction (i.e. elongated north–south), the horizontal erosion removes fewer pixels than the vertical one, so $S_h > S_v$ and SNFI approaches +1.
- Conversely, if the feature is oriented east–west, SNFI tends toward –1.

Bounding Box–Based SNFI

In this chapter an alternative (and computationally efficient) method was implemented using the axis-aligned bounding box of a feature. Let the bounding box be defined by its minimum and maximum coordinates:

- x_{min}, x_{max} (horizontal extent)
- y_{min}, y_{max} (vertical extent)

Define:

$W = x_{max} - x_{min}$, $H = y_{max} - y_{min}$

Then a bounding box–based SNFI is given by:

$$\mathrm{SNFI}_{bbox} = \frac{H - W}{H + W}.$$

Interpretation:

- A feature that is taller than it is wide (i.e. north–south oriented) will have $H > W$ and yield a positive SNFI value (near +1 if very elongated).
- If the feature is wider (east–west oriented), the index will be negative (approaching –1).

Axis-Based (Oriented) SNFI

For a more refined, rotation–invariant measure we first compute the oriented (or minimum) bounding box by rotating the feature to align its principal axis with a reference direction. Let:

- L be the length of the oriented (long) side, and
- W' be the length of the short side.

Then one formulation is:

$$\mathrm{SNFI}_{axis} = \frac{L - W'}{L + W'}$$

Alternatively, if the principal orientation angle θ is obtained from a principal component analysis and is measured from the north–south direction, then an equivalent trigonometric formulation is:

$$\mathrm{SNFI}_{axis} = \cos(2\theta)$$

Interpretation:

- When $\theta = 0°$ (i.e. the feature is aligned north–south), cos(0)=1.
- When $\theta = 90°$ (east–west orientation), cos(180°) = −1.
- This formulation is isotropic in that it removes the effect of the original image coordinate system.

Modified WSI

As represented in Liknes et al. (2017), the original windbreak sinuosity index is calculated by comparing half of a zone's perimeter (which approximates a "half-circumference") to the Euclidean distance across the zone's bounding box. In our work, we refer to this as the modified WSI. Using the bounding box defined by its minimum and maximum x- and y-coordinates x_{min}, x_{max} and y_{min}, y_{max}, the modified WSI is given by:

$$\mathrm{WSI} = \frac{0.5 \times P}{\sqrt{(x_{\max} - x_{\min})^2 + (y_{\max} - y_{\min})^2}}$$

Where:

- P is the perimeter of the zone (i.e. the contiguous patch of tree cover), and
- The denominator is the diagonal length of the zone's axis–aligned bounding rectangle.

Interpretation:

- This index tends to be higher for a compact or square-like feature (for example, a square might yield a WSI around 1.4).
- As the feature becomes more elongated (with the diagonal length approaching the length of the feature), the index decreases toward 1.
- Values above about 1.4 suggest more irregular or curvilinear borders.

Omission Rate

The omission rate (also called the false-negative rate) is the proportion of ground-truth features that the model missed. Using counts, it is expressed as:

$$\text{Omission Rate} = \frac{\text{False Negatives (FN)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

It can also be calculated using cumulative lengths if preferred.

Length Matching Rate

This metric compares the cumulative length of correctly detected (true positive) features L_{TP} to the total "ground-truth" length (true positives plus the estimated length of missed features, L_{FN}:

$$\text{Length Matching Rate} = \frac{L_{\mathrm{TP}}}{L_{\mathrm{TP}} + L_{\mathrm{FN}}}$$

For example, if 523,608 m are detected (TP) and 60,239 m are missed (FN), the matching rate is about 89.7%.

APPENDIX C - Full LSWF Extraction Methods Flowchart

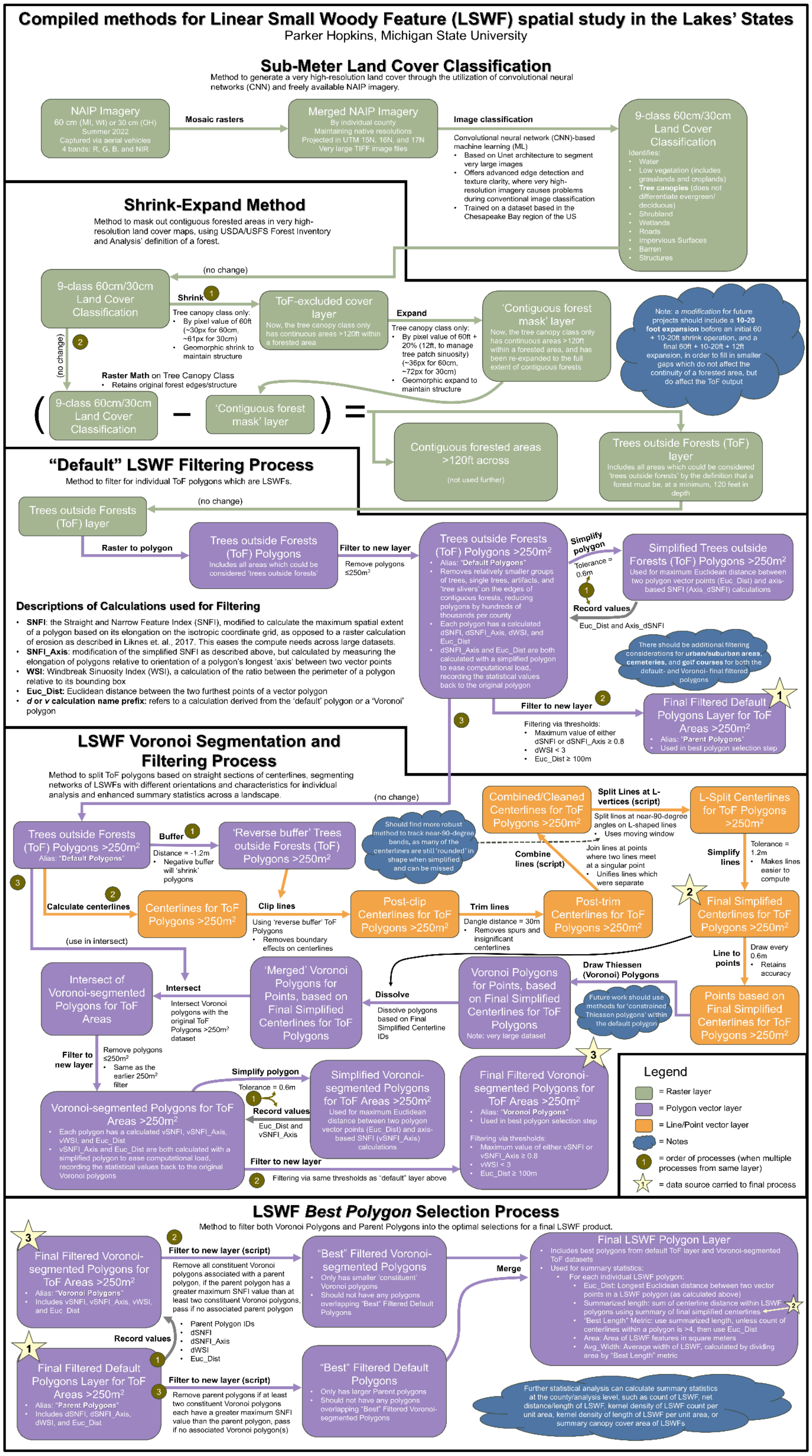

Figure 1.11.AC1: Full methods to extract LSWFs from imagery, including specific parameters set for the model at various stages.

Chapter 2: Evaluating Data Products to Better Understand LSWF Presence and Morphology in the Great Lakes States

Objectives:

- Evaluate the effectiveness of CNN-derived land use/land cover products for identifying LSWFs in the Great Lakes states.
- Compare high-resolution outputs against traditional datasets (NLCD, Sentinel imagery, Dynamic World) to assess spatial detail and accuracy improvements.
- Analyze spatial patterns and morphological characteristics of LSWFs to reveal regional agroforestry trends.
- Provide insights to guide precision conservation and land management strategies based on refined LSWF assessments.

2.0 Abstract

This chapter examines the effectiveness of machine learning-derived land use and land cover products for mapping linear small woody features (LSWFs) in the Great Lakes region. The study evaluates convolutional neural network outputs against conventional datasets, including the NLCD, Sentinel imagery, and Google Earth Engine's Dynamic World product. Spatial pattern analysis, morphological assessments, and predictive modeling were applied across 35 counties in Michigan, Wisconsin, and Ohio to characterize agroforestry-related features such as windbreaks and riparian buffers. Findings show that the CNN-derived products capture fine-scale details and delineate complex forest connectivity more accurately than traditional methods. The enhanced resolution supports improved conservation planning, identification of agroforestry extent and possibility, and informed decision-making, and it lays the groundwork for further integration of advanced machine learning techniques into regional LULC assessments.

2.1 Introduction

2.1.1 Background

Accurate land use and land cover (LULC) mapping is foundational for sustainable landscape management, particularly in mixed-use regions where agriculture, forestry, and conservation intersect. In conservation planning, precision in mapping is crucial to delineate linear small woody features such as windbreaks and riparian buffers that support ecosystem services, biodiversity, and climate resilience (Rubio-Delgado et al., 2024; Jose, 2009; Scholefield et al., 2016). Precision agriculture and forestry rely on such detailed LULC data to optimize resource use while balancing ecological integrity.

In the Great Lakes region, agroforestry (AF) practices like windbreaks and riparian buffers are pivotal in stabilizing landscapes and enhancing ecosystem services. Windbreaks, typically linear woody features abutting agricultural fields, roads, railroads, and parcel boundaries, provide soil stabilization and microclimate regulation, while woody riparian buffers mitigate nutrient runoff and enhance water quality, aligning with USDA AF definitions (Smith et al., 2022; Fortier et al., 2016; Liknes et al., 2017). Accurate mapping of these features using advanced remote sensing and geospatial analysis is essential for their effective management and scaling (Patriarca et al., 2024; Deng et al., 2023).

Integrating AF within landscape-level planning and support has enhanced agricultural sustainability and ecosystem function. Yet, the identification and mapping of small woody features (SWFs), such as windbreaks or riparian forest buffers, have historically been underrepresented in LULC studies within the U.S., especially in regions with fragmented landscapes (Rubio-Delgado et al., 2024; Liknes et al., 2017; Aksoy et al., 2010). The development of tools and data products like the Chesapeake Bay Program’s high-resolution, high-accuracy LULC datasets exemplifies progress in addressing these gaps, enabling better tree canopy feature classification and conservation planning (Deng et. al., 2022; Claggett et al., 2022; Bolyn et al., 2019).

Recent studies employing remote sensing and geospatial techniques have highlighted LSWFs’ ecological importance and role in mitigating anthropogenic pressures on landscapes (Patriarca et al., 2024; Deng et al., 2023). Emergent tools like AgBufferBuilder demonstrate how collaborative design and incorporation of woody features can optimize conservation outcomes for these features within mixed-use agricultural regions (Oelschlager, 2023).

With ongoing advancements in remote sensing and machine learning, there is increasing potential to enhance the accuracy and applicability of LULC datasets for AF planning. The body of work on AF highlights that achieving these benefits is possible with technical innovation and policy support to integrate LULC data into decision-making frameworks and support tools. There is a fundamental gap between estimates of LSWFs, realized values of LSWFs through exhaustive remote sensing, and actual validation of AF practices on the ground. Relying on remote sensing or survey-based methods in isolation to quantify the presence of AF will always have numerous inherent imperfections. Studies such as those by Lovell et al. (2021) and Garcia de Jalón et al. (2018) stress the importance of participatory approaches in AF design, ensuring that these features are both ecologically robust and socio-economically viable.

Various methods have been developed to quantify and measure the presence and significance of LSWFs, such as windbreaks and riparian buffers, in AF landscapes. These features have been assessed using high-resolution remote sensing, geospatial tools, and field-based observations. Emerging approaches increasingly leverage machine learning (ML) to enhance accuracy and efficiency in mapping LSWFs (Trivedi et al., 2024; Sharma et al., 2023). Integrating ML enables identifying and classifying LSWFs from high-resolution satellite imagery, aiding detailed landscape-level planning and management (Trivedi et al., 2024; Ellis et al., 2005).

Quantifying windbreaks' spatial extent and ecological functions often involves remote sensing and field validation. Recent studies have utilized high-resolution aerial imagery and object-based image classification techniques to delineate windbreak structures in rural landscapes, offering improved precision over pixel-based methods (Meneguzzo et al., 2013; Bolyn et al., 2019; Sarti et al., 2021; Deng et al., 2023). Advances in large-eddy simulation modeling further underscore windbreaks' ability to reduce soil erosion, highlighting their physical and environmental significance within agricultural systems (van Ramshorst et al., 2022). Additionally, geospatial tools such as GIS-based models provide valuable insights into the functional attributes of tree belts, enhancing their integration into rural landscape planning (Nowak & Pędziwiatr, 2018).

Riparian buffers, another vital component of AF systems, are critical for reducing nutrient runoff, stabilizing streambanks, reducing flood debris from being deposited on crop fields, and improving water quality. Their quantification often involves multispectral and hyperspectral remote sensing to detect vegetation types and assess spatial patterns along waterways (Sarti et al., 2021; Rizvi et al., 2020). Recent innovations in geospatial technologies have allowed for the creation of detailed maps to support the operational management of woody riparian buffers in rural landscapes (Bolyn et al., 2019; Malkoç et al., 2021). For instance, deploying Sentinel-2 imagery at 10 m spatial resolution has proven effective in identifying trees outside forests, enabling large-scale mapping of riparian buffers (Sarti et al., 2021). Research integrating multitemporal analysis has also been noted as a tool to monitor changes in riparian zones, providing critical data for long-term conservation and management strategies (Plieninger, 2012), although most of these studies occur outside North American contexts.

The continued refinement of methodologies for mapping and quantifying LSWFs is essential for understanding their roles within AF systems. Integrating technologies such as ML, GIS, and high-resolution imagery enhances mapping accuracy and contributes to precise, sustainable landscape management. For example, tools developed to analyze AF systems in Europe have demonstrated the scalability of these methods for global application, underscoring the importance of interdisciplinary approaches in capturing the complexity of LSWFs (Rubio-Delgado et al., 2024; Englund et al., 2021). These advancements provide robust datasets for assessing ecosystem services and ensuring that AF features are effectively recognized, managed, and preserved within diverse landscapes.

2.1.2 Research Gap and Objectives

Despite the extensive utility of traditional datasets like the National Land Cover Database (NLCD) and Sentinel imagery in LULC mapping, they face significant limitations in capturing small-scale features such as LSWFs like windbreaks and riparian buffers. These datasets often lack the spatial resolution or classification granularity required to delineate and assess these narrow but ecologically critical features accurately. For example, the NLCD's coarse resolution can misclassify or omit small-scale woody features, leading to an underrepresentation of their spatial extent and ecological importance (Sharma et al., 2023; Meneguzzo et al., 2013). Similarly, while Sentinel imagery offers 3x higher resolution, its standard classification schemes are not tailored to agroforestry-specific applications, leaving gaps in feature detection and mapping precision (Sarti et al., 2021). These limitations hinder the effective integration of LSWFs into conservation and landscape management practices.

Recent advancements in machine learning, particularly convolutional neural networks (CNNs), offer a promising avenue for improving LULC data granularity. CNNs have demonstrated remarkable success in extracting complex spatial patterns from high-resolution imagery with limited band context, enabling the identification of features as small as individual trees or narrow tree segments. By leveraging multi-spectral data and advanced image segmentation techniques, CNNs can address traditional datasets' scale and classification gaps. Studies integrating higher-resolution satellite products, such as Sentinel-2, have shown potential for enhancing the detection of AF components, providing datasets that are more accurate and ecologically relevant (Trivedi et al., 2024; Bolyn et al., 2019). These methods improve feature delineation and enable spatial analysis of previously overlooked components in mixed-use landscapes, often referenced within precision conservation and land management contexts.

The primary objectives of this research are threefold. First, it seeks to analyze spatial patterns of windbreaks using CNN-derived products to demonstrate the advantages of ML in detecting and characterizing LSWFs. Second, it aims to compare CNN outputs with traditional datasets, such as NLCD, Sentinel LULC products, and Google Earth Engine’s Dynamic World, to evaluate the classification accuracy and resolution improvements. Third, the research highlights the ecological and conservation relevance of high-resolution LULC data by connecting detailed feature mapping to broader ecosystem services, including soil conservation, biodiversity enhancement, and climate regulation. By addressing these objectives, this study contributes to advancing LULC mapping methods and underscores the necessity of incorporating high-resolution datasets into AF planning and management frameworks.

2.2 Study Area and Data Sources

2.2.1 Study Area

The study area extends across 35 counties in Michigan, Wisconsin, and Ohio, selected to represent the diverse land-use patterns characteristic of the Great Lakes region. The total area evaluated directly from imagery for the study is roughly 60,187 km^2, or 23,238 mi^2. This is approximately the size of the US state of West Virginia, the country of Ireland, or, locally, the water surface area of Lake Michigan. The Great Lakes region is an ideal setting for studying different types of identifiable LSWFs due to its unique mixed-use landscape, comprising agricultural fields, forests, residential/developed zones, and riparian corridors with a history of use for agriculture, forestry, and urban development. AF practices, such as windbreaks and riparian buffers, are particularly prominent in this region and some selected counties for analysis, according to results from the 2022 Census of Agriculture, playing essential roles in mitigating environmental challenges like soil erosion and nutrient runoff while supporting biodiversity and providing ecosystem services.

Figure 1: 35 counties used for LSWF analysis across Michigan, Wisconsin, and Ohio. The three counties used for the LCC validation are highlighted here.

This selection of counties includes both contiguous and spatially diverse regions to capture a broad spectrum of land-use transitions. For example, the counties feature a range of dominant agricultural activities, from row-crop production (corn, soybeans, wheat) to forage (alfalfa, hay) and specialty tree crops (e.g., cherries, apples). Additionally, largely urban and urban-fringe counties, such as Hamilton County, OH, Kent County, MI, and Ozaukee County, WI, provide examples of potential AF practices implemented within more developed landscapes, highlighting the versatility of LSWFs in diverse settings. This ensures that findings can be extended to a broader landscape analysis across the Great Lakes states.

Further steps of the analysis extend the findings from the 35 study counties to all three states, where the 35 selected counties account for roughly 11.2% of the area of all three states put together (536,221 km^2, 207,036 mi^2).

2.2.2 Datasets

The analysis leverages a combination of derived, novel, and traditional datasets to comprehensively understand LSWFs and their distribution. The primary dataset is a CNN-derived LULC product with sub-meter resolution (detailed in Chapter 1), providing unprecedented detail in identifying small-scale woody features. Several comparison datasets complement this high-resolution dataset to assess accuracy and applicability across varying spatial resolutions in the discussion:

- **NLCD**: The National Land Cover Database offers baseline LULC classifications but struggles to capture fine-scale features like LSWFs due to its coarse resolution.
- **Sentinel 10m**: Sentinel imagery provides higher resolution and multispectral capabilities but is limited by classification granularity.
- **Dynamic World 10m**: This emerging dataset on Google Earth Engine, powered by machine learning, offers global, near-real-time LULC classification and serves as a benchmark for comparison.

For validation purposes, ground-truthed data consisting of human-verified reference points from imagery were collected within three targeted counties, Clark County, WI, Jackson County, MI, and Wayne County, OH.

The predictive random-forests LSWF analysis used the NLCD Land Cover (LndCov) layer and Fractional Impervious Surface (FctImp) layer, a bicubic-interpolated 30 m upscaled product of the National Renewable Energy Laboratory (NREL) average annual windspeed at 10 m above ground level layer, Cropscape (for specific crop types in categories), and gNATSGO Soil K-factor as a proxy for soil stability. All layers were spatially aligned with the NLCD products.

2.2.3 Features of Interest

The primary features of interest are LSWFs, often associated with windbreaks, riparian buffers, and linear groupings of trees outside forests (ToFs). These LSWFs are critical components of the region's typical windbreak or riparian buffers and are essential in enhancing ecosystem services, such as mitigating wind erosion, stabilizing streambanks, and supporting biodiversity. These features also bolster farm economics; windbreaks protect livestock, crops, and farm structures from wind damage, lowering repair costs and contributing to overall operational stability. Spatial distribution and ecological functions are analyzed using CNN-derived datasets, providing a detailed understanding of their prevalence and significance across diverse landscapes.

This comprehensive dataset allows for a nuanced analysis of LSWFs, highlighting their ecological, economic, and social importance and offering insights into their integration within broader conservation and land management frameworks. Employing both classical and contemporary datasets to provide a comprehensive analysis of the opportunities and challenges associated with mapping critical elements within the Great Lakes region.

2.3 Methods

2.3.1 LSWF Data Analysis

The spatial patterns of LSWFs were analyzed to understand their structure and regional variation across the Great Lakes study area. The CNN-derived sub-meter resolution dataset identified and characterized windbreaks based on their linearity, continuity, and association with land-use types such as row-crop agriculture, forage production, and riparian zones. We also confirmed the natural distributions of LSWF outputs by measuring the net length and width of LSWF features to better assess the quality of outputs and trends in structural characteristics from segmented LSWF outputs. The aggregated and summarized orientation of each county’s LSWF outputs was evaluated along the longest axis of each LSWF polygon, quantifying predominant trends in the isotropic structure of LSWFs. This analysis provided insights into how these features vary across regions, influenced by agricultural practices, topography, and proximity to water bodies. To extend this research, connectivity metrics, such as patch adjacency and corridor linkage, can be computed to assess the ecological functionality of windbreak networks and their potential to support biodiversity and landscape resilience. The results can be further contextualized by comparing them to known land cover transitions within the study area.

2.3.2 Comparative Accuracy Assessment

The performance of the CNN-derived LULC dataset was evaluated against traditional LULC datasets, including NLCD, Sentinel imagery, and the "Dynamic World" 10 m land cover product developed using the Google Earth engine. To assess general accuracy, we created a stratified random sampling set of validation points across all classes in three counties (Jackson County, MI, Wayne County, OH, and Clark County, WI), setting at least 1000 points within each county and stratifying the accuracy validation points to classes, such that we had evaluated accuracy in each derived class sufficiently. We also generate general accuracy estimates for classes and an overall kappa statistic for the CNN product to gauge model accuracy likelihood. Additional visual assessments were conducted to evaluate performance to show LSWFs, ensuring a comprehensive understanding of CNN strengths and limitations compared to the outputs we could achieve using conventional LULC products.

2.3.3 Tree Height Evaluation

The height of windbreak trees was quantified using final windbreak products from the exhaustive dataset and cross-referenced with global 1 m tree height products published by Tolan et al. (2024). This integration enabled the detailed assessment of windbreak functionality, as height traditionally plays a critical role in LSWFs' overall structure, maturity, and perceived effectiveness for reducing wind erosion (for windbreaks) and enhancing microclimates and agricultural protection/productivity. Pixel-level data were aggregated to produce height distributions across the LSWF dataset, which were then referenced with other metrics to identify patterns.

2.3.4 Predictive Modeling

Predictive models were developed using aggregated outputs from the LSWF dataset to extend the findings to non-surveyed regions within the Great Lakes states of interest. Leveraging the diversity of the initial 35-county study area, the RF model extrapolated windbreak presence and distribution per km^2 across broader landscapes, incorporating variables such as land cover type, specific crop types, wind speed, and soil erodibility. Predictions were validated against the values observed from our exhaustive dataset. This approach allowed for identifying regions with potential hotspots or gaps in LSWF coverage, offering actionable insights for conservation planning or opportunities for further extensions of the predictive modeling method.

2.4 Results

2.4.1 Spatial Pattern Insights

Evaluation reveals clear patterns of how linear woody features vary across land covers. The analysis examines geometric properties and directional tendencies to clarify the relationship between these features and their surrounding agricultural and natural landscapes.

2.4.1.1 LSWF Distribution Across Land Cover Contexts

LSWFs in the study region are broadly associated with agricultural landscapes and linear infrastructure, such as roads, highways, and railways. These correlations align with patterns documented in prior studies, where windbreaks and small woody features tend to parallel or border human-made corridors such as roads and railways, parcel or field boundaries, or waterways and riparian areas. Agricultural expanses in southern or central Michigan and Wisconsin and the flatter portions of Ohio exhibit a higher frequency of LSWF occurrences. However, counties dominated by extensive forests display reduced counts of LSWF features.

Figure 6 illustrates these trends by presenting the distribution of LSWF centroid associations with NLCD land cover classes. Cultivated crops and pasture/hay constitute the largest shares, mirroring the prevalence of windbreaks and linear woodlots within active farming areas. As counties transition from predominantly agricultural to forested land cover, the relative frequency of LSWF detections declines, reflecting the reduced need or opportunity for linear woody structures in landscapes already characterized by extensive canopy.

Many LSWFs are “bookended” by large, contiguous woodlots, revealing how linear segments of trees can merge with broader forest tracts. This pattern underscores their role in connecting managed fields with larger blocks of woody vegetation, a structural characteristic aligned with the filtering process outlined in Chapter 1, where contiguous forested areas were excluded during the segmentation of LSWFs.

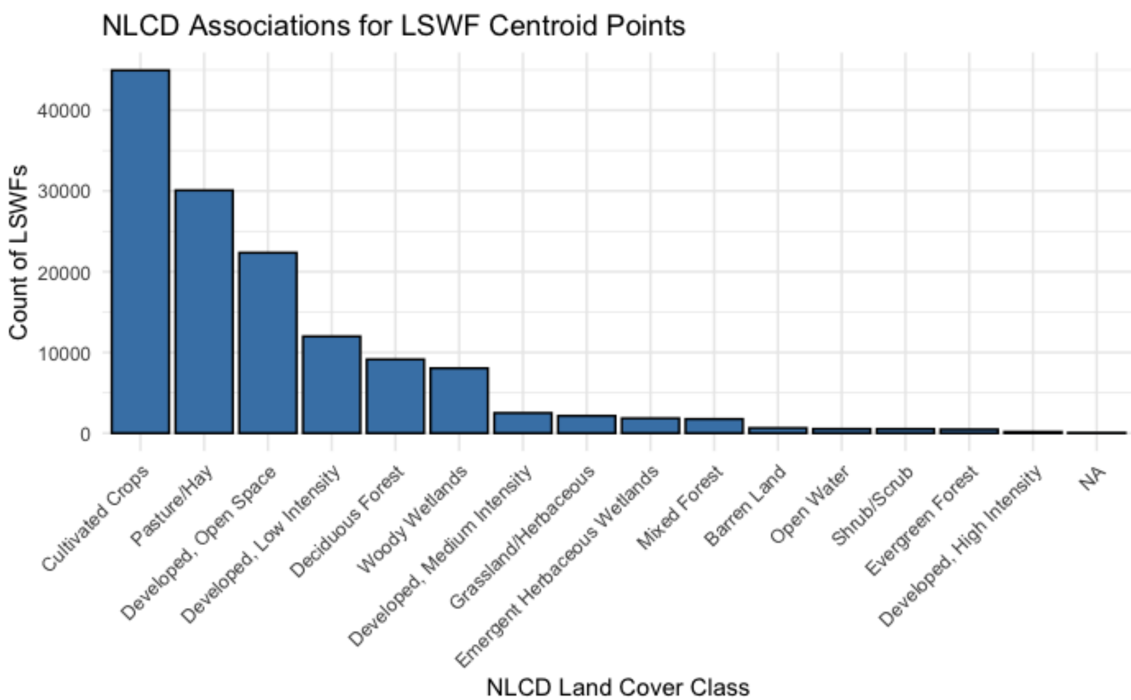

Figure 2: Distribution of LSWF centroid associations according to NLCD land cover classes, emphasizing the high incidence of LSWFs in cultivated crops and pasture/hay, along with smaller frequencies in forested categories. Bars represent the count of LSWF centroids intersecting each NLCD class.

2.4.1.2 Summary Statistics Shape Parameters of LSWFs

The length distribution of LSWFs reveals a strong right-skew (after eliminating 1% of outliers, giving us the n = 134446 LSWFs), with the majority measuring under a few hundred meters and a long tail extending up to approximately 600 m (Figure 1). Notably, eliminating outliers removes a much longer tail of multi-kilometer-long individual LSWFs. However, features of greater length would often be broken up via segmentation in the methods explained in Ch. 1, such that this representation does not necessarily indicate the extent or impact of more extensive LSWF networks. Instead, it often shows the length of individual linear sections of LSWFs in more extensive networks or dispersed, standalone LSWFs which are smaller. Preliminary fits suggest that the data follow a gamma distribution, reflecting the predominance of shorter linear segments in agricultural or semi-urban landscapes. The mean and median lengths are 180.7 and 154.35 m, respectively, highlighting the prevalence of relatively short features that connect or partition fields or run along infrastructure (roads, railroads) and waterways.

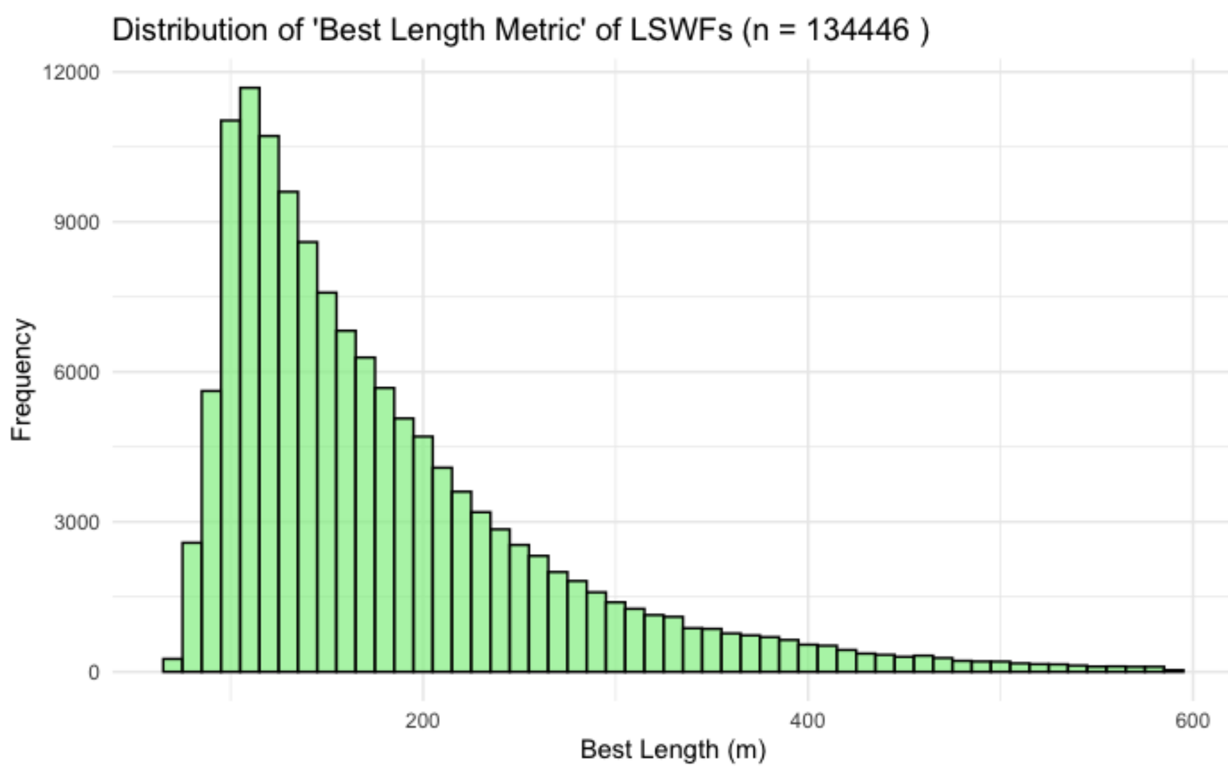

Figure 3: Frequency histogram of the "Best Length Metric" for LSWFs (n = 134,446). The distribution shows a right-skewed gamma pattern, peaking around lower lengths before tapering off near 600 m.

The evaluation of average widths (Figure 4) likewise indicates a gamma-like skew, where most LSWFs maintain a narrow profile under 15 m. The highest frequency of widths centers just over 14 m, coinciding with typical windbreak or small woodlot boundaries observed in the region. These findings suggest that LSWFs are typically narrow corridors, though a subset demonstrates expanded widths linked to broader riparian zones or field buffers.

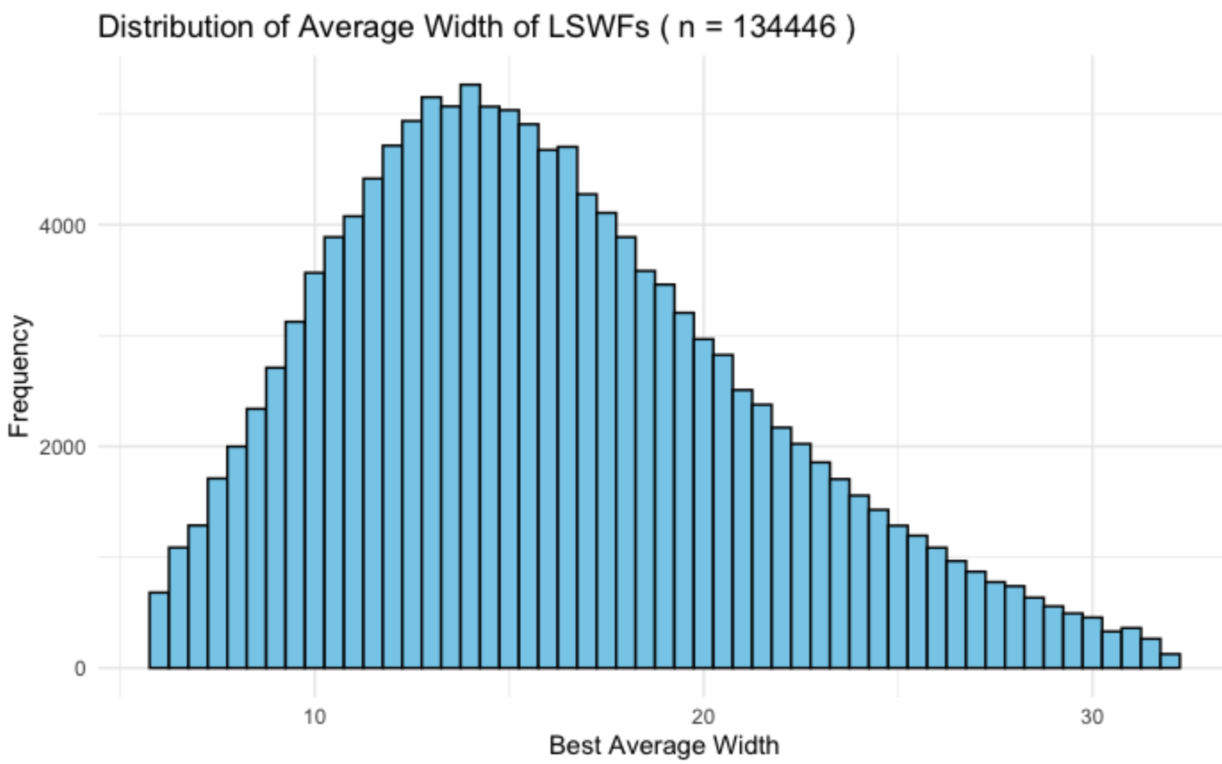

Figure 4: Frequency histogram of average width for LSWFs (n = 134,446). Most widths fall below 15 m, aligning with narrow windbreaks, hedgerows, and other linear woody features.

Figure 5 illustrates the relationship between length and shape area, serving as a control to confirm that longer LSWFs also accumulate greater area. The hexbin plot shows a general upward trend, with clustering in the length and area lower-to-mid range. This pattern likely reflects widespread use of windbreaks and other linear features that do not occupy substantial surface area compared to larger, more contiguous wooded patches.

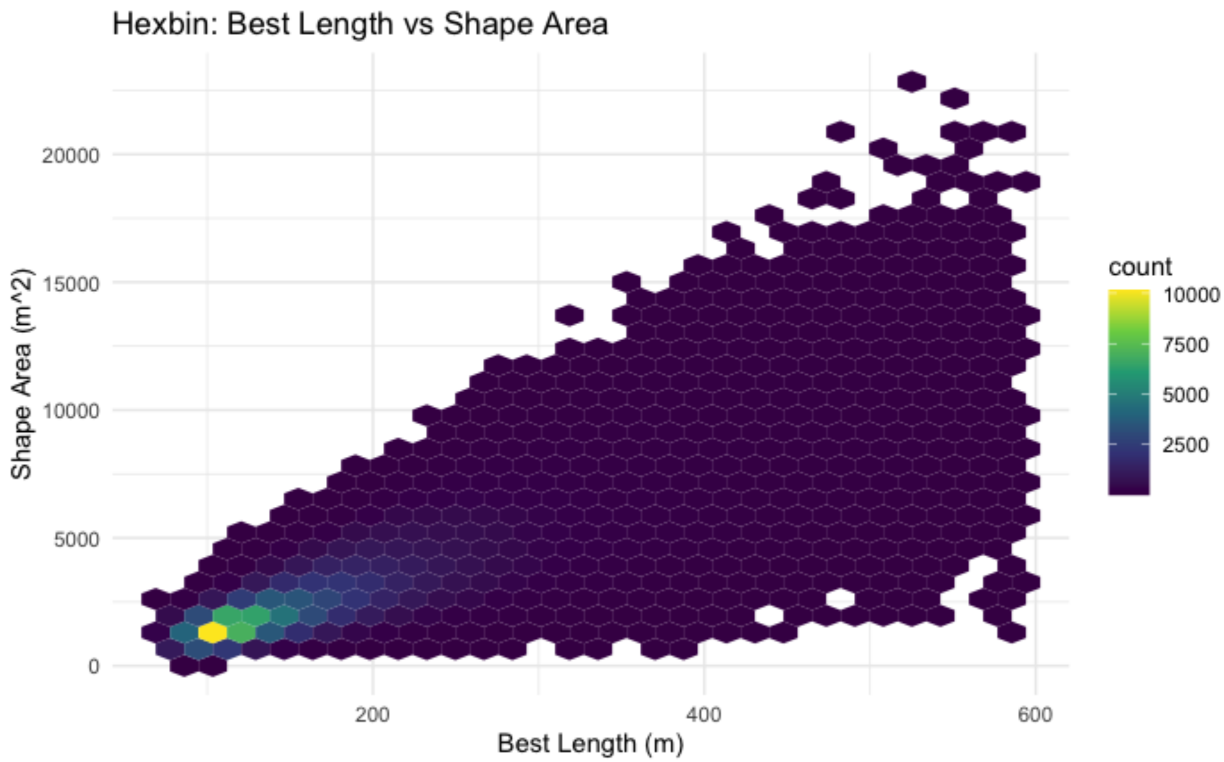

Figure 5: Hexbin plot comparing “Best Length” and shape area of LSWFs. The upper-right quadrant contains fewer but large-area features, while the lower-left quadrant exhibits many compact, shorter LSWFs. This graphic and a comprehensive listing of all shapewise relationships can be found in the appendix.

These shape parameter analyses collectively underscore the structural diversity and, likewise, trends in the shape characteristics of LSWFs across the study area. The gamma distribution profile of both length and width indicates a high concentration of smaller features, punctuated by fewer but considerably larger ones that may act as critical ecological corridors or buffer zones.

2.4.1.3 LSWF Orientations

Most LSWFs in this study strongly tend toward cardinal orientations (Figure 7), especially in flatter counties where field and parcel boundaries often follow a grid-like arrangement. This alignment highlights the anthropogenic influence on their distribution, indicating that tree rows were often planted to delineate property boundaries or to serve as windbreaks parallel to road networks. Some counties align more closely with a cardinal direction perpendicular to prevailing winds, indicating the involvement of some level of an established advisory or financial support framework, such as the Natural Resource Conservation Service (NRCS) or other state and local advisory bodies. The prevalence of cardinal alignments highlights the human dimension of land management choices, as agricultural fields and roads in many areas of Michigan, Ohio, and Wisconsin follow systematic, near-rectilinear patterns.

Counties with more varied topography, such as Athens County in the Appalachian foothills of Ohio, exhibit a lower overall density of LSWFs. However, the features that do appear in these regions often deviate from the cardinal directions, reflecting terrain-driven parcel boundaries or property lines. This divergence reveals that LSWFs adapt to local landscape constraints, as steep slopes and winding valleys necessitate non-rectilinear alignments.

The Appendix provides county-specific rose diagrams illustrating local variations for a more detailed view of orientation patterns. These additional displays demonstrate that while most counties conform to the cardinal-dominant trend, distinctive topographical or historical land survey factors can produce unique directional signatures in LSWF orientation.

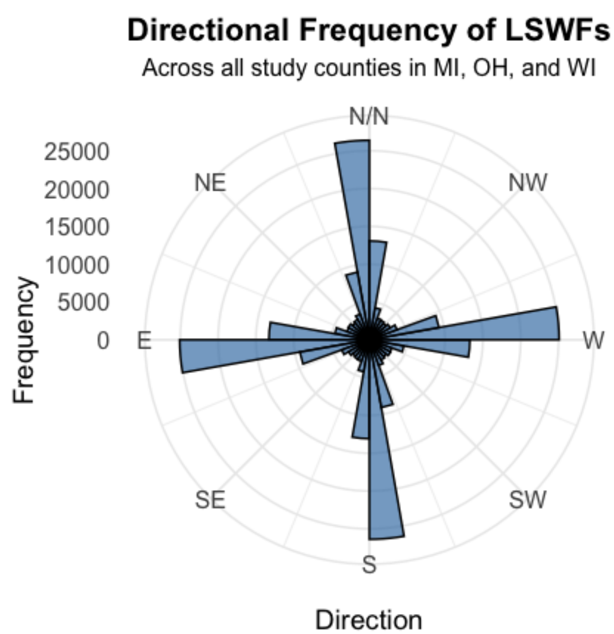

Figure 6: Directional frequency of LSWFs aggregated across all study counties in Michigan, Ohio, and Wisconsin. The radial chart shows a dominant clustering near cardinal directions, suggesting the influence of grid-based parcel boundaries and anthropogenic planting patterns.

2.4.2 CNN Land Cover Product Accuracy

The CNN-derived land cover dataset demonstrates an overall accuracy of 92.17% based on approximately 3,000 validation points distributed across three counties in Michigan, Wisconsin, and Ohio. As shown in Figure 8, the confusion matrix includes an “Ambiguous” category, representing reference points that could not be definitively classified due to marginal distinctions in spectral and textural features (e.g., wetland versus low vegetation). When these ambiguous points are excluded, the model’s accuracy increases to 98.2%, accompanied by a multiclass kappa statistic of k=0.968. This suggests that the CNN model successfully delineates most land cover classes and is rarely confounded by subtle differences at sub-meter scales.

Table 1: Confusion matrix displaying all predicted classes against reference (ground truth), including an “Ambiguous” category. Cells are shaded according to classification/misclassification frequency, illustrating where the CNN products align with our validated points.

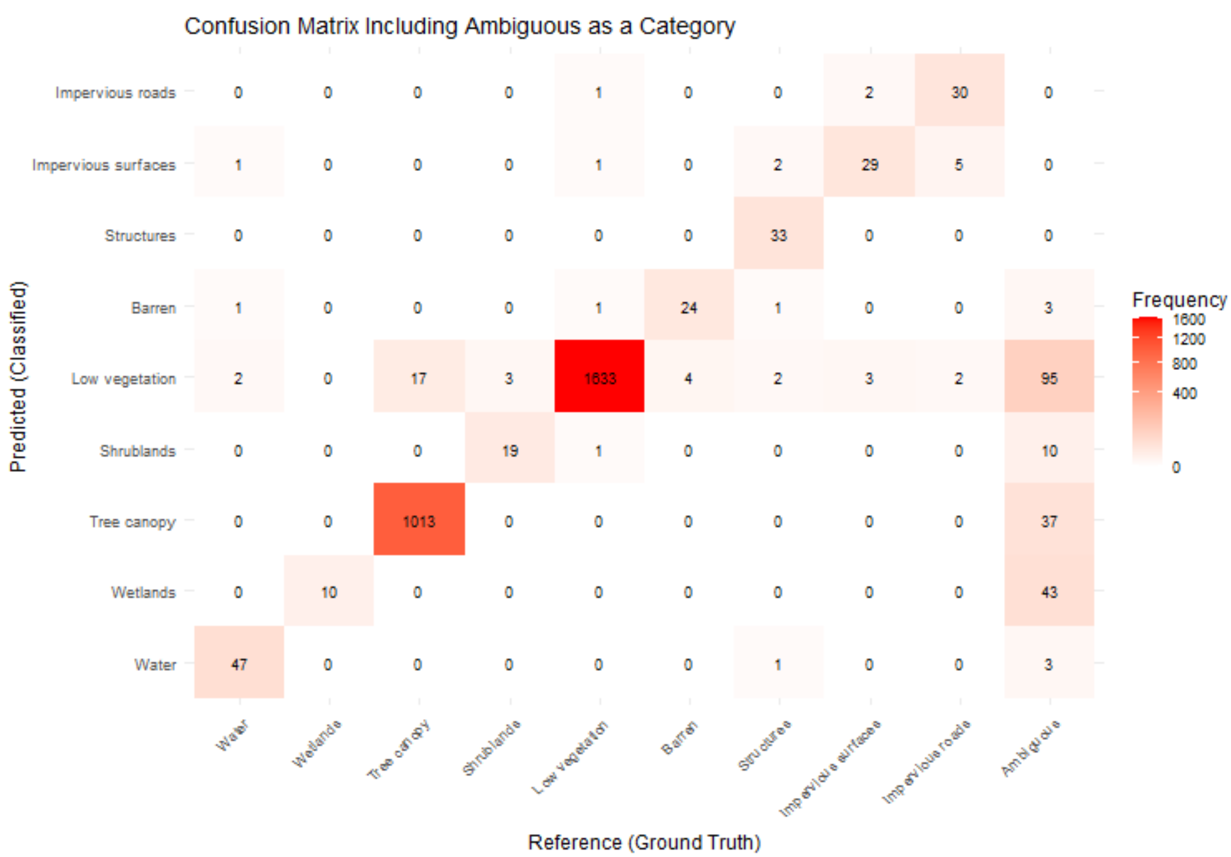

Table 2 presents performance measures by class, illustrating strong producer and user accuracy scores for water, wetlands, and tree canopy. The CNN approach excels at boundary detection, capturing small AF elements and other linear vegetation features that might be overlooked by lower-resolution or purely spectral-based methods. Sub-meter detail also contributes to precise classification in regions of complex land use, such as mixed canopies adjacent to impervious surfaces.

Table 2: Producer and user accuracy for nine main classes, excluding ambiguous assessments. Accuracy scores highlight the CNN's proficiency in distinguishing distinct land cover types, including the tree canopy class used for developing the LSWF outputs.

truth	Correct (n)	Reference (n)	Predicted (n)	Producer Accuracy (%)	User Accuracy (%)
Water	47	51	48	0.921569	0.979167
Wetlands	10	10	10	1	1
Tree canopy	1013	1030	1013	0.983495	1
Shrublands	19	22	20	0.863636	0.95
Low vegetation	1633	1637	1666	0.997557	0.980192
Barren	24	28	27	0.857143	0.888889
Structures	33	39	33	0.846154	1
Impervious surfaces	29	34	38	0.852941	0.763158
Impervious roads	30	37	33	0.810811	0.909091

The qualitative assessment indicates that the CNN effectively identifies canopy edges and small woody segments with minimal need for additional spectral context. While most classes show high accuracy, visual inspection confirms that classes with naturally gradual transitions, like low vegetation merging into shrubland, can produce slightly lower user or producer scores due to overlapping texture or color. Even so, the CNN's ability to detect structural boundaries remains robust, reflecting patterns noted in prior literature on CNN-based classification of AF features (Wolstenholme et al., 2025).

2.4.3 Tree Height Evaluation

Mean tree heights across LSWFs form a right-skewed distribution reminiscent of the gamma patterns observed for length and width (Figure 7). The majority of LSWFs exhibit mean heights in the lower-to-mid range (mean = 5.94 m, median = 5.64 m), with a small proportion extending above 10.15 m (95th percentile of mean canopy height). This skew suggests that while many segments include relatively young or short-statured trees, some locations support mature stands that exceed 11.83 m (99th percentile of mean canopy height) in average height.

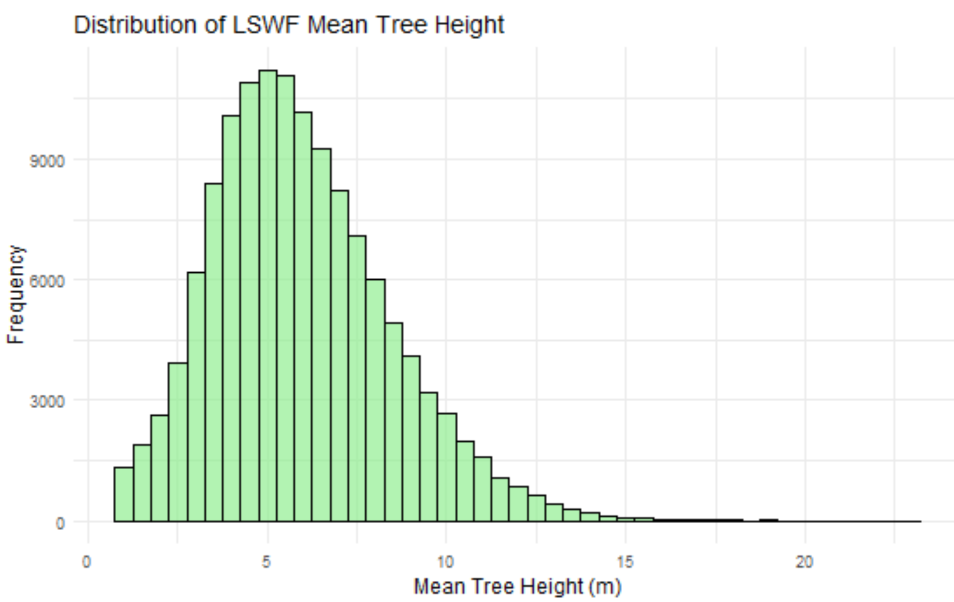

Figure 7: Frequency histogram depicting the distribution of mean tree canopy height across all identified LSWFs. Much like other metrics displayed earlier, the right-skewed pattern resembles a gamma curve, with the bulk of LSWFs exhibiting moderate heights and a smaller subset surpassing an average canopy height of 15 m.

Correlations with other variables, illustrated in the hexbin plots in the Appendix, reveal a moderate positive relationship between mean tree height and LSWF dimensions such as length, area, and width. In particular, the correlation with length (r ≈ 0.109) indicates that longer segments are slightly more likely to have taller trees. A similar pattern emerges for mean width, suggesting that broader windbreaks or riparian buffers may foster more substantial, consistent canopy height.

Further associations relate mean tree height to shape complexity indices, such as the sinuosity or SNFI. Although these correlations are generally weaker ($r \approx 0.362$ with a large cluster shown in Figure 2.8.A3), the data imply that there is a ‘goldilocks’ cluster for the typical height and sinuosity of LSWFs in the region, or in the case of SNFI, a slight negative relationship indicates that more straight and narrow features possess lower overall canopy height, seeming to reach a ceiling/bottleneck as SNFI increases. Such complexity underscores the importance of local environmental and management factors influencing growth patterns.

Subtle differences in the orthographic alignment of the 1 m height dataset occasionally introduce minor discrepancies in tree height estimates. Shadow overlaps and slight terrain-related misalignments can yield minor deviations. Nonetheless, the aggregated results provide a robust depiction of tree height trends within linear woody features, reflecting the overall structure and maturity of LSWFs in the study region.

2.4.4 Predictive Modeling for LSWF Presence

A Random Forest model was used to extrapolate LSWF densities from the 35 original study counties to the broader extents of Michigan, Wisconsin, and Ohio. This approach correlated county-level LSWF metrics (e.g., total length per km^2) with land cover variables, soil characteristics, and climatological proxies, yielding an estimated distribution for unobserved areas. Figure 6 depicts the observed LSWF distances at the county scale, and Figure 7 shows the model’s predictions for the tri-state region, illustrating how local densities relate to broader spatial trends.

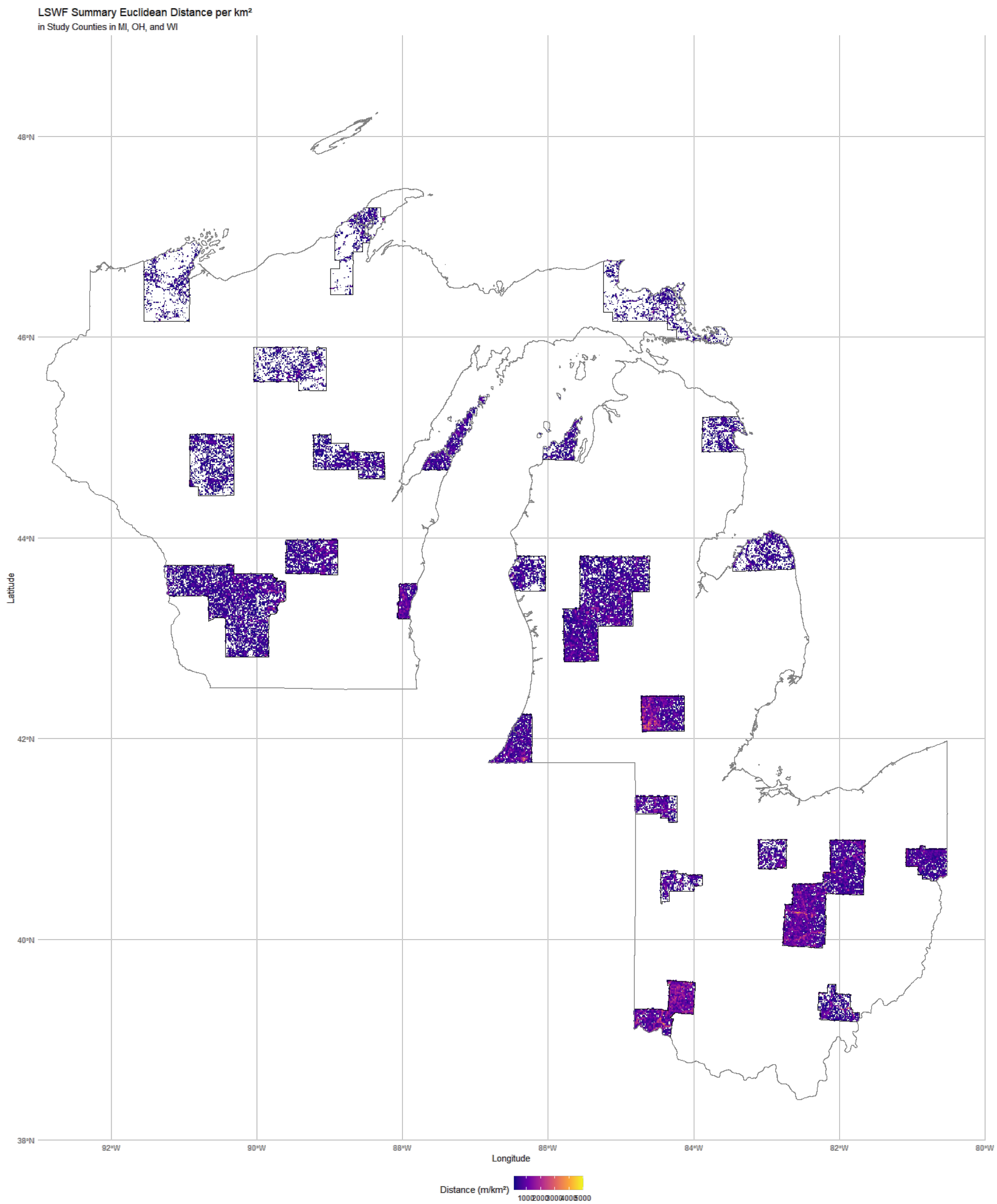

Figure 8: Observed Linear Small Woody Feature (LSWF) distances per km² in the 35 study counties, highlighting higher densities in agriculturally intensive regions. Colors indicate the estimated length of LSWFs (in meters) per km².

Results confirm a strong relationship between agricultural areas and higher densities of LSWFs, mirroring patterns identified in the original counties. Regions dominated by row-crop production consistently exhibit more windbreaks or woody buffers, suggesting that fields bounded by roads or property edges have sustained corridors of perennial vegetation. An extension of this observation would examine the presence of in-field LSWFs in relation to edge-of-field LSWFs, where in-field LSWFs are more likely to provide additional enhanced crop protection. This could reflect a landowner's interest in the exposure-reducing production benefits of introducing woody barriers in an agricultural landscape. In contrast, sparsely cultivated landscapes, especially those with limited infrastructure or smaller fields, register fewer predicted LSWFs.

Impervious surfaces emerged as another influential predictor, likely capturing the presence of roads that commonly support linear tree plantings. Model outputs initially indicated high LSWF densities near urban roads, though these areas were later masked to avoid conflating urban tree lines with features typically classified as agriculturally relevant LSWFs like windbreaks or riparian buffers. Despite the masking, the predictive maps reinforce the idea that road networks and agricultural parcels collectively drive a significant portion of LSWF variability across the region.

Northern portions of Michigan and Wisconsin reflect a lower predicted density of LSWFs, aligning with their predominantly forested landscapes. Extensive continuous canopy coverage in mostly forested areas reduces the need or possibility for discrete windbreaks or narrow riparian strips. The model's tendency to estimate minimal LSWF presence in such forests underscores the importance of distinguishing small, linear woody elements from large continuous tree cover in future regional analyses.

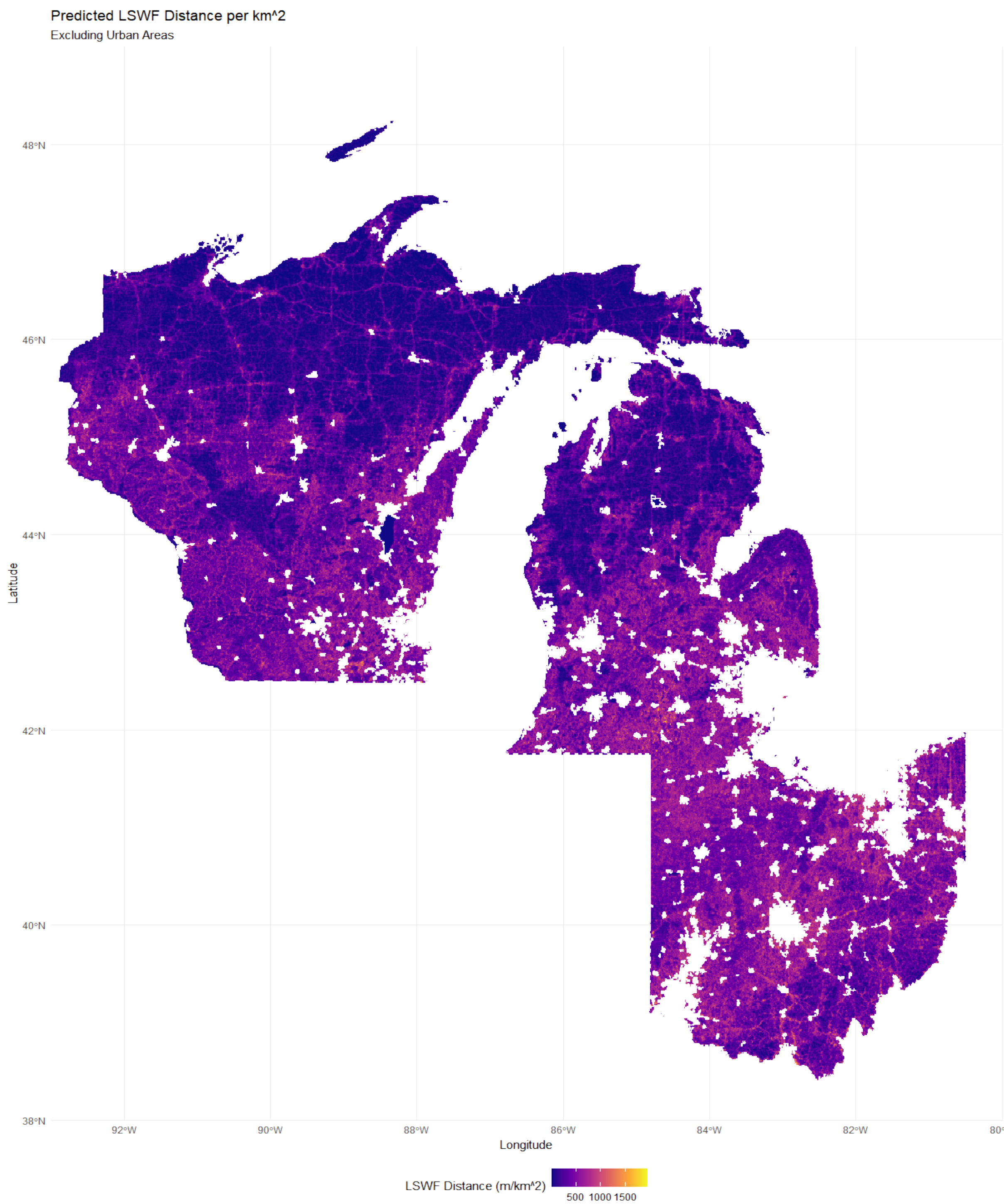

Figure 9: Random Forest predictions of LSWF distance across Michigan, Wisconsin, and Ohio, excluding densely urbanized areas. Colors indicate the estimated aggregate length of LSWFs (in meters) per km², revealing spatial variability associated with road networks and agricultural land use.

2.5 Discussion

2.5.1 Strengths of CNN-Based LULC Products

The CNN-derived dataset displayed a pronounced advantage in detecting and classifying small-scale LSWFs, outperforming coarser-resolution products like NLCD or Sentinel 10m in identifying linear elements. This outcome aligns with previous studies indicating that CNNs require fewer spectral bands than traditional classifiers, thanks to their capacity for detailed texture analysis. Sub-meter imagery further enhances these capabilities by capturing subtle boundary details and minimizing errors introduced by pixel aggregation.

Another key strength is the reduced need for extensive contextual or ancillary data. High-resolution inputs and specialized CNN architectures, including operations such as max-pooling, bolster edge detection in fragmented, heterogeneous landscapes where smaller tree canopies or narrow buffers might otherwise be overlooked. These features are especially vital for precision conservation or more extensive strategic land management planning, where fine-scale mapping of AF components can support targeted interventions and management strategies.

Although the current model demonstrates broad applicability in the Great Lakes region and possibly a wider area, additional training data would likely improve performance in regions with distinct land cover and ecological profiles. Because the initial network was trained in the Chesapeake Bay area, transferring it to the Great Lakes region necessitated calibration for various agricultural systems and forest types. Acknowledging that, it is remarkable how adaptable the Chesapeake Bay data was to the Great Lakes region without much additional calibration. As more comprehensive training datasets become available, CNN-based models can be refined to address emerging challenges in multi-regional land use planning and agroforestry research.

2.5.2 Comparative Insights

The CNN products offer substantially higher spatial detail than Sentinel 10 m LULC products (Figure 10), capturing features such as hedgerows or narrow tree lines that conventional datasets frequently overlook. Furthermore, the Sentinel 10 m dataset claims an overall accuracy of 75%, which we greatly improve upon in our validation efforts (Venter et al., 2022). Similar assessments were made on NLCD products (which typically achieve an overall accuracy of around 83% (Wang and Mountrakis, 2023), despite their 30 m resolution (roughly one-third that shown in Figure 10), and in alternative LULC models at "high" resolution at 10 m such as the Dynamic World 10 m LULC (which has a claimed accuracy of about 72% (Venter et al., 2022)). This enhanced resolution is especially valuable in agricultural zones with many linear woody elements. Sentinel-based products often classify small or fragmented woody features as part of broader vegetation classes. By contrast, sub-meter CNN outputs enable the precise delineation of these features, improving estimates of their structural attributes and economic and ecological roles.

Figure 10: Side-by-side comparison of 50% transparent Sentinel 10 m LULC overlaid on imagery (left) and CNN-derived land cover (right) in Jackson County, MI, with abundant LSWFs. The CNN classification captures the intricate linear woody strips in far greater detail,

demonstrating the limitations of coarser-resolution products in identifying fragmented or narrow features.

However, no nationwide, authoritative LULC product currently exists at sub-meter resolution, highlighting a key gap in geospatial resources. While Vermont's 0.5 m LULC and the Chesapeake Bay Conservancy's regional product demonstrate the viability of high-resolution techniques, expanding these efforts beyond local or regional coverage poses significant challenges. The computational power required to process such large imagery volumes and the hosting infrastructure needed for public access underscores the infrastructural hurdles in scaling to a national dataset.

Compared with Random Forest methods, CNN-driven classification shows incremental benefits in handling linear, fragmented features. Neural architectures, designed for detailed pattern recognition, capitalize on sub-meter pixel sizes to capture finer edges and boundaries with fewer auxiliary inputs. This advantage stands out where small woody features cross multiple land-use types or blend with background vegetation, leading to misclassifications in lower-resolution or purely spectral-driven approaches.

Analyzing LSWFs at resolutions as fine as 0.6 m or even 0.3 m enables more nuanced width, connectivity, and canopy structure measurements than prior literature has attempted. Such granularity facilitates ecosystem service evaluations—like carbon sequestration or wind mitigation—and reveals the ubiquity of small woody strips in agricultural settings. These findings are congruent with European assessments, which have noted the overlooked significance of linear woody features for local ecology, carbon markets, and small-scale timber or fiber production (Rubio-Delgado et al., 2024).

2.5.3 New Knowledge Gained

Analyses of minor woody feature structures have enhanced understanding of LSWFs' shape indices, connectivity, and density, enabling their measurement with consistent criteria across different land-use contexts. Foremost, this work, combined with the methods used in chapter 1, indicates that there is a near-ubiquity of LSWFs in midwestern landscapes, not only on farms or in agricultural operations as most studies previously seek out, but rather in varying land uses and topography throughout the Midwestern landscape. This suggests working towards a census of these features on a more thorough, full analysis. The granular approach uncovered in the last two chapters explores how subtle variations in width, length, or adjacency can affect ecological functionality, including potential habitat linkages or field-level environmental benefits. This research contributes to a standardized and adaptable framework for comparing LSWFs across varied agricultural and forestry systems by defining uniform parameters for these features. Beyond structure, the project has improved the detection of LSWFs and clarified their spatial characteristics within the study counties. Enhanced classification at sub-meter resolution reveals how these linear features often form corridors between larger forest patches or align with cropping or parcel boundaries. Documenting these patterns underscores the economic, ecological, and practical significance of retaining or promoting woody strips for wind mitigation, soil stability, and localized biodiversity support.

Predictive modeling extends these insights beyond the sampled counties, offering suggestions for where LSWFs may occur in landscapes lacking examination. Incorporating land cover, hydrological, and anthropogenic variables has yielded maps that highlight both current and potential LSWF distributions. These data support targeted recommendations on landscape design, especially in regions seeking to integrate agroforestry more thoroughly for sustainable management purposes.

In addition, the study provides new quantification and summary assessments of woody features traditionally underrepresented in agricultural literature. By identifying and mapping LSWFs at scale, this research pinpoints their frequency, extent, and spatial variations, equipping policymakers and landowners with evidence-based metrics to guide production and conservation efforts. Observing how these elements interact with crop fields, water bodies, or impervious surfaces confirms that even small clusters of trees can exert measurable environmental and agronomic impacts.

Finally, the inclusion of canopy height measurements from LiDAR and aerial sources can enrich the functional narrative of LSWFs. Evaluating tree height distributions highlights how certain regions or land uses foster more mature stands, while others maintain primarily younger vegetation. These patterns can illuminate management opportunities for carbon sequestration, potential timber production, and further agroforestry applications, reinforcing the central importance of LSWFs in both local and broader-scale landscape planning.

2.5.4 Applications in Conservation

High-resolution LULC data can support precision conservation by revealing subtle vegetation patterns that help locate potential sources of pollution or areas requiring targeted mitigation. For instance, finely resolved tree canopy maps and segmented buffer zones may detect localized runoff pathways or compromised streambank stretches. Identifying these areas enables more precise management actions, whether through riparian enhancements, sediment control structures, or pinpoint drainage modifications that protect downstream habitats.

Beyond pinpointing threats, the predictive model results offer a regional overview of where LSWFs are most prevalent and where gaps in coverage persist. These “hotspots” and gaps guide stakeholders in deciding where interventions may yield the greatest ecological benefits or agricultural protection. Improving connectivity in sparse regions, for example, can create continuous habitat corridors or reduce soil erosion in vulnerable areas with minimal forest cover. Furthermore, stakeholders can engage in more accurate assessments of woody biomass outside of previously available coarser datasets. This is because the added resolution enables more thorough analysis and precise landscape quantification, such as carbon sink potential, wildlife corridor analysis, or hydrological flow, in landscapes where inexact estimates have been made previously using very coarse data that may not capture LSWFs.

This level of detail also supports integrated landscape planning and advisory services. Extension agents, landowners, and conservation agencies can use these insights to expand windbreaks or riparian buffers that will likely benefit landscape and individual operational resiliencies. By combining fine-scale vegetation maps with local land-use data, decision-makers can align plantings with existing agricultural practices or identified climate adaptation priorities, ensuring that woody features serve multiple production and ecosystem service objectives. Assessments of LSWF distributions and canopy conditions inform watershed management by highlighting how dense or fragmented woody strips influence hydrology, water quality, and biodiversity. Woody corridors along streambanks can reduce nutrient runoff and bolster aquatic habitat diversity. By quantifying these features across broad extents, conservation practitioners can identify watersheds with deficient buffers or suboptimal habitat networks, then tailor restoration efforts to address local constraints.

Integrating LULC data with parcel ownership, landowner survey results, and land management databases can further refine these strategies. Linking high-resolution canopy maps to individual parcels allows targeted outreach for potential windbreak expansions, while cross-referencing with existing conservation easements can spotlight synergies between farmland preservation and agroforestry adoption. This fusion of datasets enables data-driven collaborations among local governments, land trusts, and producers, fostering broad-scale improvements in land stewardship.

2.6 Conclusion

CNN-based methods have demonstrated a distinct advantage in identifying agroforestry features, particularly LSWFs, within fragmented or mixed-use landscapes. The approach unveils patterns in LSWF ubiquity and ecological interactions that would go unseen in coarser datasets by leveraging high-resolution imagery to detect subtle boundaries and finely scaled structures. These findings confirm the efficacy of CNN products for characterizing spatially complex land cover types, reinforcing their value for regions that require precise delineation or censusing of windbreaks, riparian buffers, and other small woody features. High-resolution LULC data is a powerful tool for guiding agroforestry management and landowner decision-making. By pinpointing the presence and nature of LSWFs, these datasets facilitate strategic interventions to bolster soil conservation, biodiversity, and on-farm resilience. Such granular mapping further supports land planning efforts, as local governments, conservation agencies, and producers can target specific parcels or watersheds where increasing woody cover or improving buffer quality may yield stacked production and ecosystem service benefits.

Future efforts can expand and enhance this framework by incorporating LiDAR or hyperspectral imagery to refine structural and compositional assessments of LSWFs, capturing nuances like understory density or species composition. Extending these analyses to additional regions or a complete statewide coverage would fill critical data gaps, enabling the development of robust, region-specific agroforestry assessments. Such expansions promise a richer understanding of how high-resolution LULC data can inform policy and practice, helping to integrate agroforestry more fully into landscape-scale management.

REFERENCES

Aksoy, Selim, et al. "Automatic Mapping of Linear Woody Vegetation Features in Agricultural Landscapes Using Very High Resolution Imagery." *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 1, Jan. 2010, pp. 511–22. *IEEE Xplore*, https://doi.org/10.1109/TGRS.2009.2027702.

Bolyn, Corentin, et al. "Automated Classification of Trees Outside Forest for Supporting Operational Management in Rural Landscapes." *Remote Sensing*, vol. 11, no. 10, 10, Jan. 2019, p. 1146. *www.mdpi.com*, https://doi.org/10.3390/rs11101146.

Claggett, Peter, et al. *Chesapeake Bay Program's One-Meter Resolution Land Use/Land Cover Data: Overview and Production*. Sept. 2022.

Deng, Rongxin, Qunzuo Guo, et al. "Extraction of Farmland Shelterbelts from Remote Sensing Imagery Based on a Belt-Oriented Method." *Frontiers in Forests and Global Change*, vol. 6, Sept. 2023. *Frontiers*, https://doi.org/10.3389/ffgc.2023.1247032.

Deng, Rongxin, Zhengran Xu, et al. "Farmland Shelterbelt Age Mapping Using Landsat Time Series Images." *Remote Sensing*, vol. 14, no. 6, 6, Jan. 2022, p. 1457. *www.mdpi.com*, https://doi.org/10.3390/rs14061457.

Ellis, Edward A., et al. "Development of a Web-Based Application for Agroforestry Planning and Tree Selection." *Computers and Electronics in Agriculture*, vol. 49, no. 1, Oct. 2005, pp. 129–41. *ScienceDirect*, https://doi.org/10.1016/j.compag.2005.02.008.

Englund, Oskar, et al. *Beneficial Land-Use Change in Europe: Deployment Scenarios for Multifunctional Riparian Buffers and Windbreaks*. 2020. *ResearchGate*, https://doi.org/10.21203/rs.3.rs-128604/v1.

Fortier, Julien, et al. "Potential for Hybrid Poplar Riparian Buffers to Provide Ecosystem Services in Three Watersheds with Contrasting Agricultural Land Use." *Forests*, vol. 7, no. 2, 2, Feb. 2016, p. 37. *www.mdpi.com*, https://doi.org/10.3390/f7020037.

García de Jalón, Silvestre, et al. "How Is Agroforestry Perceived in Europe? An Assessment of Positive and Negative Aspects by Stakeholders." *Agroforestry Systems*, vol. 92, no. 4, Aug. 2018, pp. 829–48. *Springer Link*, https://doi.org/10.1007/s10457-017-0116-3.

Jose, Shibu. "Agroforestry for Ecosystem Services and Environmental Benefits: An Overview." *Agroforestry Systems*, vol. 76, no. 1, May 2009, pp. 1–10. *Springer Link*, https://doi.org/10.1007/s10457-009-9229-7.

Liknes, Greg C., et al. "Shape Indexes for Semi-Automated Detection of Windbreaks in Thematic Tree Cover Maps from the Central United States." *International Journal of Applied Earth Observation and Geoinformation*, vol. 59, July 2017, pp. 167–74. *ScienceDirect*, https://doi.org/10.1016/j.jag.2017.03.005.

Lovell, Sarah T., et al. “Agroforestry at the Landscape Level.” *ASA, CSSA, and SSSA Books*, edited by Harold E. “Gene” Garrett et al., 1st ed., Wiley, 2021, pp. 417–35. *DOI.org (Crossref)*, https://doi.org/10.1002/9780891183785.ch14.

Malkoç, Eylül, et al. “Countrywide Mapping of Trees Outside Forests Based on Remote Sensing Data in Switzerland.” *International Journal of Applied Earth Observation and Geoinformation*, vol. 100, Aug. 2021, p. 102336. *ScienceDirect*, https://doi.org/10.1016/j.jag.2021.102336.

Meneguzzo, Dacia M., et al. “Mapping Trees Outside Forests Using High-Resolution Aerial Imagery: A Comparison of Pixel- and Object-Based Classification Approaches.” *Environmental Monitoring and Assessment*, vol. 185, no. 8, Aug. 2013, pp. 6261–75. *Springer Link*, https://doi.org/10.1007/s10661-012-3022-1.

Nowak, Maciej Marcin, and Katarzyna Pędziwiatr. “Modeling Potential Tree Belt Functions in Rural Landscapes Using a New GIS Tool.” *Journal of Environmental Management*, vol. 217, July 2018, pp. 315–26. *ScienceDirect*, https://doi.org/10.1016/j.jenvman.2018.03.118.

Oelschlager, Patrick T. *AGBUFFERBUILDER FOR DECISION SUPPORT IN THE COLLABORATIVE DESIGN OF VARIABLE-WIDTH CONSERVATION BUFFERS IN THE SAGINAW BAY WATERSHED*. Aug. 2023.

Patriarca, Alessio, et al. “Wide-Scale Identification of Small Woody Features of Landscape from Remote Sensing.” *Land*, vol. 13, no. 8, 8, Aug. 2024, p. 1128. *www.mdpi.com*, https://doi.org/10.3390/land13081128.

Pillay, Manisha, and Christian M. Rogerson. “Agriculture-Tourism Linkages and pro-Poor Impacts: The Accommodation Sector of Urban Coastal KwaZulu-Natal, South Africa.” *Applied Geography*, vol. 36, Jan. 2013, pp. 49–58. *ScienceDirect*, https://doi.org/10.1016/j.apgeog.2012.06.005.

Plieninger, Tobias. “Monitoring Directions and Rates of Change in Trees Outside Forests through Multitemporal Analysis of Map Sequences.” *Applied Geography*, vol. 32, no. 2, Mar. 2012, pp. 566–76. *ScienceDirect*, https://doi.org/10.1016/j.apgeog.2011.06.015.

Rubio-Delgado, Judit, et al. “Small Woody Features in Agricultural Areas: Agroforestry Systems of Overlooked Significance in Europe.” *Agricultural Systems*, vol. 218, June 2024, p. 103973. *ScienceDirect*, https://doi.org/10.1016/j.agsy.2024.103973.

Sarti, Maurizio, et al. “Trees Outside Forest in Italian Agroforestry Landscapes: Detection and Mapping Using Sentinel-2 Imagery.” *European Journal of Remote Sensing*, vol. 54, no. 1, Jan. 2021, pp. 610–24. *Taylor and Francis+NEJM*, https://doi.org/10.1080/22797254.2021.1986678.

Scholefield, P., et al. “A Model of the Extent and Distribution of Woody Linear Features in Rural Great Britain.” *Ecology and Evolution*, vol. 6, no. 24, Dec. 2016, pp. 8893–902. *EBSCOhost*, https://doi.org/10.1002/ece3.2607.

Sharma, Prashant, et al. “Geospatial Technology in Agroforestry: Status, Prospects, and Constraints.” *Environmental Science and Pollution Research*, vol. 30, no. 55, Nov. 2023, pp. 116459–87. *Springer Link*, https://doi.org/10.1007/s11356-022-20305-y.

Smith, Matthew M., et al. “Agroforestry Extent in the United States: A Review of National Datasets and Inventory Efforts.” *Agriculture*, vol. 12, no. 5, 5, May 2022, p. 726. *www.mdpi.com*, https://doi.org/10.3390/agriculture12050726.

Tolan, Jamie, et al. “Very High Resolution Canopy Height Maps from RGB Imagery Using Self-Supervised Vision Transformer and Convolutional Decoder Trained on Aerial Lidar.” *Remote Sensing of Environment*, vol. 300, Jan. 2024, p. 113888. *ScienceDirect*, https://doi.org/10.1016/j.rse.2023.113888.

Trivedi, Shivam, et al. “Geospatial Assessment of Agroforestry Land Use Systems Using Very High-Resolution Satellite Images and Artificial Intelligence.” *Agroforestry Systems*, vol. 98, no. 8, Dec. 2024, pp. 2875–95. *Springer Link*, https://doi.org/10.1007/s10457-024-01042-2.

van Ramshorst, Justus G. V., et al. “Reducing Wind Erosion through Agroforestry: A Case Study Using Large Eddy Simulations.” *Sustainability*, vol. 14, no. 20, 20, Jan. 2022, p. 13372. *www.mdpi.com*, https://doi.org/10.3390/su142013372.

Venter, Zander S., et al. “Global 10 m Land Use Land Cover Datasets: A Comparison of Dynamic World, World Cover and Esri Land Cover.” *Remote Sensing*, vol. 14, no. 16, 16, Jan. 2022, p. 4101. *www.mdpi.com*, https://doi.org/10.3390/rs14164101.

Wang, Zhixin, and Giorgos Mountrakis. “Accuracy Assessment of Eleven Medium Resolution Global and Regional Land Cover Land Use Products: A Case Study over the Conterminous United States.” *Remote Sensing*, vol. 15, no. 12, June 2023, p. 3186. *DOI.org (Crossref)*, https://doi.org/10.3390/rs15123186.

Weninger, T., et al. “Ecosystem Services of Tree Windbreaks in Rural Landscapes—a Systematic Review.” *Environmental Research Letters*, vol. 16, no. 10, Sept. 2021, p. 103002. *Institute of Physics*, https://doi.org/10.1088/1748-9326/ac1d0d.

Wolstenholme, J. M., et al. “Automated Identification of Hedgerows and Hedgerow Gaps Using Deep Learning.” *Remote Sensing in Ecology and Conservation*, vol. n/a, no. n/a. *Wiley Online Library*, https://doi.org/10.1002/rse2.432. Accessed 31 Mar. 2025.

APPENDIX

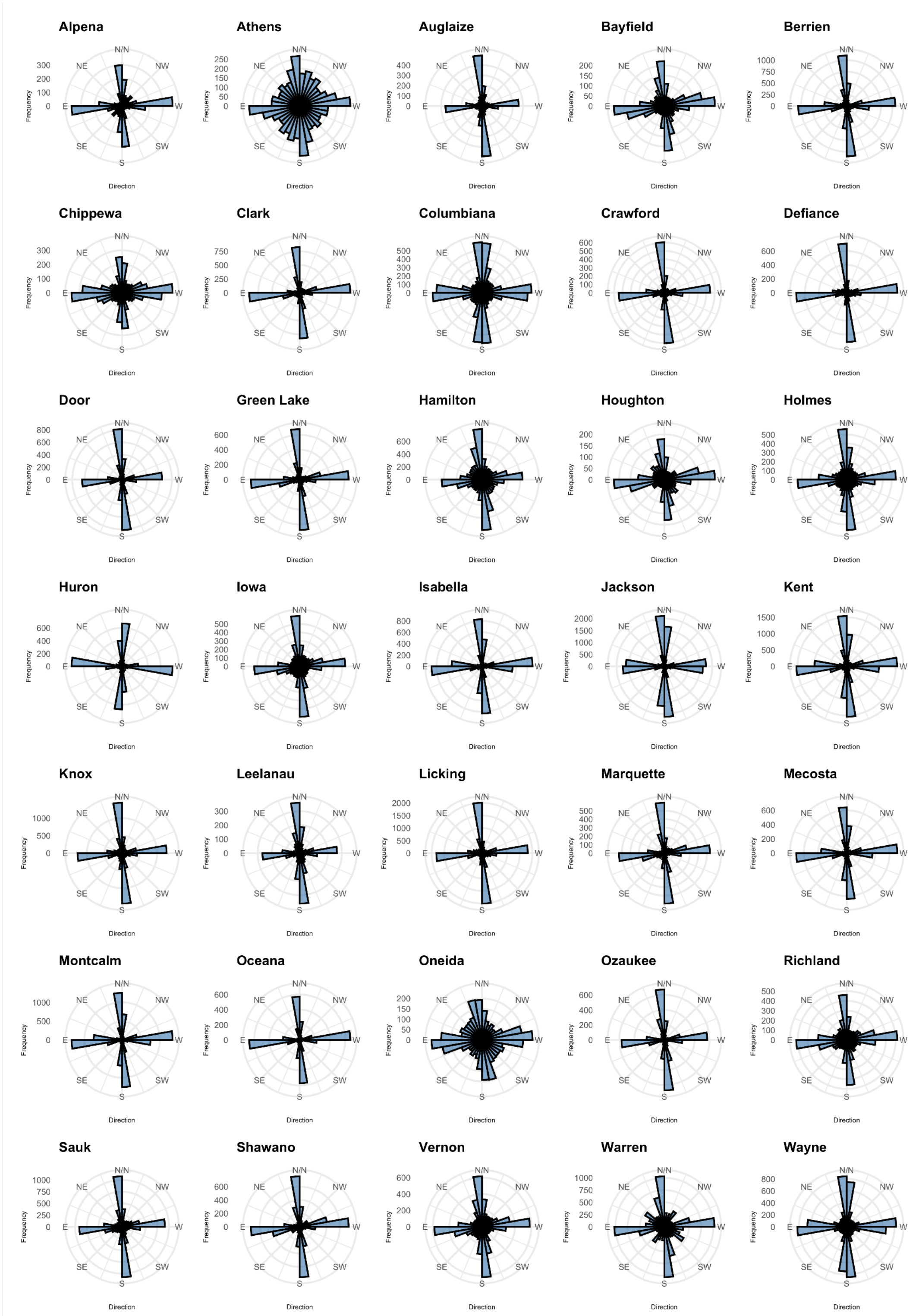

Figure 2.8.A1: Rose diagrams of LSWFs as observed across each of the 35 counties in the study region. Note that some counties have very direct and strict relationships between the

Figure 2.8.A1 (cont'd):

…orientation of LSWFs and a cardinal platting grid. Other counties have a conflicting topography or a predominantly wooded setting that prevents the uniform platting that leads to those trends in agrarian LSWF orientation, namely counties like Athens, OH, or Oneida, WI. Other counties have a lengthwise spatial orientation pattern leading to a predominant direction. Door County, WI, primarily runs north to south, and linear woody features follow that geography. Some counties are very square in dimension yet show favorability to either a north-south or an east-west orientation. Two primarily agricultural counties in Ohio have more prevalent north-south orientations, Crawford County and Licking County, OH. Other counties have predominant east-to-west orientations, such as Mecosta County, MI, or Clark County, WI.

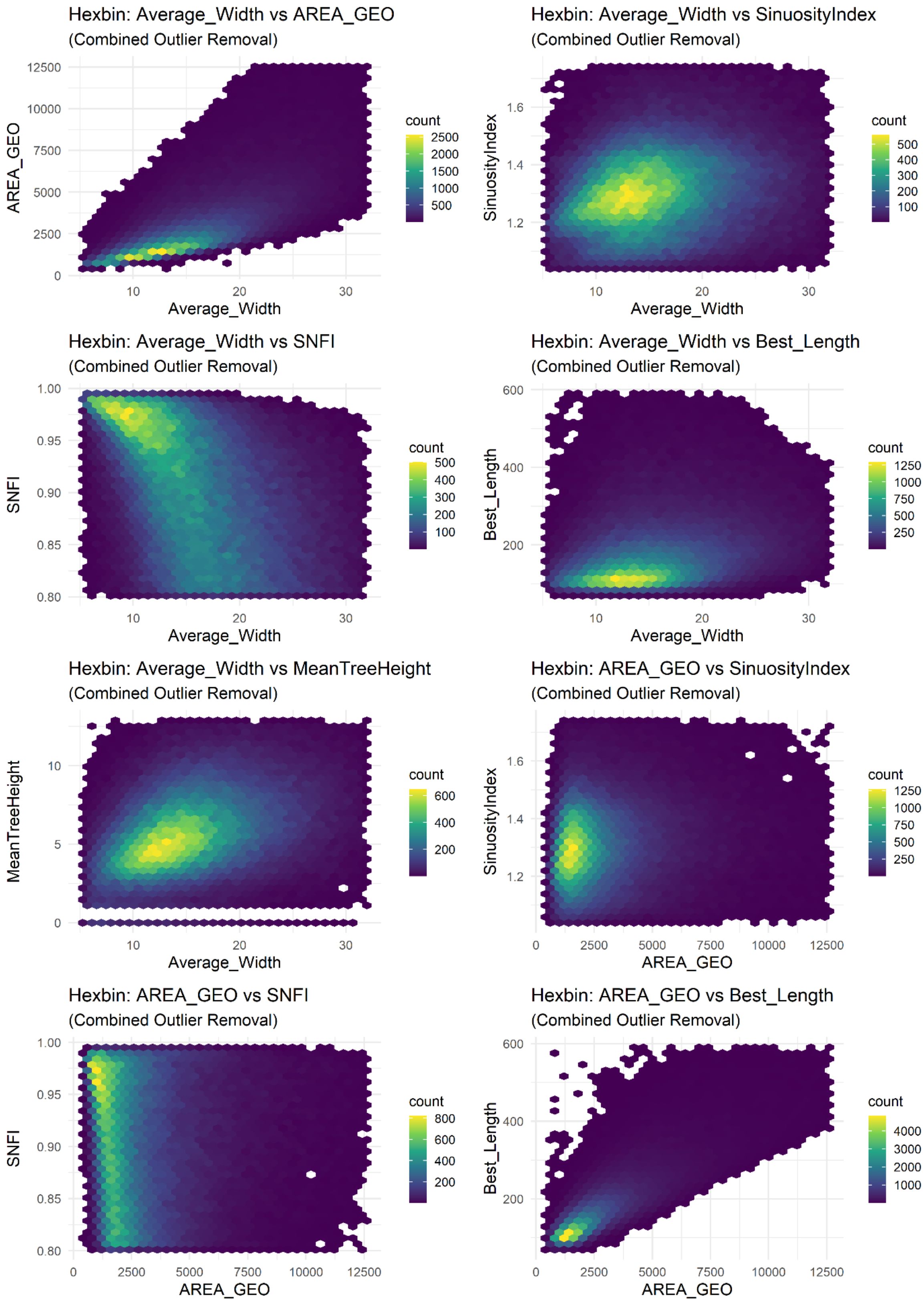

Figure 2.8.A2: Different correlative relationships between shape parameters in the final LSWF

Figure 2.8.A2 (cont'd):
…dataset, including tree height. These visualizations were made using n = 120967 LSWFs after removing 1% of outliers for all of the evaluated fields for all surveyed counties, which is displayed as the "Combined Outlier Removal." *Note*: All non-index units are in meters, AREA_GEO refers to the area of individual LSWFs in m^2.

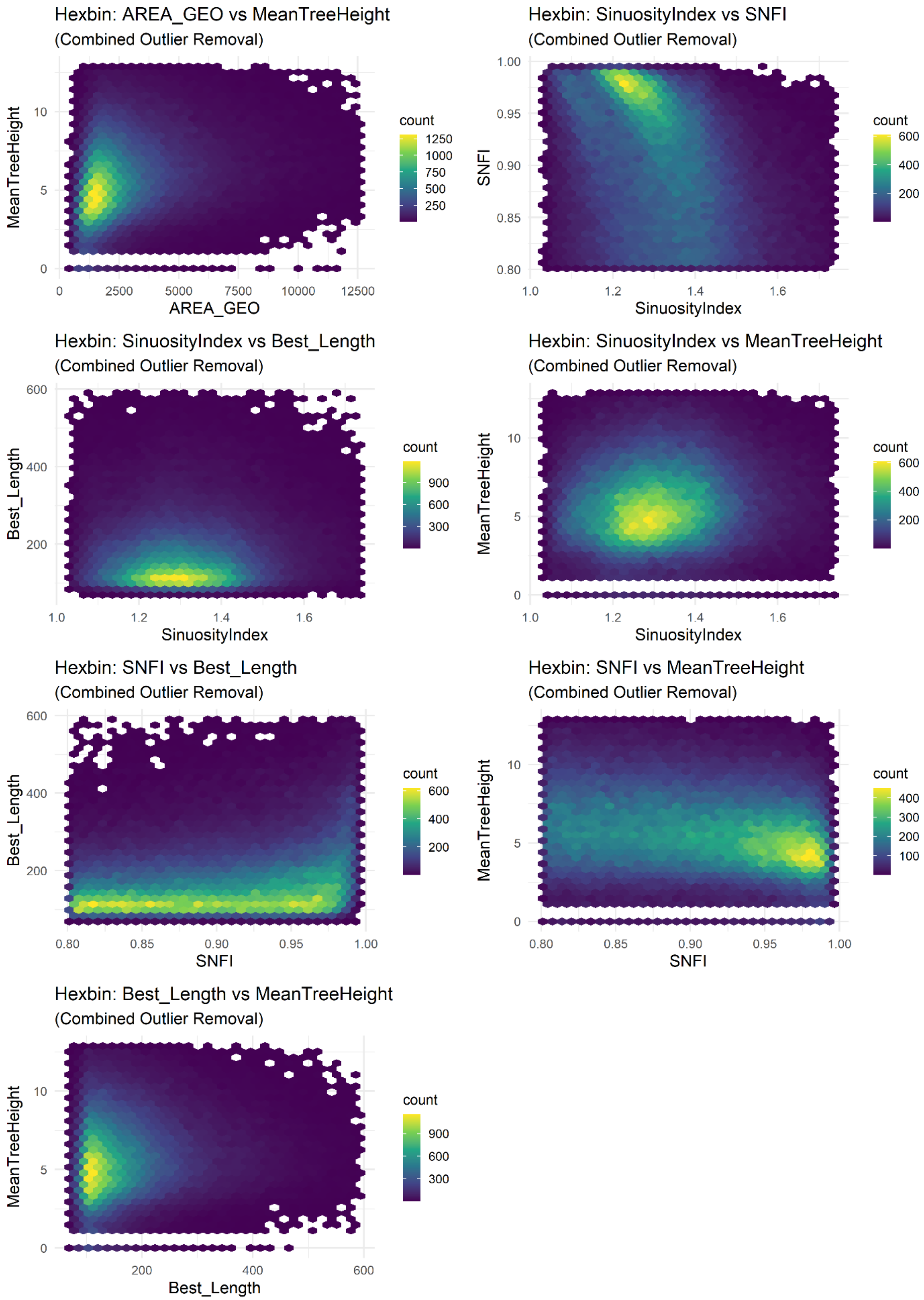

Figure 2.8.A3: Different correlative relationships between shape parameters in the final LSWF

Figure 2.8.A3 (cont'd):
…dataset, including tree height. These visualizations were made using n = 120967 LSWFs after removing 1% of outliers for all of the evaluated fields for all surveyed counties, which is displayed as the "Combined Outlier Removal." Note: All non-index units are in meters, AREA_GEO refers to the area of individual LSWFs in m2.

Chapter 3: A Lightweight Framework for the Functional Classification of Tree Canopies in Mixed-use Landscapes of the Upper Midwest: An Applied use of a Sub-meter Land Cover Classification for Enhanced Spatial Analysis of Anthropogenic-Woody Feature Interaction

Objectives:

- Synthesize findings and extend methods to categorize tree canopies identified through CNN super-resolution land cover products into several valuable categories.
- Introduce a method to quantify the presence of woody riparian buffers.
- Describe a method to organize the categorization of tree canopy classes in super (<1m) resolution data, including the “order of operations” for categorization.
- Discuss the applications of these categorizations and defend their utility.
- Emphasize a conceptual approach, laying the groundwork for a more detailed, publishable paper.

3.0 Abstract

Accurate classification of tree canopies is essential for effective ecological management and landscape analysis, particularly within the diverse mixed-use landscapes of the Upper Midwest's Lakes States. This chapter presents a lightweight framework that leverages a convolutional neural network (CNN) or alternatively-produced super-resolution land cover data to categorize tree canopies at sub-meter resolution by human-influenced functional categories. The methodology introduces the Riparian Buffer Index (RBI), a novel metric for quantifying woody riparian buffers with very high-resolution sub-1m land cover products. It outlines a systematic approach for organizing five functional tree canopy classes within high-resolution datasets. The RBI framework accommodates linear and polygonal riparian features by integrating vector-based and more straightforward raster-based approaches. The proposed categorization encompasses distinct forest structure classes, including continuous woodlands or forests, linear small woody features, riparian buffers, urban woody areas, and isolated trees or patches. Each category's utility is also examined, demonstrating the theoretically enhanced precision in forest structure surveying and improved capacity for detecting subtle changes in canopy composition or human impact. Applications of this framework extend to conservation planning, urban forest

management, and the assessment of human-forest interactions, underscoring its relevance for policymakers and stakeholders in the region. This conceptual approach advances existing methodologies and lays the groundwork for a more detailed study that exercises the categorization, highlighting the potential for broader application across various ecological contexts. Future research will focus on implementing and refining the categorization techniques, as well as expanding the framework's applicability to other geographic regions.

3.1 Background

3.1.1 Overview of Forest Structure Categorization

Accurately characterizing forest structure is essential for understanding how canopy cover, species composition, and successional stages interact to shape broader ecological processes (Meneguzzo et al., 2013). Traditional forest definitions typically emphasize contiguous stands and often overlook smaller, scattered woody features, which can underrepresent the full complexity of mixed-use landscapes (Schnell et al., 2015), or the human influences that led to the dispersed presence of Trees outside Forests (ToFs). Recent efforts to address this gap acknowledge that ToFs are ubiquitous in most agricultural regions worldwide and are significant contributors to carbon storage, habitat connectivity, and local land-use patterns, particularly when identified using sub-meter or very high-resolution data (Malkoç et al., 2021). By combining structural metrics—such as canopy height, density, and spatial configuration—with ToF presence attributes, researchers can gain a deeper understanding of how forest patches, riparian corridors, small groups of trees, and individual trees collectively support ecosystem services. Researchers can also gain a better understanding of how dynamic human influences and decision-making processes affect the inclusion of woody features in agricultural settings, and how these factors impact both anthropocentric and ecological outcomes.

3.1.2 Existing Methods for Categorizing Forestland Structure Using VHR Data

3.1.2.1 Remote Sensing Techniques

Broadly, fine-scale forest structure classification relies on fusing 1) high-resolution optical imagery and/or land cover products and 2) LiDAR-derived height information (Swatantran et al., 2016). Optical imagery from UAVs or aerial orthophotos can achieve sub-meter resolution (Li et al., 2020), capturing small forest patches, woody riparian buffers, or isolated trees. LULC efforts can then typically produce an early categorization of land cover, for instance, producing a tree canopy class. LiDAR, meanwhile, provides canopy height, foliage height diversity, and 3D structural metrics (Huang et al., 2019; Dubayah et al., 2020; Lang et al., 2022). Hybrid approaches that combine LiDAR's vertical detail with optical data's spectral richness often yield the best results, though cost and inconsistent coverage of both products pose challenges (Meneguzzo et al., 2013).

3.1.2.2 Machine Learning and CNN Approaches

Machine learning—and specifically, convolutional neural networks (CNNs)—have recently shown promise for classifying high-resolution tree cover in heterogeneous landscapes (Fricker et al., 2019; Zhang et al. 2022). These models use both spatial context and spectral signals, outperforming traditional random forest or maximum likelihood methods when detecting fine-scale features like small woodlots or linear hedgerows (Subedi, 2005). Despite higher accuracy, computational demands and the need for region-specific training data remain significant hurdles (Fricker et al., 2019; Li et al., 2020).

3.1.2.3 Advantages and Limitations

Each data source has strengths— LiDAR excels at vertical complexity but can be expensive for broad areas, and high-resolution optical images cover large extents at lower cost but struggle in overlapping canopies, or under atmospheric effects and cloud cover (Makido, 2006).

While these challenges persist, the rise of sub-meter CNN classification and advanced data-fusion methods fosters increasingly accurate forest structure mapping at regional and national scales (Meneguzzo et al., 2013; Fricker et al., 2019; Li et al., 2020).

3.1.3 Categorizing a Single Forest Canopy Class

Many classification schemes group all tree canopies—regardless of species—into a single "forest canopy" label or, more commonly, dichotomous 'deciduous' or 'evergreen' labels. This generic approach can overlook subtle intra-canopy variations in structure and phenology, as traditional spectral methods may fail to capture nuances like undergrowth density or seasonal leaf changes (Lee et al., 2023). In some cases, multi-seasonal imagery and shape-based metrics help reduce classification errors, especially in homogenous canopies where pines, spruce, or beech-maple stands dominate (Fricker et al., 2019). However, earlier work in the Lakes States shows that physiographic factors, disturbance regimes, and successional gradients add complexity when applying one broad "forest canopy" category to varied patches on the landscape (Scull, 1996). As a result, advanced segmentation strategies, such as the methods explained in Chapter 1, or through object-based image analysis (OBIA)—combined with high-resolution data and targeted validation—are essential to accurately identify stands or capture the fine-scale heterogeneity often obscured by a single canopy label.

3.1.4 Using a Single Tree Canopy Class in Functional Land-Use Frameworks

In agricultural or mixed-use landscapes, tree cover outside of woodlots or forests often appears as scattered patches of trees, hedgerows, or riparian strips, many of which fall outside traditional "forest" definitions. Lumping these varied canopies into one "tree canopy" class is a practical starting point for a functional categorization, especially in land-use and social-ecological research. This broad-brush approach can help illustrate human dimensions of tree management, highlighting, for instance, where landowners plant windbreaks, maintain riparian buffers, or practice agroforestry (Schnell et al., 2015; Díaz et al., 2016; Li et al., 2020). By treating all canopy types as one, analysts can more easily link tree presence to land-use decisions, such as soil conservation measures, habitat corridors, or aesthetic plantings, before refining those distinctions further (Subedi, 2005).

Yet, mapping all woody cover under a single label inevitably risks masking crucial differences in species composition, structural attributes, and potential management regimes. For instance, intensively managed pine rows vs. mixed broadleaf woodlots may offer distinct ecological benefits or social values. Still, starting with a single tree category can be justified for broad-scale inventories and policy considerations prioritizing how tree cover, in general, intersects with agricultural production and rural development (Fricker et al., 2019; Schnell et al., 2015).

Despite its utility, a single tree canopy label can conceal the functional diversity of woody vegetation on farms, in urban green spaces, or along watercourses. Numerous remote sensing approaches attempt to subdivide that generic canopy into meaningful functional types—like windbreaks, riparian buffers, orchard blocks, or small forest patches—based on canopy shape, adjacency to croplands, or hydrologic features (Gatziolis, 2003; Kaase & Katz, 2012; Schnell et al., 2015; Liknes et al., 2017; Schiefer et al., 2020; Lee et al., 2023). Others incorporate multi-seasonal data to separate evergreen shelterbelts from deciduous hedgerows (Lee et al., 2023; Subedi, 2005) or use CNNs for distinguishing linear woody features from blocky woodlots (Li et al., 2020; Fricker et al., 2019). These functional subdivisions recognize that not all “trees” fulfill the same roles: some are managed for wind protection or livestock shade, others for riparian filtration or cultural amenities. Researchers can apply shape-based metrics, height profiles, or spectral thresholds to allocate tree patches into more granular functional classes by building on an initial single-canopy map.

In the Lakes States region—where sugar maple (*Acer saccharum*), red pine (*Pinus resinosa*), aspen (*Populus tremuloides*), and countless small woodlots or shelterbelts abound—a simple “tree canopy” layer has proven beneficial for initial land-use planning and policy analyses (Schnell et al., 2015; Subedi, 2005). It reveals, for example, how much woody vegetation is retained on farms or near waterways. However, finer distinctions often prove essential for economic, ecological, and social outcomes: working lands with narrow riparian buffers vs. large intact forest patches exhibit different management pressures, carbon potentials, and wildlife habitat value (Zhang et al., 2020; Liknes et al., 2017). While LiDAR and CNN-based methods show promise in separating these subcategories, many frameworks still lack regional calibration datasets, limiting the accuracy of functional designations. Moving forward, robust, locally-informed training data and high-resolution mapping approaches are needed to transform a single tree canopy class into a truly functional classification, capturing the rich variety of human-driven management practices and ecological roles across the Lakes States.

3.1.5 Geographical Focus: Michigan, Wisconsin, and Ohio

Overview of LULC Composition and Diversity in Michigan, Wisconsin, and Ohio

The Lakes States comprise a mosaic of agricultural land, forest patches, urban centers, and wetlands, making them highly diverse in land use and cover (Kromm 1966; Donnelly 1986). Substantial areas of mixed hardwoods and coniferous stands exist alongside intensive agriculture, resulting in fragmented landscapes where riparian woodlands and isolated tree lines are common (Palik 1988; Tang 1991).

Prior classification projects in the Midwestern U.S., such as county-level forest inventories, have mapped broad canopy categories but often omitted small woody patches (Subedi 2005). While LiDAR-based studies and satellite-driven classifications have reasonably well identified riparian forests and wetland edges, the resolution gap remains a consistent challenge from decades ago (Gatziolis, 2003; Makido, 2006; Mottus et al., 2021). Initiatives incorporating sub-1m-resolution approaches hold promise for better capturing linear riparian features and isolated forest fragments (Meneguzzo et al. 2013; Liknes et al. 2017).

Local variations in topography, disturbance regimes, and historical land use necessitate regionally tailored classification strategies (Kromm 1966; Tang 1991). For instance, lowland hardwood stands in southern Michigan and aspen-dominated systems in northern Wisconsin differ substantially in canopy structure. A one-size-fits-all classification can misrepresent these unique forest types, highlighting the need for a cross-regionally robust method to categorize tree canopy and its effects, or at least, a generalizable method that refrains from extrapolating too much from generalized practices (Lucas et al., 2024).

3.1.6 Example of Categorization: Evergreen vs. Deciduous Canopy Separation

Sub-meter imagery and LiDAR-based assessments have traditionally focused on differentiating broad categories of evergreen vs. deciduous forests (Gatziolis 2003). This distinction generally relies on differences in canopy phenology, spectral signatures (e.g., near-infrared reflectance), and LiDAR height/variance measures (Makido 2006; Fricker et al. 2019). Automated classification pipelines—whether maximum likelihood or CNN-based—readily achieve moderate-to-high accuracy when distinguishing these major canopy types (Lee et al., 2023). A wealth of research underscores the effectiveness of multi-season data in clarifying evergreen–deciduous distinctions. Leaf-off imagery highlights structural differences in deciduous species, while conifers maintain dense canopies year-round (Gatziolis 2003; Schiefer et al., 2020). LiDAR's ability to characterize vertical canopy complexity further aids in separating multi-layered deciduous stands from often more uniform coniferous stands (Gatziolis 2003). From an ecological standpoint, evergreen and deciduous canopies differ in phenology, nutrient cycling, and wildlife habitat value (Kromm 1966; Palik 1988; Lee et al., 2023). Management decisions—such as timber rotations or riparian buffer designs—often hinge on these distinctions. Classifying canopy type precisely is paramount to assessing carbon budgets, habitat suitability, and resilience to disturbances like pests or extreme weather events (Tang 1991; Donnelly 1986; Zhang et al., 2020).

Separating evergreen and deciduous canopies informs everything from wildlife corridor designs to climate adaptation strategies (Fricker et al., 2019). For instance, climate-sensitive species reliant on evergreen cover for winter shelter may be disproportionately affected by conifer decline, whereas deciduous stands influence leaf litter quality and aquatic nutrient fluxes in riparian zones (Gatziolis 2003; Donnelly 1986; Schiefer et al., 2020). Thus, an accurate canopy classification remains essential for comprehensive ecosystem management.

3.1.7 Utility of Shape-Based Metrics in Forest Structure Analysis

Beyond traditional canopy measures, shape-based metrics—such as patch compactness, edge-to-area ratio, and fragmentation indices— can offer insights into how forests are distributed spatially (Liknes et al. 2017). These metrics can illuminate landscape connectivity, forest fragmentation trends, and anthropogenic impacts (Basu et al., 2015). Combining shape-based evaluations with spectral or LiDAR data strengthens classification outputs by highlighting linear features (e.g., shelterbelts, riparian buffers) or small, isolated woodlots (Meneguzzo et al. 2013; Lucas et al., 2024).

Liknes et al. (2017) introduced a suite of shape indices to characterize discrete forest patches and corridors. These indices quantify canopy geometry (e.g., shape complexity, elongation) and detect transitions from continuous woodland to narrow, linear corridors typical in agricultural or riparian contexts (Liknes et al. 2017; Kaase & Katz 2012). Such metrics are especially helpful in mapping small or linear woody features frequently missed by coarse-scale classification (Subedi 2005). Typical metrics include fractal dimension, patch perimeter–area ratio, and shape complexity indexes. For instance, fractal dimension can distinguish simpler, rounder patches from elongated hedgerows or irregular riparian buffers (Meneguzzo et al. 2013). Perimeter–area ratios highlight small, linear features with disproportionately large perimeters, such as single-row windbreaks or riparian strips (Liknes et al. 2017; Kaase & Katz, 2012).

Shape-based metrics often correlate with land use intensity, agricultural field boundaries, and zoning regulations (Nowak & Greenfield, 2012). For instance, high perimeter–area ratios near agricultural zones can signal deforestation pressure or corridor planting for windbreaks (Tang 1991; Pourpeikari Heris et al., 2022). Similarly, linear forest patches adjacent to urban boundaries inform policies on greenbelt continuity and ecological connectivity (Meneguzzo et al. 2013). By integrating shape indices, classifiers can differentiate subtle anthropogenic influences on canopy structure.

Prior chapters introduce the multi-faceted importance of forest canopy classification and emphasize diverse methods—machine learning, LiDAR, and shape-based indices—for capturing structural nuances. The methods for delineating canopy classes, especially sub-meter precision in riparian or small-wooded contexts, build on the ecological underpinnings presented earlier (Kromm 1966; Bryant 1963). Integrating shape-based techniques from Chapter 1 with ecological insights from Chapter 2 advances a holistic classification framework geared toward functional delineation of canopy types (Liknes et al. 2017; Donnelly 1986; Thomas et al., 2021; Lucas et al., 2024). This synergy underpins the more detailed workflows, including the proposed Riparian Buffer Index (RBI) and CNN-based canopy segmentation, which will be detailed in subsequent chapters.

3.1.8 Quantifying Woody Riparian Buffers

Riparian buffers—those forested or woody vegetative zones adjacent to streams, rivers, lakes, and wetlands—play a critical role in filtering pollutants, stabilizing streambanks, and maintaining ecological connectivity. Their value extends beyond water quality, including microclimate regulation, carbon storage, and biodiversity support (Donnelly 1986, Weigelhofer et al., 2012). As intensively managed landscapes expand, quantifying the extent and continuity of riparian woody vegetation is critical for sustainability (Kaase & Katz 2012).

Traditional methods rely on buffer-width thresholds (e.g., 30 m from streambanks), sometimes ignoring local topography or vegetation height (Subedi 2005). More sophisticated approaches, like the Stream Index Division Equations (SIDE) algorithm, separate left- and right-bank contributions of topography, refining hydrological models (Grabs et al. 2010; Meneguzzo et al. 2013). LiDAR data coupled with machine learning also enable 3D delineations of riparian zones, capturing canopy height and density along meandering streams (Gericke et al., 2020; Rutherford, 2023).

Most existing methods either oversimplify riparian buffers by applying uniform widths and weights or neglect small-scale morphological variability (Rutherford, 2023). The proposed study, with sub-meter CNN-based classification and shape-based indices (Liknes et al. 2017, Malkoç et al., 2021; Lucas et al., 2024), aims to address these gaps by quantifying riparian buffers that adjust to steam morphology and vegetation structure. However, it does not seek to supplant theory on the intentional and intensive approach needed to establish and maintain a properly managed riparian buffer. This approach can better inform nutrient mitigation strategies, corridor conservation, and estimates of other biotic and abiotic factors associated with tree canopy proximity to riparian features (i.e., shade, biomass contributions) in intensively used watersheds across the Lakes States (Kaase & Katz 2012; Zhang et al. 2020).

3.1.9 Landscape-Level Impacts of Forest Structure

Landscape ecology emphasizes how patch configuration, connectivity, and fragmentation drive ecological processes (Donnelly 1986; Palik 1988). Metrics like shape complexity, fractal dimension, and core area fraction reveal how forest structure influences habitat availability, species dispersal, and edge effects (Liknes et al. 2017, Malkoç et al., 2021). Integrating these metrics with 3D canopy data or CNN-based classification refines our understanding of how forest patches function within agricultural or mixed-use mosaics (Meneguzzo et al. 2013). Combining shape-based indices with canopy height or biomass metrics can yield multidimensional forest maps describing composition and configuration (Gatziolis 2003; Li et al., 2020). For instance, a patch with high structural complexity and tall canopy might support specialized species requiring layered habitats. Meanwhile, linear riparian corridors function as dispersal pathways even with moderate canopy height (Tang 1991; Palik 1988; Schiefer et al., 2020).

Clear visualizations of how forest structure intersects with land use intensity guide management interventions—such as targeted buffer expansions, small-woodlot protection, or connectivity enhancements. Identifying areas of high biodiversity potential helps decision-makers prioritize reforestation or corridor establishment, ultimately contributing to more resilient landscapes (Subedi 2005; Zhang et al. 2020).

3.1.10 Human Dimensions of Forest Canopy Structure

Human activities like agricultural expansion, urban development, and selection-based timber harvesting directly shape canopy density, composition, and patch configuration (Bryant, 1963; Tang, 1991; Thomas et al., 2021). Riparian zones are particularly vulnerable to agricultural encroachment or urban sprawl, altering buffer continuity and functionality (Kaase & Katz, 2012). Understanding these relationships is crucial for sustainable forestry, water resource protection, and rural development planning (Tang, 1991; Donnelly, 1986; Pourpeikari Heris et al., 2022). Socioeconomic research shows landowner objectives, market pressures, and policy incentives drive land-use decisions impacting canopy extent and quality (Thomas et al., 2021). For example, farmland owners may retain small, wooded patches for wind protection or tax incentives, while urban planners might prioritize street trees and parks for aesthetic or ecosystem service benefits (Subedi, 2005; Palik, 1988). Understanding these drivers aids in designing effective management interventions that align with local community goals (Thomas et al., 2021).

As cities expand, fragmented forest patches often become “urban woodlands” with altered species composition, invasive pressure, and compromised connectivity (Pourpeikari Heris et al., 2022). Surviving urban trees outside forests—such as in parks, riparian corridors, or street plantings—remain vital for ecosystem services like temperature regulation and stormwater management (Meneguzzo et al., 2013). Tracking these urban canopies with sub-meter classification can highlight critical zones for urban forestry initiatives, bridging the gap between natural resource management and urban planning (Gatziolis, 2003; Subedi, 2005; Schiefer et al., 2020).

3.2 Proposed Methods

3.2.1 Describing the Riparian Buffer Index

We quantified riparian buffers adjacent to streams, rivers, lakes, and wetlands using a framework that integrates spatial analysis with functional indicators. The approach defines criteria for classifying buffer zones based on measurable features such as buffer width, vegetation density, and proximity to a riparian feature. These criteria allow us to detect areas with limited riparian buffer presence and support the selection of sites for restoration and mitigative efforts. This section outlines a set of criteria used to categorize riparian buffers, emphasizing the integration of spatial analysis with functional indicators of riparian health.

3.2.1.1 Vector-Based Riparian Buffer Index Calculation

The vector-based approach to calculating the Riparian Buffer Index (RBI) involves delineating riparian features—such as streams, rivers, and lakes—from vector data and then assessing the proximity of tree canopies to these features. First, riparian features are defined and identified using high-resolution vector datasets. These datasets accurately represent the boundaries of flowing water bodies (streams, rivers, aqueducts, and canals) and still water bodies (lakes, wetlands, and ponds). The RBI is calculated along both sides of a centerline for flowing features. In contrast, for still features, the index is derived from the single exterior side of the polygon representing the water body.

The RBI is recorded as an impact score that reflects the protective influence of woody vegetation along the riparian edge. This impact score follows a cosine wave pattern: tree canopies immediately adjacent to a riparian feature are assigned an impact score of 1, and this score gradually decreases in a cosine-like fashion until it reaches 0 at a distance of 120 feet from the riparian boundary. For example, if an area is continuously wooded for the entire 120-foot extent, it receives an RBI of 1. Conversely, if the buffer is fully present only along the immediate riparian edge and then clears out before reaching 60 feet, the RBI value is calculated to be approximately 0.8, reflecting a high but not complete protective influence. Areas with no woody buffer within 120 feet are assigned an RBI of 0.

Equation: Riparian Buffer Index (RBI) – Vector-Based Calculation
This index is designed so that points immediately adjacent to the riparian boundary (i.e., at distance *d* = 0) receive a score of 1, and the impact decays in a cosine-shaped fashion to 0 at a maximum effective distance *D* (e.g., 120 feet). One formulation is:

$$\mathrm{RBI}_v(d) = \begin{cases} \cos\!\left(\frac{\pi}{2}\,\frac{d}{D}\right) & \text{if } 0 \le d \le D, \\ 0 & \text{if } d > D. \end{cases}$$

Here,

- *d* is the perpendicular distance from the riparian boundary, and
- *D* is the defined maximum distance over which the buffer is considered to have an impact.

To handle partial buffers, the methodology quantifies the degree of buffer continuity along perpendicular transects extending from the riparian boundary. Riparian buffers are segmented at regular intervals—every 10 meters, for example—to calculate an RBI per unit distance along the vector. This segmentation provides a detailed spatial representation of buffer effectiveness, allowing for visualizing areas where woody vegetation is either abundant or lacking. For flowing features, RBI values are derived for both sides of the stream, while for still features, the RBI is determined along the single exterior side. This dual approach makes sure that the index accurately reflects the ecological and erosional dynamics associated with each type of water body.

The vector-based method precisely measures the spatial relationship between tree canopies and riparian features. It facilitates targeted interventions by highlighting specific areas along a watercourse that require buffer enhancement, ultimately guiding management practices to improve water quality and ecosystem resilience.

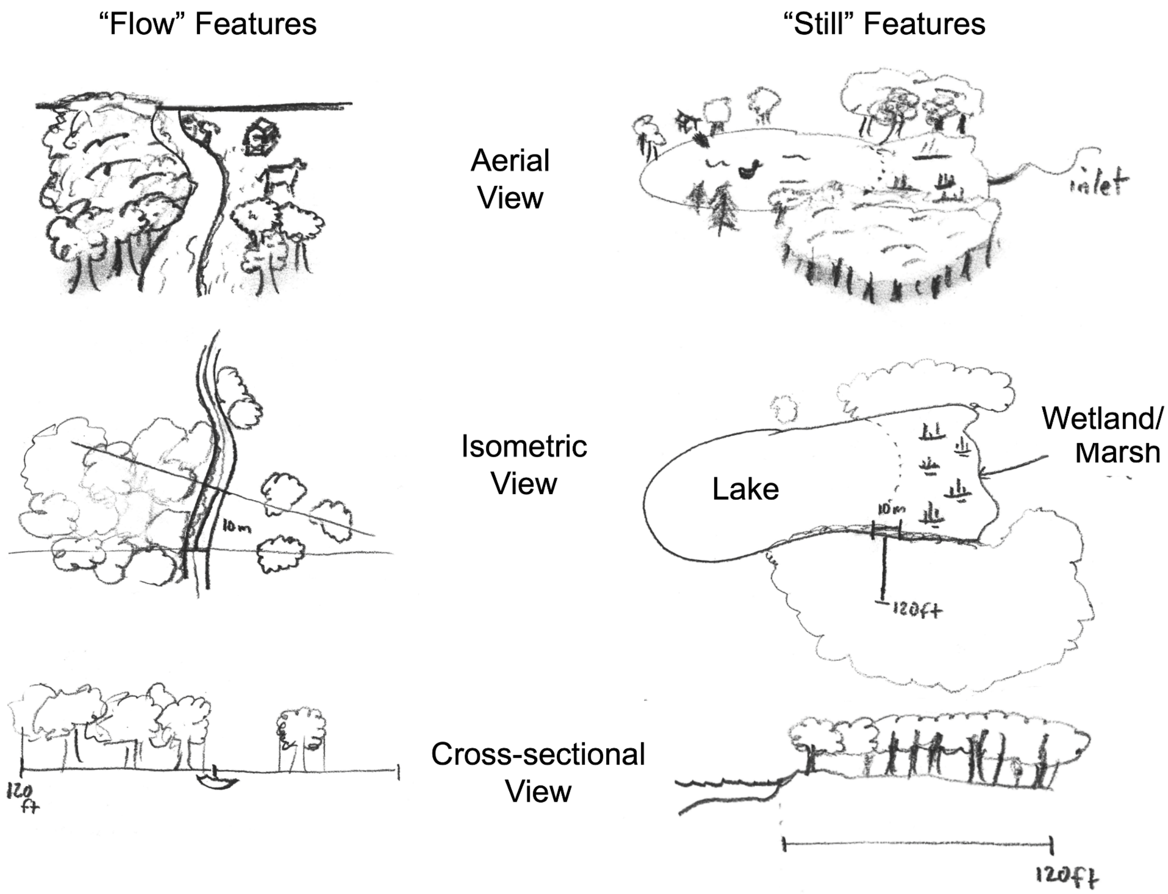

Figure 1: A visual representation of a two-sided and a one-sided vector calculation of the Riparian Buffer Index (RBI) around flowing features such as a river or stream and a 'still' feature like a lake or wetland, respectively. As an example of a vector calculation, the 'left' bank of the flow feature with continuous forest would have an RBI value of near one over the 10 meters of evaluated distance on that side of the stream (which is one-half of the flow feature RBI calculation), and the 'right' bank's RBI would fall somewhere under '0.5' but not zero, since there is limited canopy on that side. To calculate an RBI value for that distance of a flow feature, you would take the average (or spatially-weighted average) of both sides, the left and right bank, to evaluate the riparian buffer's effectiveness along that length of a riparian feature. The impact of tree canopy presence decreases, extending outward from a riparian feature in a cosine wave pattern. The concept is the same for still features, except that measurement is judged from just one side, based on the extent of the riparian feature.

3.2.1.2 Raster-Based Direct Measurement

In contrast to the vector-based approach, the raster-based direct measurement method involves establishing a continuous buffer zone around riparian features using a raster grid. A buffer of 120 feet is created around the defined riparian boundaries, consistent with forest definitions employed in forest inventories. Within this raster buffer, contiguous tree canopies are classified based on spectral, spatial, and textural information derived from high-resolution imagery.

The raster-based method benefits from its simplicity and computational efficiency, particularly when processing large spatial extents. By converting the riparian buffer into a raster format, each cell within the buffer is automatically evaluated for the presence or absence of woody vegetation. The resulting data are then aggregated to produce an overall measure of buffer integrity across the study area. Although this approach may lack the nuanced, per-unit distance detail provided by the vector-based method, it offers a rapid and consistent means of assessing woody cover in riparian zones.

Equation: Riparian Buffer Index (RBI) – Raster-Based Measurement (Simple Linear Decay)

One may also use a simpler, linear decay function in a raster implementation. For example:

$$\mathrm{RBI}_r(d) = \begin{cases} 1 - \frac{d}{D} & \text{if } 0 \leq d \leq D, \\ 0 & \text{if } d > D. \end{cases}$$

This equation linearly reduces the impact from 1 at the boundary to 0 at distance *D*.

When comparing the two methods, the vector-based approach provides a more detailed, continuous measurement of riparian buffer effectiveness by using impact scores based on proximity, which are sensitive to the cosine wave pattern of diminishing influence. While more straightforward and less computationally intensive, the raster-based method is best suited for situations where a rapid, broad-scale assessment is required or where vector data may be incomplete. In practice, the choice between these methods will depend on the spatial resolution of available data, computational resources, and the study's specific objectives. Both approaches can contribute to a more informed and precise management of riparian ecosystems by identifying areas where buffer enhancement is necessary and by facilitating the monitoring of changes over time.

Equation: Extended Impact Score (Optional Modification)
Lastly, to account for a gradual "tail" of influence beyond the initial *D* (for instance, if some impact persists beyond the strict buffer limit), one may define an extended linear RBI as follows:

$$\mathrm{RBI}_e(d) = \begin{cases} 1 - \frac{d}{D} & \text{if } 0 \le d \le D, \\ \beta\left(1 - \frac{d-D}{E}\right) & \text{if } D < d \le D + E, \\ 0 & \text{if } d > D + E, \end{cases}$$

where

- *E* is the additional distance beyond *D* over which the extended impact decays to 0, and
- β (with $0<\beta<1$) is the maximum extended impact score at $d = D$.

3.2.2 Categories to Evaluate Forest Structure

The evaluation of forest structure is pivotal for understanding landscape-level ecological processes and informing effective management practices. In this section, forested areas are classified based on canopy continuity, spatial configuration (including aspects related to shape), and proximity to water bodies and urban development. Most of the categories listed in the following section are derived by following the steps in Chapter 1, namely the continuous forests layer, standalone trees/small groups of trees, and linear small woody features. The inclusion of an RBI to categorize riparian-associated woody features and a simple filter for woody features in developed urban or peri-urban areas makes it conceptually easy to extend the method. This extension categorizes nuanced, detailed impacts and interactions between humans and woody features on the landscape, such as their presence, genesis, and individual or typical characteristics. In summary, these categories provide a systematic framework allowing a more nuanced interpretation of forest composition and function in mixed-use landscapes.

3.2.2.1 Defined Categories for Forest Structure

Woodlands and Woodlots (Continuous Forested Areas):

Continuously forested areas, also called woodlands or woodlots, are defined by an uninterrupted expanse of tree cover that often extends over broad areas. These regions exhibit well-developed canopy layers with high tree density and significant structural complexity. In this category, the inclusion criteria are deliberately broad to allow for overlap with woody wetlands, thereby ensuring that areas where forested conditions coexist with hydric soils are not excluded. The ecological significance of these areas is underscored by their roles in maintaining biodiversity, stabilizing soil, and regulating hydrological processes. Of the categories presented, these are least often actively managed and influenced by anthropogenic factors.

Linear Small Woody Features (LSWFs):

Linear Small Woody Features (LSWFs) are characterized by narrow, elongated patches of tree cover that frequently occur within agricultural landscapes or along linear corridors. They can be, but are not always, associated with agroforestry practices such as windbreaks and hedgerows. As detailed in Chapter 1, LSWFs are distinguished by their reduced width and discontinuous nature relative to continuous woodlands. Their ecological importance lies in serving as corridors that facilitate species movement, enhance habitat connectivity, and mitigate edge effects. Despite their modest size, these features contribute significantly to landscape heterogeneity and provide essential ecosystem services in human-dominated environments.

Riparian Woodlands and Buffers:

Riparian woodlands and buffers are identified based on their proximity to water bodies and are quantified using the Riparian Buffer Index (RBI) criteria. These areas are critical for protecting water quality, regulating stream temperatures, and providing habitat for both aquatic and terrestrial species. The classification differentiates riparian buffers from other forest categories by incorporating both the RBI impact score and the spatial proximity to streams, lakes, and wetlands. This method guarantees that only areas directly affecting riparian functions are classified as riparian woodlands.

Urban/Peri-Urban/Suburban/Exurban Woody Features:

Urban woody features, which may also be termed peri-urban, suburban, or exurban woody areas, are distinguished by their occurrence within or adjacent to human settlements. The classification of these features is informed by Census Designated Place (CDP) polygons, which help segregate urban areas from more natural forest settings. Urban woody features typically exhibit a higher degree of fragmentation or, as measured in chapter 1, a higher canopy sinuosity, with canopy structures often interrupted by infrastructure and impervious surfaces, or with added sinuosity to fit anthropogenic needs in a developed setting. Their characterization is essential for assessing urban ecosystem services such as cooling, air quality improvement, and stormwater management.

Single Trees/Small Groups of Trees:

This category encompasses isolated trees and small clusters as discrete elements within the landscape. Identification criteria are based on canopy size and spatial distribution, with single trees or groups lacking the continuity of larger forest patches. Despite their limited spatial extent, these tree elements are essential for maintaining landscape connectivity, providing habitat for various species, and contributing to overall carbon sequestration. They also serve as critical markers for ecological restoration and urban greening efforts.

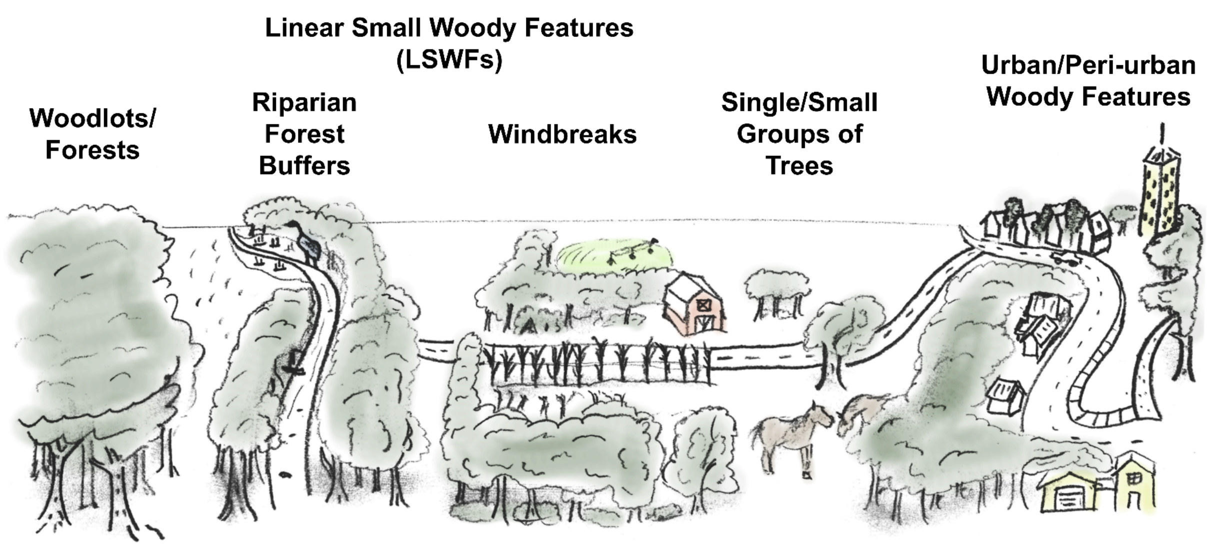

Figure 2: Proposed categories of tree canopies in the categorization scheme.

3.2.2.2 Proposed Order of Operations for Tree Canopy Categorization

A structured, multi-step procedure is proposed to ensure a systematic and replicable classification of tree canopies across diverse landscapes. This order of operations is designed to optimize the integration of high-resolution, super-resolution data with both vector- and raster-based analytical methods.

Step 1: Extraction of Riparian Woodlands and Buffers

The process begins with applying the Riparian Buffer Index (RBI) criteria to identify riparian woodlands and buffers. Using vector data, riparian features are delineated and the RBI is calculated to assign an impact score to adjacent tree canopies. This step is critical in isolating areas where riparian functions—such as water quality protection and habitat connectivity—are most pronounced.

Step 2: Identification of Continuously Wooded Areas

Following the extraction of riparian buffers, the next step involves detecting areas of uninterrupted forest cover beyond the riparian zones. Leveraging super-resolution data ensures that the detection process captures the fine-scale continuity of woodlands, thereby distinguishing extensive, continuous forest areas from more fragmented patches.

Step 3: Integration of 'Slivers' into Continuous Woodlands

In many landscapes, narrow or fragmented canopy patches, which, for this paper are called 'slivers', occur at the periphery of continuous woodlands. This step involves reclassifying these slivers based on criteria that assess spatial continuity and canopy density. The goal is to merge these fragmented patches back with larger contiguous woodlands where appropriate, thereby refining the overall classification of forest structure.

Step 4: Classification of Urban/Peri-Urban Woody Features

Urban woody features are then segregated from natural and riparian woodlands. This could be achieved in the US using Census Designated Place (CDP) or urban areas polygons, which draw neat lines around urban areas. Characteristics such as fragmentation, canopy interruption by infrastructure, and distinct spectral signatures are used to differentiate urban woody features from their more natural counterparts.

Step 5: Extraction and Classification of Linear Small Woody Features (LSWFs)

Utilizing methodologies outlined in Chapter 1, linear small woody features (LSWFs) are extracted from the landscape. These features are classified based on their narrow, elongated morphology and are integrated into the overall forest structure categorization. Their identification is essential for understanding landscape connectivity, particularly in agricultural settings.

Step 6: Filtering and Classification of Remaining Tree Canopies

The final step involves assigning any residual tree canopies that have not been categorized in the previous steps. These remaining canopies are classified into appropriate categories, such as single trees or patches, based on criteria such as canopy size, shape, and spatial distribution. Rigorous quality control and validation measures are implemented to ensure the accuracy and consistency of the classification.

Collectively, this ordered approach provides a comprehensive framework for categorizing tree canopy structures, enabling a detailed evaluation of forest composition across varied landscapes. By integrating vector and raster-based methodologies with high-resolution remote sensing data, this framework supports the development of targeted management practices that enhance ecological resilience and promote sustainable land use.

3.3 Discussion

3.3.1 Context Within the Human/Forest Interface

The refined categorization of forest structure presented in this study offers significant benefits at the intersection of human activity and forested landscapes. By deploying high-resolution, sub-meter classification methods, this framework enhances our understanding of how forest ecosystems shape and impact human interactions. Detailed forest structure categorization allows for the precise mapping of diverse canopy elements—ranging from continuous woodlands and riparian buffers to urban woody features and isolated trees—which, in turn, supports a more nuanced analysis of land use dynamics. This precision is essential for evaluating the impact of anthropogenic activities on ecological integrity and identifying zones where conservation efforts may be most urgently required.

Accurate measurement of woody features is paramount for effective forest management and policy development. The capability to detect subtle changes in forest structure using advanced RS and ML techniques ensures that even minor modifications—whether resulting from natural disturbance or human intervention—are captured and quantified. Such detailed data provide a critical foundation for informed decision-making, allowing managers to anticipate ecosystem service shifts and design interventions that maintain or enhance habitat connectivity and resilience. High-resolution categorization plays an indispensable role in the early detection of degradation in riparian zones and urban forests, where the balance between development and ecological preservation is most delicate.

The implications of this refined categorization extend directly into forest management and conservation. Integrating detailed forest structure data into broader ecological and socio-economic frameworks enables the development of targeted management strategies. For instance, enhanced mapping of riparian buffers through the Riparian Buffer Index (RBI) supports precise buffer enhancement efforts to protect water quality and mitigate erosion. Similarly, accurate delineation of urban woody features facilitates better urban forest planning, critical for reducing urban heat island effects, improving air quality, and sustaining biodiversity in highly modified landscapes.

Moreover, by embedding these high-resolution measurements into policy and management practices, stakeholders are better equipped to address land use changes. The ability to assess forest fragmentation and connectivity on a fine scale informs local conservation initiatives and regional and national strategies for ecosystem management. Ultimately, the framework established in this study provides a robust tool for synthesizing ecological data with socio-economic considerations, thereby promoting sustainable development practices that are both environmentally sound and socially equitable.

3.3.2 Using FIA Definitions

Integrating Forest Inventory and Analysis (FIA) definitions into this framework confers several advantages. FIA definitions provide a standardized basis for forest categorization, ensuring that results are comparable with national forest data and that the criteria for classification align with established ecological and management objectives. This standardization fosters consistency in monitoring forest conditions over time and can improve data sharing across agencies and regions. Moreover, the comprehensive nature of FIA criteria—encompassing factors such as canopy cover, tree density, and stand structure—supports the rigorous assessment of forest ecosystems, reinforcing the reliability of the categorization scheme presented here.

Nevertheless, the application of FIA definitions is not without drawbacks. A notable limitation is the potential mismatch between the coarse metrics traditionally employed by FIA and the fine-scale spatial detail provided by high-resolution remote sensing data. FIA definitions were developed primarily for national forest inventories and may not capture the nuanced variations in tree canopy structure that are observable at sub-meter resolutions. Additionally, since FIA metrics are often expressed in non-metric units and designed around a particular operational definition of a forest, alternative definitions could offer greater flexibility or precision when categorizing tree canopies into functional classes. This recognition of limitations has prompted an exploration of alternative frameworks that better accommodate the intricacies of urban, riparian, and fragmented landscapes.

Despite these limitations, FIA definitions were selected for this study because they offer a well-established, robust benchmark widely recognized by the forest management community in the U.S. Their compatibility with existing datasets and alignment with national monitoring objectives make them a practical choice for integrating high-resolution data into a larger, policy-relevant framework. This decision also ensures that the categorization results are directly comparable with broader forest health and management trends, thereby enhancing the findings' applicability to academic and operational contexts.

3.3.3 Utility of the Method and Categorization

The categorization method developed herein offers substantial utility for analyzing and managing forests in the Upper Midwest. By leveraging high-resolution remote sensing data and a refined classification framework, this approach provides detailed, functionally relevant insights into forest structure that traditional methods have not achieved.

First, identifying **Woodlands and Woodlots (Continuous Forested Areas)** accurately represents extensive, uninterrupted forest cover. These continuous areas serve as critical reservoirs of biodiversity and carbon, and their delineation enables managers to monitor large-scale deforestation and forest degradation. In addition, allowing for overlap with woody wetlands enriches our understanding of hydrological connectivity and the role of these areas in water retention and flood mitigation.

Second, the classification of **Linear Small Woody Features (LSWFs)**, as outlined in Chapter 1, captures the unique ecological characteristics of narrow, elongated patches of vegetation. These features, which often appear along field margins, roadsides, or riparian zones, are essential for maintaining habitat connectivity and providing corridors for wildlife movement. Their precise mapping in agricultural landscapes fills a critical gap in traditional forest inventories and supports targeted conservation initiatives.

Third, delineating **Riparian Woodlands and Buffers** using the Riparian Buffer Index (RBI) criteria is particularly impactful. By defining buffers based on proximity to water bodies and integrating a cosine wave-based impact score, this method precisely quantifies the protective role of riparian vegetation. Such a detailed assessment is invaluable for water quality management and for designing buffer enhancements that safeguard aquatic ecosystems.

Fourth, the classification of **Urban/Peri-Urban/Suburban/Ex-urban woody Features** distinguishes human-modified landscapes from natural woodlands. Utilizing Census Designated Place (CDP) polygons to segregate these areas provides a practical approach for urban forest management. This categorization not only aids in monitoring urban tree canopy health but also informs strategies to mitigate urban heat island effects and to promote sustainable urban planning.

Fifth, identifying **Single Trees/Small Groups of Trees** captures elements that, while fragmented, contribute to greater landscape ecology. These isolated trees and small clusters can enhance ecological connectivity and provide localized ecosystem services like shade, air quality improvement, and microhabitat creation. Recognizing and mapping these features allow for more comprehensive assessments of forest cover and formulating management practices that support even the smallest woody elements.

Overall, the proposed categorization framework—encompassing these five distinct classes—enhances our capacity to analyze forest structure with unprecedented precision. By integrating detailed, high-resolution data into a coherent, multi-class system, this method not only advances the academic understanding of forest ecosystems but also offers practical tools for conservation planning, urban forest management, and formulating adaptive management strategies in the Upper Midwest.

3.4 Takeaways

In summary, this study has introduced a suite of novel methodologies that can advance the functional classification of tree canopies in the Upper Midwest. Integrating convolutional neural network (CNN) super-resolution data with a novel Riparian Buffer Index (RBI) framework achieves unprecedented sub-meter precision in delineating forest structure. The methodology synthesizes vector-based and raster-based techniques to identify continuous woodlands, linear small woody features, riparian woodlands and buffers, urban woody areas, and isolated trees or patches. These advancements not only enhance the resolution and accuracy of canopy mapping but also provide a standardized framework compatible with national data sources such as the FIA. This integration represents a significant methodological leap that improves our ability to monitor and manage forest ecosystems, particularly in complex, mixed-use landscapes.

The categorization framework exhibits substantial utility for forest management, conservation planning, and ecological research. It offers actionable insights for policymakers and stakeholders by enabling targeted interventions—such as buffer enhancement, urban forest planning, and the maintenance of environmental connectivity—across the Lakes States region. Moreover, the study identifies clear avenues for future research, including further refinement and validation of classification methods, expanding the framework to additional geographic areas, and incorporating supplementary data layers to capture even more nuanced ecological processes. Overall, these findings not only lay the groundwork for a publishable, detailed study but also contribute significantly to the evolving field of spatial forest analysis, promising broader application and impact in sustainable land management and conservation policy.

REFERENCES

Ayrey, Elias, et al. "Synthesizing Disparate LiDAR and Satellite Datasets through Deep Learning to Generate Wall-to-Wall Regional Inventories for the Complex, Mixed-Species Forests of the Eastern United States." *Remote. Sens.*, vol. 13, 2021. https://doi.org/10.3390/rs13245113.

Bowman, Anthony Winston. *DRIVERS OF 3-D CANOPY FUNCTIONAL DIVERSITY IN A TEMPERATE FOREST*. 2024. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/JQVN-YS34.

Bryant, Robert Louis, 1928-. *The Lowland-Hardwood Forests of Ingham County, Michigan*. 1963. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/G94R-R846.

Cherti, Mehdi, et al. "Reproducible Scaling Laws for Contrastive Language-Image Learning." *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2023, pp. 2818–29. *Semantic Scholar*, https://doi.org/10.1109/CVPR52729.2023.00276.

Coulston, John W., et al. "Modeling Percent Tree Canopy Cover: A Pilot Study." *Photogrammetric Engineering & Remote Sensing 78(7): 715–727*, vol. 78, 2012, pp. 715–27.

Donnelly, Gerard T. *Forest Composition as Determined by Canopy Gap Dynamics: A Beech-Maple Forest in Michigan*. 1986. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/Z6K5-GZ24.

Evangelista, Heloísa B., et al. "Shade Provided by Riparian Plants and Biotic Resistance by Macrophytes Reduce the Establishment of an Invasive Poaceae." *Journal of Applied Ecology*, edited by Lara Souza, vol. 54, no. 2, Apr. 2017, pp. 648–56. *DOI.org (Crossref)*, https://doi.org/10.1111/1365-2664.12791.

Forio, M., et al. "Small Patches of Riparian Woody Vegetation Enhance Biodiversity of Invertebrates." *Water*, 2020. https://doi.org/10.3390/w12113070.

Fricker, G. A., et al. "A Convolutional Neural Network Classifier Identifies Tree Species in Mixed-Conifer Forest from Hyperspectral Imagery." *Remote. Sens.*, vol. 11, 2019. https://doi.org/10.3390/rs11192326.

Gericke, A., et al. "Deriving a Bayesian Network to Assess the Retention Efficacy of Riparian Buffer Zones." *Water*, 2020. https://doi.org/10.3390/w12030617.

Grabs, T., et al. "Calculating Terrain Indices along Streams: A New Method for Separating Stream Sides." *Water Resources Research*, vol. 46, 2010. https://doi.org/10.1029/2010WR009296.

Humphreys, Rubens Dias. *Evaluation of Multilevel Sampling Techniques for Forest Inventory in Northern Michigan*. 1989. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/SC20-1A14.

Jayasuriya, Maneesha, et al. “Applying the ‘Goldilocks Rule’ to Riparian Buffer Widths for Forested Headwater Streams across the Contiguous U.S.—How Much Is ‘Just Right’?” *Forests*, vol. 13, Sept. 2022, p. 1509. *ResearchGate*, https://doi.org/10.3390/f13091509.

Kaase, Christopher T., and Gabrielle L. Katz. “Effects of Stream Restoration on Woody Riparian Vegetation of Southern Appalachian Mountain Streams, North Carolina, U.S.A.” *Restoration Ecology*, vol. 20, no. 5, 2012, pp. 647–55. *Wiley Online Library*, https://doi.org/10.1111/j.1526-100X.2011.00807.x.

Kromm, David E. *A Functional Geographic Approach to the Utilization of the Northern Michigan Forest Resource*. 1966. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/HWF8-X306.

Lee, Eu-Ru, et al. “Mapping Tree Species Using CNN from Bi-Seasonal High-Resolution Drone Optic and LiDAR Data.” *Remote. Sens.*, vol. 15, 2023. *consensus.app*, https://doi.org/10.3390/rs15082140.

Liu, Siyu, et al. “The Overlooked Contribution of Trees Outside Forests to Tree Cover and Woody Biomass across Europe.” *Science Advances*, vol. 9, 2023. https://doi.org/10.1126/sciadv.adh4097.

Lucas, Moritz, et al. “Mapping Trees Outside Forests Using Semantic Segmentation.” *IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium*, 2024, pp. 4435–38. *IEEE Xplore*, https://doi.org/10.1109/IGARSS53475.2024.10641035.

Makido, Yasuyo Kato. *Land Cover Mapping at Sub-Pixel Scales*. 2006. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/274D-1E90.

Malkoç, Eylül, et al. “Countrywide Mapping of Trees Outside Forests Based on Remote Sensing Data in Switzerland.” *International Journal of Applied Earth Observation and Geoinformation*, vol. 100, Aug. 2021, p. 102336. *ScienceDirect*, https://doi.org/10.1016/j.jag.2021.102336.

Mondino, E. Borgogno, et al. “How Far Can We Trust Forestry Estimates from Low-Density LiDAR Acquisitions? The Cutfoot Sioux Experimental Forest (MN, USA) Case Study.” *International Journal of Remote Sensing*, vol. 41, 2020, pp. 4551–69. https://doi.org/10.1080/01431161.2020.1723173.

Mottus, Matti, et al. “Patch Size Selection for Analysis of Sub-Meter Resolution Hyperspectral Imagery of Forests.” *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, IEEE, 2021, pp. 2035–38. *DOI.org (Crossref)*, https://doi.org/10.1109/IGARSS47720.2021.9554257.

Nowak, David J., and Eric J. Greenfield. "Tree and Impervious Cover in the United States." *Landscape and Urban Planning*, vol. 107, no. 1, July 2012, pp. 21–30. *ScienceDirect*, https://doi.org/10.1016/j.landurbplan.2012.04.005.

Palik, Brian Josef. *Composition and Structure of Forest Edge in Beech-Sugar Maple and Oak Fragments in Central Lower Michigan*. 1988. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/7ZXT-5433.

Pourpeikari Heris, Mehdi, et al. "Assessing the Accuracy and Potential for Improvement of the National Land Cover Database's Tree Canopy Cover Dataset in Urban Areas of the Conterminous United States." *Remote Sensing*, vol. 14, no. 5, 5, Jan. 2022, p. 1219. *www.mdpi.com*, https://doi.org/10.3390/rs14051219.

Reemts, Charlotte Murray. *Temperate Deciduous Forest Fragments: Edge Effects, Invasion by Non-Native Plants, and Long-Term Change in Mature Forest Structure*. 2005. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/Z0T2-YF88.

Rutherford, J. Christopher. "Meandering Reduces the Influence of Stream Orientation on Riparian Shade." *Hydrological Processes*, vol. 37, no. 4, Apr. 2023, p. e14859. *DOI.org (Crossref)*, https://doi.org/10.1002/hyp.14859.

Sarti, Maurizio, et al. "Trees Outside Forest in Italian Agroforestry Landscapes: Detection and Mapping Using Sentinel-2 Imagery." *European Journal of Remote Sensing*, vol. 54, no. 1, Jan. 2021, pp. 610–24. *Taylor and Francis+NEJM*, https://doi.org/10.1080/22797254.2021.1986678.

Schiefer, Felix, et al. "Mapping Forest Tree Species in High Resolution UAV-Based RGB-Imagery by Means of Convolutional Neural Networks." *ISPRS Journal of Photogrammetry and Remote Sensing*, 2020. https://doi.org/10.1016/j.isprsjprs.2020.10.015.

Tang, Swee May. *Lower Michigan's Forest Patches*. 1991. Michigan State University. *DOI.org (Datacite)*, https://doi.org/10.25335/MD85-W604.

Thomas, N., et al. "Trees Outside Forests Are an Underestimated Resource in a Country with Low Forest Cover." *Scientific Reports*, vol. 11, 2021. https://doi.org/10.1038/s41598-021-86944-2.

Vogeler, J., et al. *Evaluating GEDI Data Fusions for Continuous Characterizations of Forest Wildlife Habitat*. 2023. https://doi.org/10.3389/frsen.2023.1196554.

Weigelhofer, Gabriele, et al. "Effects of Riparian Forest Buffers on In-Stream Nutrient Retention in Agricultural Catchments." *Journal of Environmental Quality*, vol. 41, no. 2, 2012, pp. 373–79. *Wiley Online Library*, https://doi.org/10.2134/jeq2010.0436.

Zhang, Bin, et al. “Three-Dimensional Convolutional Neural Network Model for Tree Species Classification Using Airborne Hyperspectral Images.” *Remote Sensing of Environment*, vol. 247, Sept. 2020, p. 111938. *ScienceDirect*, https://doi.org/10.1016/j.rse.2020.111938.

Zurqani, H., et al. “Evaluating the Integrity of Forested Riparian Buffers over a Large Area Using LiDAR Data and Google Earth Engine.” *Scientific Reports*, vol. 10, 2020. https://doi.org/10.1038/s41598-020-69743-z.

Chapter 4: The State of Agroforestry Presence in Lakes States and the Role of Intentionality in its Management: Initial Survey Returns

Objectives:

- Present a tailored survey instrument to capture landowner motivations, management intensity, and intentionality in upper Midwestern agroforestry practices.
- Detail the survey development process and stratified random sampling approach to ensure broad representation across parcel sizes and states.
- Explore landowner intensity and intent dimensions, distinguishing between inherited features and actively managed agroforestry systems.
- Analyze initial survey responses to identify regional and demographic trends in agroforestry adoption.

4.0 Abstract

This chapter details the survey methodology and initial findings from a study to assess landowner interest in agroforestry and current adoption across the Great Lakes region. It describes the development of a tailored survey instrument aimed at capturing the nuanced motivations, decision-making processes, and agroforestry management practices of private landowners in the Upper Midwest. By building on previous instruments, such as the National Agroforestry Survey, and incorporating insights from regional studies, the survey was uniquely designed to measure intentionality and intensity as key factors characterizing the adoption and maintenance of agroforestry systems. Methodological innovations include parcel-specific identifiers for anonymized geospatial analysis and a stratified random sampling framework targeting private parcels across Wisconsin, Michigan, and Ohio, categorized by acreage. The survey was implemented in two waves to balance cost efficiency and response rates, beginning with a brief initial survey to establish baseline data, followed by an in-depth second wave targeting respondents from the first. The second wave primarily emphasized landowner priorities, conservation objectives, and management intensity. Initial response patterns, demographic characteristics, and descriptive statistics reveal significant regional and

demographic trends in agroforestry adoption. This establishes a methodological foundation for future studies while contributing to a broader understanding of how intentionality and intensity shape agroforestry practices in temperate regions.

4.1 Introduction

4.1.1 Background

Agroforestry (AF) brings together trees, shrubs, and agricultural production for benefits, including enhanced farm resilience, economic diversification, and ecosystem services (USDA 2019; Jose 2019). Its success depends on the decisions landowners make. Yet, one significant gap in AF research involves understanding the motivations and goals that prompt landowners to begin or maintain these integrated practices. Recent empirical work in the Great Lakes region (Benning 2024) reinforces that while traditional demographic factors may be less predictive of AF adoption, producers' perceptions of constraints—such as the labor required for tree management—and the availability of financial incentives are critical drivers of whether they adopt these practices. Scholars often note that landowner decisions are driven by a mix of economic, environmental, and cultural factors, but the precise role of intentionality—meaning an owner's motivation and planning horizon—remains underexamined in many AF studies (Arbuckle et al. 2009; Carlisle 2016). For example, Huff et al. (2019) compared family forest owners with and without farmland and found that overall forest management behaviors were remarkably similar, despite some differences in landholding characteristics, suggesting that owner intentionality may be influenced more by intrinsic motivations than by the type of land owned.

Intentionality has been broadly considered in agriculture, forestry, and behavioral research as an individual's capacity to envision and pursue specific outcomes based on personal values or goals (Montambault and Alavalapati 2005; Carlisle 2016; Floress et al. 2019). Early adoption models frequently emphasize attitudes, risk tolerance, and searching for new information

(Amare and Darr 2020; Prokopy et al. 2019). These constructs refer to an owner's mindset, yet few metrics exist for capturing the degree of purposefulness or planning within AF contexts (Stubblefield 2021). Agencies like the USDA offer definitions of AF systems as "intentional" integrations of trees with crops or livestock (USDA 2019), but they rarely include consistent frameworks to measure how and why landowners decide to integrate or maintain tree-based systems within working landscapes (Patel-Weynand et al. 2017; Bentrup et al. 2018).

The current study proposes a more systematic way of quantifying landowner intentionality in AF adoption to address this gap. This chapter uses the word "adoption" to define a landowner's or operator's intent to manage an existing agroforestry practice (either through a change in land tenure or through the subtraction of existing woody features to accommodate an AF practice) or actively plan for one continuously. The focus is on motivation (e.g., a drive for ecosystem services or long-term profit) and future planning (e.g., establishing multi-decade silvopasture rotations) rather than solely on observable land management steps. This differs from management intensity, which centers on the frequency and depth of interventions such as pruning, fertilizing, or livestock rotations (Jose 2019; Smith et al. 2021). A landowner might plant trees for wind protection with minimal upkeep—an instance of high intentionality yet lower intensity. Another might actively prune and thin on a short cycle for timber, indicating both strong planning and frequent interventions.

In the Great Lakes region, agroforestry practices include alley cropping of fruit or nut trees, silvopasture in marginal woodlots, and forested riparian buffers to protect water quality (Patel-Weynand et al. 2017). Research suggests that AF in this region can improve ecological health and offer economic returns through specialty products. Yet, the effect of landowner intentions on long-term success is poorly understood (Stubblefield 2021). This chapter aims to advance a framework for quantifying landowner intentionality in managing AF systems that range from low-maintenance buffers to high-investment silvopasture. This approach aims to clarify how motivation and future planning shape AF implementation and inform policy and practice in temperate farming–forest landscapes.

4.1.2 Literature Review

4.1.2.1 Role of Intentionality in Agroforestry

Agroforestry (AF) is frequently categorized under a “4 I’s” framework, which describes the integration of trees, shrubs, crops, and livestock through practices that are intentional, intensive, interactive, and integrated (USDA 2019; Patel-Weynand et al. 2017). The emphasis on intentionality is based on the idea that landowners or managers set clear objectives and then design and maintain AF configurations that meet these goals (Montambault and Alavalapati 2005; Carlisle 2016; Bentrup et al. 2018). Measuring intent, however, poses difficulties because it requires evaluating the purposeful planning and decision-making behind diverse management actions (Stubblefield 2021; Jose 2019). This can be complicated by variations in local climates, physical landscapes, and socioeconomic conditions that shape both the feasibility of AF activities and the evidence of purposeful adoption (Trozzo et al. 2014; Carlisle 2016).

Efforts to capture how strongly a manager intends to maintain AF features often hinge on whether the practices remain within definitional guidelines, such as integrating trees with crops or livestock in a systematically designed system (USDA 2019; Patel-Weynand et al. 2017). Efforts to capture intentionality have proven challenging because they require assessing observable management practices and the underlying motivations driving these decisions (Stubblefield, 2021; Benning, 2024). In some instances, individuals may have initially planted trees or shrubs to gain benefits like shade or shelter but later reduce upkeep or cease active management. This transition can lead to features that no longer fit standard AF categories, especially if the tree-crop or tree-livestock interactions become incidental (Bentrup et al. 2018). Researchers stress that identifying genuine intentionality involves distinguishing between landowners who actively invest in and perpetuate AF elements and those who allow their practices to lapse into unmanaged, tree-dotted fields or other forms of land use that lack deliberate design (USDA 2019a; Stubblefield 2021), although some forms of agroforestry function better without deliberate design and active management, such as riparian forest buffers.

4.1.2.2 Role of Land Tenure in Agroforestry

AF maintenance frequently requires intensive management, which includes careful tree establishment, ongoing thinning or pruning, and targeted grazing rotations (Jose 2019; Agroforestry Strategic Framework 2019–2024, USDA 2019b). In cases where a landowner inherits AF features, there may be uncertainty about the practices' original design and intent, leading to challenges in replicating or sustaining prior management regimes (Arbuckle et al. 2009; Montambault and Alavalapati 2005). If the new owner lacks awareness of the system's initial goals or has limited technical guidance, intentional and intensive management can lapse, causing the features to deviate from AF parameters (Stubblefield 2021).

Conversely, individuals with longer land tenure and a clear commitment to establishing AF systems typically show higher consistency in management intensity (Miller et al. 2012; Carlisle 2016). This consistency includes a willingness to invest in pruning schedules, livestock movement plans, and tree species diversification. Studies indicate that these long-tenured managers are more likely to sustain carefully planned interactions between the tree and crop or livestock components (Bentrup et al. 2018; Strong and Jacobson 2005). As a result, the land remains within a definitional AF framework, supporting ecosystem services like soil protection and improved habitat structure (Jose 2019; Patel-Weynand et al. 2017).

4.1.2.3 Landowner Intentionality Across Domains

Studies on landowner intention in agriculture underscore the variety of drivers behind adopting new practices, including profitability, environmental stewardship, and cultural values (Arbuckle et al. 2009; Carlisle 2016). Farmer intent is frequently linked to risk tolerance, social norms, and awareness of potential benefits, such as improved yields or resilience to market fluctuations (Carlisle 2016; Prokopy et al. 2019). Several models suggest that economic incentives and supportive networks often encourage farmers to experiment with novel approaches, although knowledge gaps can impede broader implementation (Stubblefield 2021).

Within the woodland or forest management scope, forester intent focuses on sustainability targets and ecological outcomes (Montambault and Alavalapati 2005; Kilgore et al. 2017). This can mean balancing timber production with long-term stewardship goals like carbon sequestration, wildlife habitat, and soil protection (Bentrup et al. 2018). Agroforestry intent, situated at the intersection of these domains, often arises from multiple motivations. For instance, while studies have traditionally linked AF intent with risk tolerance and access to new information (Carlisle 2016; Prokopy et al. 2019), recent regional surveys (Benning 2024) indicate that even when land managers value agroforestry's environmental benefits, challenges related to cost and technical knowledge can significantly constrain adoption. Some landowners center on profit, pursuing specialty crops or integrated livestock systems (Jose 2009). Others highlight conservation or climate adaptation, seeing tree-based practices as a path to soil restoration, biodiversity, or reduced climate risks (Patel-Weynand et al. 2017; Stubblefield 2021). Mixed motivations are common, reflecting the multifunctional nature of agroforestry (Trozzo et al. 2014).

4.1.2.4 Surveys in Agriculture, Forestry, and Agroforestry

Several approaches have emerged to measure the "adoption" of AF and other conservation practices, using instruments like the National Census of Agriculture and the National Agroforestry Survey (Smith et al. 2021; USDA 2019). The Census of Agriculture collects information on farm operations, land use, and practices related to agroforestry, but it may not always clearly differentiate AF features (Smith et al. 2021) or provide very much spatial precision in reported results. The National Agroforestry Survey, though more targeted, depends on respondents recognizing or classifying their systems as AF, posing challenges when the term itself is unfamiliar or variably applied (Stubblefield 2021; Patel-Weynand et al. 2017). Local and regional surveys also provide insights, as shown by Stubblefield's Master's Project in Missouri, which examined awareness of AF definitions and measured willingness to adopt specific practices (Stubblefield 2021). Similarly, Benning (2024) conducted a comprehensive survey among Minnesota and Wisconsin producers, revealing that while traditional demographic factors had limited influence, the way landowners perceived specific constraints (such as tree management labor and equipment incompatibility) and opportunities (like financial and technical assistance) strongly shaped AF adoption. This work underscores the importance of using tailored survey instruments to capture the nuanced intentionality behind land-use decisions. A landowner or operator's mindset—whether they are actively pursuing a practice or resisting change—creates a dynamic of "lock-in." Lock-in can refer to a commitment to current practices or the difficulty of shifting away from them, and these patterns shape AF adoption or a stakeholder's capacity and willingness to change practices or dedicate space to an AF practice (Goldstein et al., 2023). We emphasize that diligent survey design, sampling approaches, and follow-up measures are critical for capturing the subtle motivations and intensities behind AF adoption and/or lock-in (Prokopy et al. 2019). Researchers and extension professionals frequently encounter sampling challenges in the Great Lakes region, including identifying landowners who engage in partial AF without labeling it as such (Arbuckle et al. 2009; Smith et al. 2021). Consequently, tailored survey instruments and follow-up interviews are often recommended to clarify whether and how respondents incorporate trees, shrubs, and perennial species within working landscapes (Stubblefield 2021, Kellerman et al., 2025).

4.1.3 Survey Design and Methodological Challenges

4.1.3.1 Addressing Survey Response Rates

Improving survey response rates is a critical methodological challenge addressed by adopting targeted incentives and systematic follow-up procedures, although survey response rates continue to decline nationwide within the US. Several studies have demonstrated that offering monetary and non-monetary incentives can effectively motivate potential respondents, while subsequent follow-up contacts—such as reminder postcards or emails—prompt additional participation (Strong & Jacobson, 2005; USDA, 2019). These techniques have been shown to increase overall response rates and enhance the representativeness of the survey sample by reaching segments of the population that might otherwise remain unresponsive.

In addition, integrating digital and mail-based survey approaches has proven beneficial in broadening outreach. Digital surveys offer rapid, cost-effective distribution and are particularly useful for engaging respondents who are comfortable with online communication. Conversely, mail surveys ensure that individuals with limited internet access or lower digital literacy are not excluded from the survey process. This dual-mode strategy, supported by evidence from both AF and broader land use studies, facilitates comprehensive coverage and reduces mode-specific biases (Montambault & Alavalapati, 2005; Arbuckle et al., 2009).

4.1.3.2 Insights from Survey Best Practices for Environmental and Land Use Studies

Best practices in survey research within environmental and land use studies consistently emphasize the importance of clear communication and the establishment of trust with respondents. Literature in this field supports the use of well-crafted survey instruments that incorporate personalized contact strategies—such as tailored invitations and follow-up communications—to foster a sense of engagement and commitment among participants (Trozzo et al., 2014). Such practices help to mitigate common concerns about survey relevance and confidentiality, thereby improving participation rates.

Moreover, combining digital and mail survey methods expands outreach and enhances data quality by accommodating diverse respondent preferences. This integrated approach enables researchers to leverage the strengths of each modality while minimizing their limitations. The resultant survey design is more likely to yield reliable, high-quality data that can inform robust analyses in environmental and land use research (USDA, 2019; Arbuckle et al., 2009).

4.2 Methods

4.2.1 Development of Survey Instrument

The survey instrument builds on foundational instruments such as the National Agroforestry Survey (USDA 2019) and other farmer-focused questionnaires that have assessed landowner practices and motivations (Smith et al. 2021). It also incorporates lessons from a recent Master's project in Missouri, which spotlighted how definitions and awareness shape AF willingness-to-adopt (Stubblefield et al., 2024). Early drafts underwent iterative revision with input from extension staff, agroforestry researchers, and university partners and collaborators to ensure language clarity and contextual relevance.

A central feature of the instrument novel to the study is the measurement of landowner intentionality. Drawing on frameworks highlighting motivational and planning horizons in AF adoption, the questionnaire uses carefully phrased items to differentiate between landowners who manage trees and crops with a specific purpose in mind and those whose land use or inclusion of an AF practice might be incidental or inherited. Questions are worded to allow respondents to indicate how frequently or intensely they conduct key tasks to gauge landowner activity within a definitive AF framework. As examples from the second wave of the survey instrument, the following intent questions capture the timing of windbreak or riparian buffer establishment, the frequency of their monitoring, and the specific maintenance practices employed, revealing the degree of intentionality in landowners' AF management. The full survey instruments are included in 4.8 Appendix B.

S4. When were windbreaks/riparian buffers first established on the land/this operation?

- ☐ Less than 5 years ago
- ☐ 5 years - less than 10 years ago
- ☐ 10 years - less than 15 years ago
- ☐ 15 years or more
- ☐ Don't know

S5. How often do you monitor your windbreaks/riparian buffers?

- ◯ Periodic assessments (ie, monthly, seasonally, annually) for integrity
- ◯ Non-periodically, but as needed for reporting or for alignment with land management
- ◯ Sporadically, spending on resource/time availability
- ◯ Rarely, only when there is a noticeable problem
- ◯ Never

S6. How do you maintain your windbreaks/riparian buffers? (Check all that apply)

- ☐ Periodic planting or replanting of buffer vegetation
- ☐ Regular pruning or thinning of vegetation
- ☐ Monitoring and managing for pests, invasive species, and disease
- ☐ Natural growth with no specific interventions

Likert scales from the Wave 2 instrument can also allow respondents to rank conservation priorities, economic objectives, and operational goals, while several open-ended prompts invite qualitative input. Combining these formats can facilitate richer data collection, allowing respondents to elaborate on unique motivations, barriers, or technical concerns. This mixed-style format expands on earlier surveys' structured responses and aligns with recommendations to capture quantitative and narrative nuances in AF decision-making (Stubblefield 2021; Strong & Jacobson 2005).

4.2.2 Study Area

The study focuses on the Great Lakes region, encompassing Wisconsin, Michigan, and Ohio. These three lakes states offer a critical window into temperate AF because they host abundant forested patches alongside extensive agricultural operations (Patel-Weynand et al. 2017). The region's climate supports perennial crops such as fruits and nuts, making it suitable for silvopasture, alley cropping, forest farming, and otherwise diversified woodlots. Varied topography and soils also support opportunities for tree-based conservation practices in both riparian and upland sites.

Numerous research and extension initiatives in the Great Lakes basin have introduced farmers and woodland owners to tree-crop systems for soil conservation, habitat enhancement, and economic returns (USDA 2019). Although industrial-scale agriculture remains prominent, there is also a vibrant network of smaller parcels under private ownership, where integrated tree practices can meet productivity and conservation goals (Bentrup et al. 2018). These features make the Great Lakes region instructive for evaluating how intentional AF management shapes landowner decisions.

Opportunities for new tree-based ventures, including specialty fruit and nut markets, show promise in these states. Concurrently, the region faces land-use pressures from urban expansion, legacy resource extraction, and shifting economic conditions (Arbuckle et al. 2009). The need to reconcile agricultural productivity with resource stewardship underscores the importance of examining AF adoption and management strategies in this region.

4.2.3 Sampling Framework

The study employed a stratified random sampling strategy, drawing on parcel-level ownership data from Wisconsin, Michigan, and Ohio. Parcels were filtered to exclude public or institutional owners, such as government entities, churches, and infrastructural organizations, to target individual and business landholders most likely to make land-use decisions in AF contexts (Stubblefield 2021). To capture variation in land size and potential management intensity, we divided parcels into three acreage groups—1–10 acres, 10–50 acres, and 50+ acres—and sampled equally from each stratum within each state, with 1000 surveys distributed for each state's distribution.

This framework ensures a spatially random and equitable representation of private parcels across the three states. We attached unique parcel identifiers to each survey, which enables anonymous linkage of a respondent's answers to specific property attributes (Patel-Weynand et al. 2017). This design supports more detailed geospatial analysis without compromising confidentiality. Unlike previous surveys that targeted self-identified farmers or foresters, this inclusive approach reflects the reality that many AF practitioners do not always align with conventional agricultural or forestry labels (Smith et al. 2021).

Varying parcel sizes, geographies, and management priorities can influence both the intensity of agroforestry (AF) management and the degree of intentionality in system design. Smaller landholders may engage with tree-based practices for personal use or aesthetic considerations, while larger operations often integrate AF into broader economic or land management strategies (Strong & Jacobson 2005). To capture this variation, we stratified our sample by acreage category. While no comprehensive dataset currently describes farm size patterns of AF systems at a national scale, this stratification offers a pragmatic approach given the limitations of existing data. Regional studies have provided some insight, but many suffer from limited sample sizes that restrict generalizability. Although data from the National Adaptation Plans (NAPs) initiative will eventually improve the resolution of farm size information, these data were not available at the time of study design. In the interim, proportional sampling across acreage categories remains the most viable method for examining how farm size influences AF adoption and maintenance.

4.2.4 Multiple-wave Survey Distribution

A two-wave survey approach was adopted to maximize both cost efficiency and response rates. In Wave 1, all sampled landholders received an introductory two-page (single sheet front and back) questionnaire designed to gauge general AF awareness and capture basic demographic information. A reminder postcard followed, featuring a QR code for those preferring an online response, and an additional hard-copy mailer. This first wave establishes a baseline understanding and encourages initial participation through a concise format.

Wave 2 targets respondents who completed the first questionnaire, providing a longer, 18-page booklet that probes more deeply into AF practices, motivations, and management intensities. This expanded format avoids redundancy by relying on previously collected demographic data, which is linked through each parcel/respondent’s unique and anonymous stratified parcel identifier. As with Wave 1, we plan to mail reminder postcards and offer an online response option, anticipating higher engagement from participants already invested in sharing their viewpoints.

The projected response rate draws on earlier AF surveys, which typically range from 10% to just under 50% when multiple follow-ups and calling efforts are utilized (National Agroforestry Survey, USDA 2019; Missouri master's project, Stubblefield 2021, Benning 2024). The two-wave strategy balances resource constraints with rigorous data collection, recognizing that an inexpensive initial mailing can prime interest. At the same time, the costlier, in-depth second wave elicits richer responses from already-engaged landholders who indicated a current or former interest in AF in some form as a land management practice.

4.3 Results

Wave 1 survey results are reported here based on responses collected between July and December 2024. This material reflects an initial subset of data as a follow-up initial wave of responses is underway. A second distribution of Wave 1 surveys began in January 2025, and Wave 2 mailings are active for those who participated in the initial survey window. Further analyses will incorporate these additional respondents and are expected to produce a more comprehensive view of landowner engagement with AF in the Great Lakes region.

4.3.1 Response Rates

Approximately 1,000 surveys were distributed in each state (Wisconsin, Michigan, and Ohio) per distribution cycle, with each parcel-size stratum (1–10 acres, 10–50 acres, 50+ acres) receiving roughly 333 mailings per state. A slightly adjusted total of 334 surveys was sent to the 1–10 acre group, bringing the sum for that stratum to precisely 1,000 per state. Each state's mailings had its respective institution branding represented on the survey cover letter for that state, which described AF and the five common AF practices as described by the National Agroforestry Center (NAC). The July–December 2024 mailings were not as strategically timed to align with periods when land managers were more likely to respond, noting that initial feedback that midsummer into harvest season mailings can often yield suboptimal returns due to high workloads or seasonal transitions (Arbuckle et al. 2009), or in a special case for the timing of this study, the timing of other frequent mailings around the 2024 election cycle. The second distribution in January–Spring 2025 aims to capture additional respondents during a period when agricultural and forestry workloads are typically slow, providing a second "window" for better coverage of a different set of landowners who had not responded in the first mailing.

A geographic overview of returns shows that respondents are relatively evenly dispersed across the three states, with visual inspection of parcel response point data indicating no discernible clusters or anomalies. The absence of concentrated pockets of respondents suggests a balanced spatial distribution, reflecting the effort to stratify sampling by both acreage and location across all three states. This geographic uniformity also implies minimal regional bias at this stage, though subsequent waves may illuminate patterns related to particular AF practices or local land-management networks (USDA 2019).

Preliminary total returned surveys indicate a moderately consistent response rate among the three parcel-size strata. Notably, thanks to extensive filtering and a manual checking of parcel-extracted mailing lists before the initial distribution of Wave 1, there were only 15 undeliverable surveys in the 3000-address distribution. Factoring in undeliverables, our adjusted total response rate for the first distribution of Wave 1 was 11.1%. Figure 1 depicts that the most significant portion of early returns comes from the 10–50 acre group, followed by the 50+ acre group, and then the 1–10 acre category. These early figures align with prior surveys showing that mid- to large-sized holdings can have somewhat higher engagement due to ongoing operational investments in both agricultural and forestry components (Stubblefield 2021).

Although responses are nearly even across states, Michigan had the highest response rate, followed by Wisconsin and then Ohio.

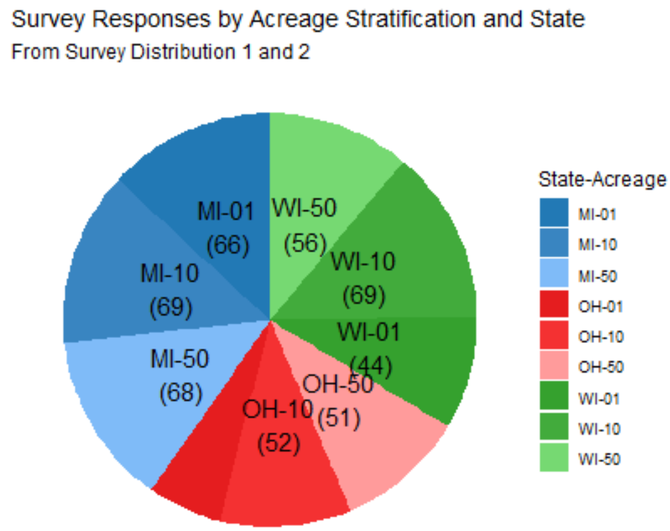

Figure 1: Survey responses by acreage stratification and state. This pie chart displays the distribution of survey responses from the first survey wave, categorized by state (Michigan, Ohio, and Wisconsin) and parcel size (1–10 acres, 10–50 acres, and 50+ acres). Each segment represents the number of respondents within a specific state-acreage group, illustrating a balanced return rate across both landholding categories and states. The OH-01 stratification is not labeled for this visualization; there were 29 responses from that state stratification.

Demographically, respondents vary in age, education, and tenure, with many landowners reporting long-term management of their parcels. A substantial subset has held their properties for over three decades, which may correlate with a deeper knowledge of AF practices and the inclination to consider integrated land uses. Educational attainment levels are generally above national averages for rural landowners, with a notable proportion holding associate's, bachelor's, or graduate degrees. Primary land use data reflect a mixture of cropland, forest land, and smaller segments dedicated to pasture or miscellaneous activities.

Overall, while these data represent only the first phase of Wave 1 returns and partial responses from the second Wave 1 distribution, the initial response rate and demographic breakdown suggest that the full subsequent distribution and the forthcoming Wave 2 survey will significantly enrich the dataset. As more responses are received, deeper cross-tabulations—particularly those linking tenure length, education level, and parcel size to AF adoption—will be possible, offering a clearer picture of how landowners across the Great Lakes region approach and implement integrated systems.

4.3.2 Descriptive Statistics

This section summarizes the demographic and land-related attributes of the 331 individuals who responded to the initial Wave 1 distribution of surveys and 173 responses from the second Wave 1 distribution of surveys, for a total of 504 responses. Not all responses received from this first wave had complete or valid responses, as the first qualifier question in our wave one instrument asked if respondents made at least $1000 in on-farm revenue. Key variables in this first response include parcel size, land tenure, education level, reliance on off-farm income, and self-reported agricultural or forested acreage use, in addition to questions on AF or AF-adjacent practice adoption. The data provide a foundational snapshot of Great Lakes region landowners, offering context for subsequent analyses of AF adoption and management decisions.

Parcel stratification was designed to capture different acreage groups—1–10 acres (01), 10–50 acres (10), and 50+ acres (50)—evenly distributed across Wisconsin (WI), Michigan (MI), and Ohio (OH). Michigan yielded 203 total responses, Ohio 132, and Wisconsin 169. Within these, the 10–50 acre category accounted for the highest proportion of respondents (37.7%, or 190), followed by those owning more than 50 acres (34.7%, or 175), and then the 1–10 acre group (27.6%, or 139). Preliminary results show Michigan having the largest response count.

Operator-reported acreage reflects the actual area each landowner manages, which sometimes extends beyond the single parcel used for sampling. Respondents report diverse land-use priorities, with cropland averaging 157.6 acres (n=233), forest land at 63.4 acres (n=256), other land uses at 53.6 acres (n=96), and permanent pasture at 50.8 acres (n=111). Land tenure shows a broad range, with a mean of 33.4 years of ownership.

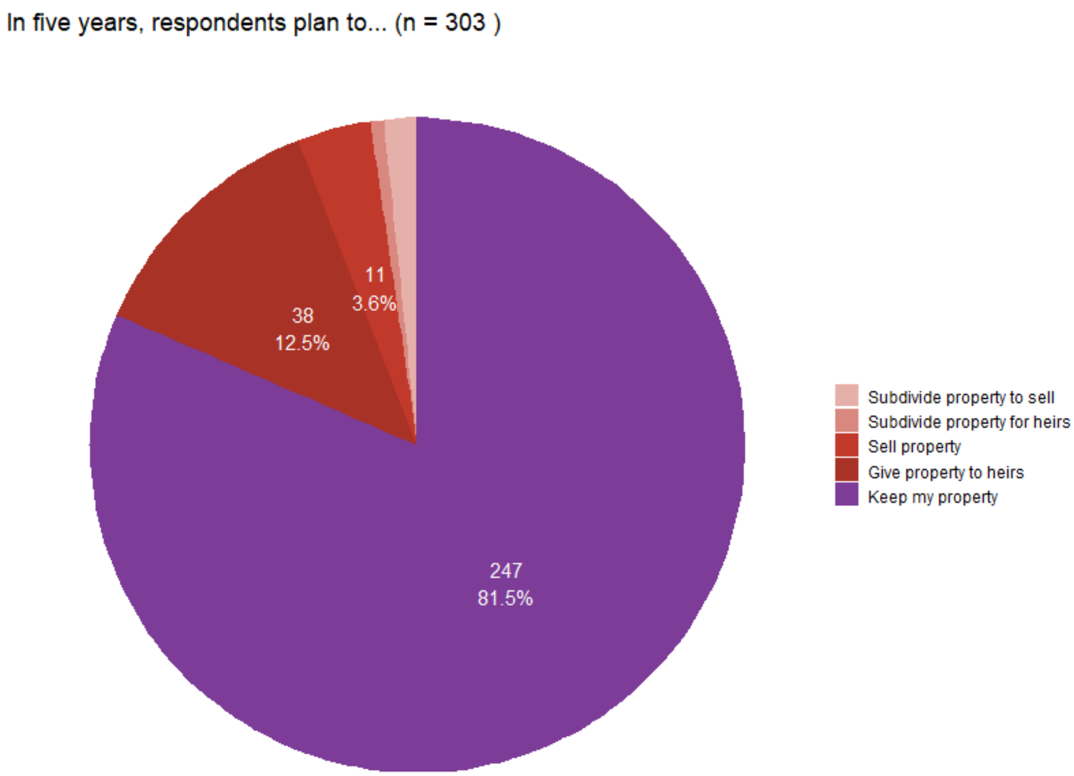

Figure 2: Future land management intentions of respondents. This pie chart illustrates how surveyed landowners (n = 303) plan to manage their landholdings over the next five years. The majority (81.5%) intend to keep their property, while 12.5% plan to pass it down to heirs. A smaller portion anticipates selling or subdividing their land, with subdivision for heirs or sale representing the least common future intentions. These findings indicate a strong preference for land retention and continuity in ownership.

Educational attainment among respondents is higher than typical rural landowner profiles, with 26.6% holding a bachelor's degree, 21.3% reporting graduate-level education, 19.7% some college, 21.3% a high school diploma, and 9.7% an associate's degree. Gender distribution remains predominantly male (79.4%), with 19.3% female and 1.3% responding with "Other/Prefer not to say".

Respondents represent a wide range of ages, with many individuals falling into middle-aged or older cohorts. The mean land tenure is approximately 33.4 years, suggesting a substantial history of property ownership. In parallel, many participants come from agrarian or forestry-related backgrounds, with 67.9% of respondents growing up on a farm, 64.2% with direct experience with woodlands, and nearly half reported prior farming involvement before acquiring their current parcels (Figure 3).

Renting or leasing land appears relatively uncommon within this sample. Out of 318 responses, 81.8% reported that they do not rent any portion of their owned acreage, 21.1% rent or lease less than half of the land they operate on (which they do not own), and 9.1% rent out all the land they own. Plans for the next five years underscore a strong commitment to current holdings: 81.5% intend to retain their properties, 12.5% plan to bequeath them to heirs, and a small subset anticipates selling or subdividing. These figures underscore the longer-term land-use stability among surveyed owners.

Income reliance indicates that 73.7% of respondents rely on off-farm income, 15.7% mainly rely on farm income, and 10.6% depend exclusively on farm-based revenue. Crops represent the most important source of on-farm income (154 responses), followed by “Other” (58), forest products (48), and livestock (34).

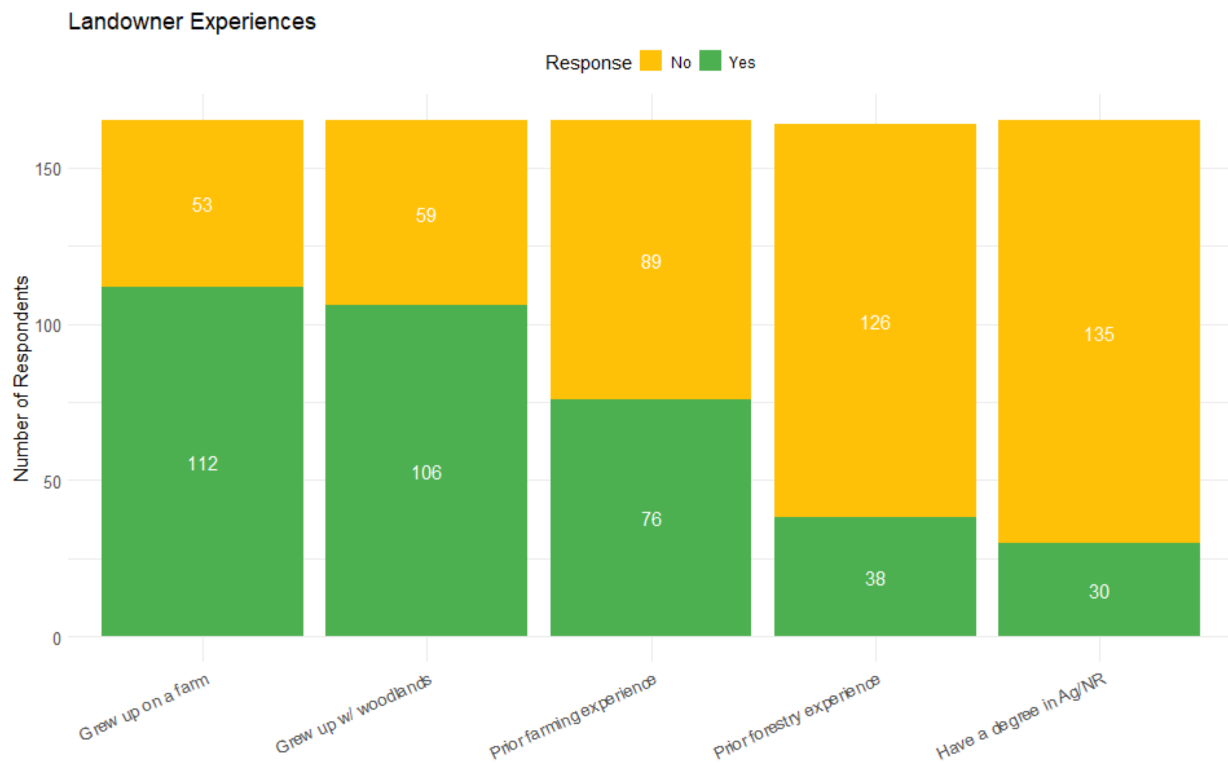

Figure 3: Landowner experiences related to agriculture and forestry. This stacked bar chart illustrates the number of survey respondents who reported having prior experience in various land-use activities. Categories include growing up on a farm, growing up with woodlands, prior farming experience, prior forestry experience, and holding a degree in agriculture or natural resources (Ag/NR). Green bars represent respondents with relevant experience, while yellow bars indicate those without. The data highlight the prevalence of backgrounds in farming and forestry among survey participants.

Beyond demographic and economic traits, the survey requested information on current and former AF practices. Responses indicate that the most common AF practices are windbreaks and riparian buffers, whereas practices like silvopasture and alley cropping show more significant segments of disinterest. A second version of the AF presence graph omitting “Not Interested” categories (see Appendix Figure 4.7.A1) underscores a pocket of interest in forest farming, maple syrup production, and other diversified systems. Such patterns set the stage for more detailed analysis in upcoming sections, especially as Wave 2 data becomes available.

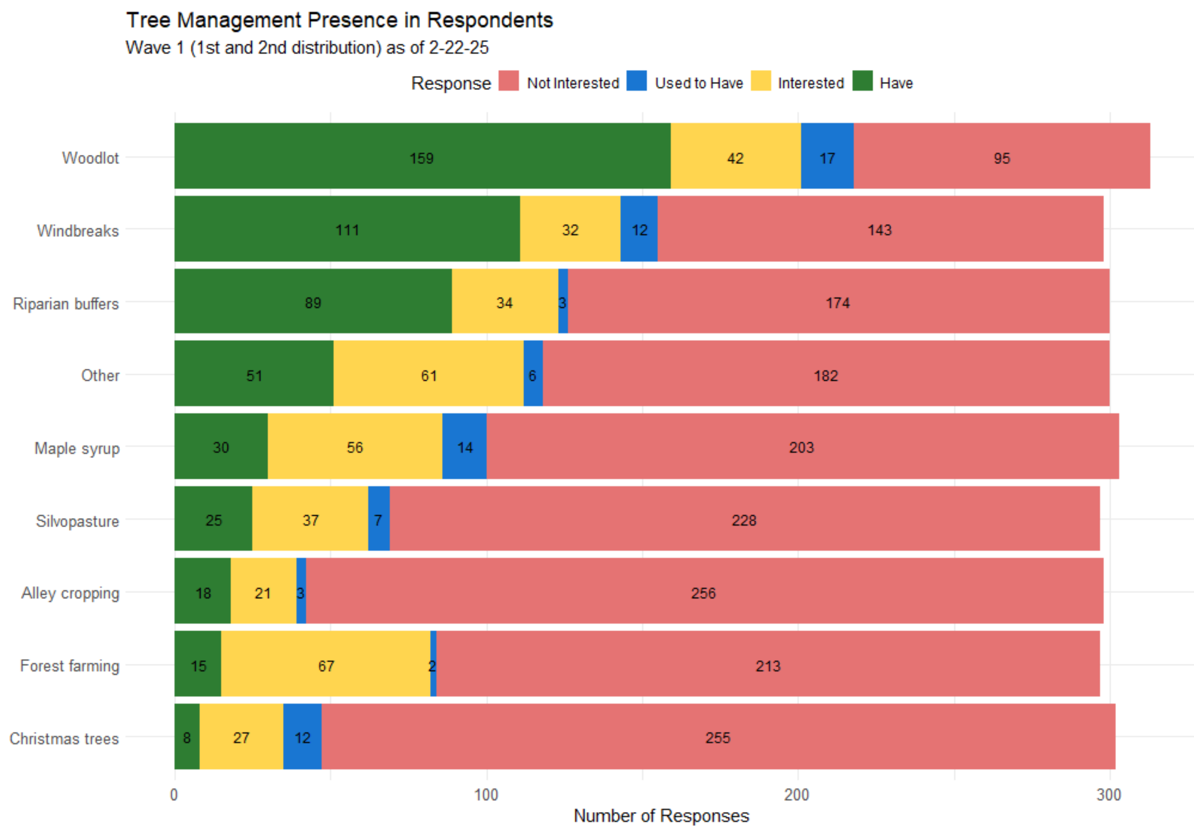

Figure 4: Agroforestry (AF) presence among respondents, including interest and past engagement. This bar chart illustrates the distribution of current, past, and prospective engagement in various AF practices as of Wave 1 (February 1, 2025) first distribution's final results. The responses are categorized into four groups: currently practicing AF (green), used to practice (blue), interested in adopting (yellow), and not interested (red). Windbreaks and riparian buffers show the highest current adoption, while silvopasture, and maple syrup production have moderate interest. Forest farming, although low in adoption rates possesses high levels of interest relative to its adoption rate. Alley cropping has a distinct general disinterest among respondents, highlighting potential barriers to adoption. Woodlots and christmas tree farming, although land use practices, were included on the survey and in the figure although they are not explicitly agroforestry practices. This figure provides insight into the growth potential and challenges for different AF practices among landowners.

4.3.3 Initial Patterns/Correlations

An initial correlation matrix highlights several relationships among the demographic and land management variables gathered through the survey. As a control, "Age" and "Years Operated" have a strong positive correlation (r = 0.387), which aligns with the finding that older participants typically report holding their properties for longer periods. This pattern is consistent with a tendency for family-owned parcels or multigenerational holdings, though the current dataset alone does not explain whether inheritance or active expansion drives this trend.

“Agroforestry Adoption,” based on the five USDA-defined agroforestry practices and Maple Syrup Production, and Experience Score also display a moderate positive correlation (r = 0.114*). This suggests that those who have engaged in farming or forestry tasks in the past—and thus hold more knowledge of land-based enterprises—report higher rates of integrating AF components. By contrast, reliance on farm income shows a weaker relationship with AF adoption (r = 0.135*). Its negative correlation with years operated (r = -0.256***) indicates that respondents who have farmed longer tend to diversify income streams instead of relying solely on agricultural pursuits.

When examining parcel size, educational attainment, and adoption, several statistical trends indicate that landowners with more formal education appear more likely to adopt AF. However, these education-related effects differ across states, suggesting that local conditions, networks, or extension programs may shape the decision-making process. A weak negative association between age and AF adoption (r = -0.099.) suggests that younger landowners could be more open to AF, although the overall pattern remains subtle.

Another relationship reveals that off-farm income correlates weakly with AF adoption (r = 0.135*). Landowners who rely on external employment or businesses may have additional flexibility to invest in long-term resource management strategies, while those who depend predominantly on farm income may perceive agroforestry’s lengthy establishment phase as an economic risk. The dataset does not indicate whether off-farm earners are more likely to receive grants or technical assistance; subsequent analyses could probe such mechanisms further.

Regional comparisons show that Wisconsin respondents exhibit modestly higher reported adoption rates of AF practices than their counterparts in Michigan and Ohio. These variations may stem from differences in cost-share programs, extension outreach, or historical familiarity with AF concepts. A companion chart contrasting adoption with stated interest suggests that

Michigan and Ohio contain more landowners who are intrigued by the idea of an AF practice yet have not implemented it, hinting at possible barriers around capital availability, technical guidance, or clarity on the perceived benefits.

Finally, stratification by acreage reveals that larger parcels (10-50 acres or more than 50 acres) display higher average adoption rates than smaller ones (1-10 acres). The correlation between years land was operated and AF adoption is weak (r = -0.107). Although response rates at this stage can have an impact on net results, Wisconsin parcels between 10 and 50 acres demonstrate the highest mean level of AF adoption, followed by all three states' 50-or-more-acre parcel responses, whereas 1-10 acre parcels across all three states show the lowest. This gap underscores the relevance of landholding size when considering the viability or attractiveness of AF practices. Although the current data do not explicitly clarify the reasons for this discrepancy, the finding underscores an important structural factor in the region's emerging AF landscape.

4.4 Discussion

4.4.1 Interpretation of Initial Findings

The demographic and geographic patterns observed in the results underscore a multifaceted interplay between landowner characteristics and AF adoption. Landowners with more years of operation, particularly those with diverse farm or forestry experiences, appear more likely to integrate tree-based agroforestry practices into their landscapes. Meanwhile, the data suggest that younger landowners could be open to experimentation, though the extent of their engagement may hinge on access to technical support and financial resources.

Education emerged as a factor that correlates with higher levels of adoption, reflecting how educational achievement may increase familiarity with AF concepts. Additionally, reliance on off-farm income corresponds with the willingness to pursue longer-term management horizons. This finding highlights the significance of economic stability in shaping decisions, as owners who depend less on immediate farm revenue may face fewer barriers when considering time-intensive or capital-intensive practices.

Regional nuances illustrate how policy environments, local outreach, and land-use histories can shape adoption rates. In some states, cost-share or incentive programs may align with higher levels of AF integration. Wisconsin exhibited the highest adoption rate out of the three states surveyed, although adoption of AF had a relatively inverse relationship with interest when compared to Michigan and Ohio (see Figure 4.7.A11). This may be due to statewide outreach efforts or incentives to adopt AF practices, or as a product of local organizations like the Agroforestry Coalition or Savanna Institute in Wisconsin, which have an impact on overall recognition of AF practices and some competencies associated with AF. Yet, even in areas of interest, potential adopters appear stymied by limited financial and technical guidance, as indicated by the general rate of 'disinterest' across all AF practices. These gaps emphasize the importance of local networks in facilitating both the introduction and refinement of tree-based management strategies on agricultural landscapes.

Across parcel sizes in our stratification, smaller holdings show lower participation in AF, implying that these practices may be perceived as more challenging to implement on limited acreage. Larger properties exhibit higher adoption, perhaps due to greater operational flexibility to accommodate AF practices or economies of scale. These findings suggest that AF uptake is shaped by a confluence of personal background, economic considerations, and external support structures, all warrant further examination as the survey expands to additional respondents and Wave 2 data.

4.4.2 Implications for Policy and Practice

The nuanced influences of land tenure, experience, and off-farm income underscore a need for carefully targeted policies. Incentive structures that account for these variables may encourage more widespread adoption by reducing upfront costs, clarifying technical requirements, or supporting long-term maintenance. Policymakers could tailor assistance to specific demographics—such as first-time landowners, smaller-acreage managers, or those in regions with historically low engagement—to address distinct barriers and foster inclusive participation. Landowner characteristics also hint at the usefulness of parcel-level outreach strategies. For instance, linking site-specific property data with educational or planning materials (such as the novel commercial CanopyCompass tool, although it is not peer reviewed) could enhance relevance and encourage adoption among landowners uncertain about the feasibility of tree-based systems. Extension services can bolster confidence in agroforestry's practicality by demonstrating potential returns or co-benefits in a localized context. Digital tools and personalized consultations can further strengthen these initiatives.

In addition, field programs that integrate economic modeling or training could appeal to landowners worried about the financial implications of time-intensive tree establishment. Showcasing successful, context-specific demonstrations—particularly in areas where AF has a track record of stable or profitable results—may help dispel concerns about risk. Many efforts in AF communities of practice in the Midwest are being put towards developing AF demo farms to advance this mission. Cooperative ventures, including shared equipment or marketing support, can be facilitated through these channels, lowering the perceived hurdles associated with new management practices.

Finally, regional customization of extension efforts holds promise. Aligning outreach with state-level policies, local knowledge networks, and existing agricultural programs may streamline the integration of AF into diverse production systems. Tailored workshops, cost-sharing frameworks, and mentorship opportunities could connect landowners to both technical expertise and supportive peer networks. Such a holistic approach positions AF as a viable path to ecological resilience and economic diversification across varying property sizes and ownership backgrounds.

4.4.3 Comparison with Previous Surveys

Our findings align with national AF surveys, demonstrating that our study's general adoption trends and demographic patterns mirror those reported on a broader scale, although we attempt to provide much more spatial detail across a swath of land ownership categories with our sampling framework. For instance, the distribution of landholding sizes and the prevalence of off-farm income in our sample corroborate national data, lending credibility to our survey instrument and reinforcing the consistency of these influential factors across diverse agricultural settings (Smith et al., 2021; Smith et al., 2022).

In addition, our results are consistent with regional studies from the Midwest (Huff et al., 2019; Stubblefield, 2021; Stubblefield et al., 2024; Benning et al., 2024) that have noted higher AF adoption among larger landholders and the nuanced role of economic stability in AF adoption. This convergence between our data and previous local surveys underscores the reliability of our findings while highlighting the continuing relevance of factors such as education and local policy environments. Together, these cross-references validate our approach and suggest that the key drivers identified in our study have broad applicability.

4.4.4 Future Research Directions

The upcoming Wave 2 of our survey offers a promising opportunity to deepen our understanding of AF adoption. By comparing data from both waves, we expect to clarify emerging trends and better capture the dynamics of landowner engagement over time. This longitudinal insight is essential for distinguishing between short-term fluctuations and more persistent behavioral shifts.

Future studies should focus on tracking qualitative individual landowner adoption trajectories over successive growing seasons. Such longitudinal tracking would help pinpoint critical transition moments and assess the long-term effectiveness of financial incentives, technical assistance, and educational outreach. Understanding these temporal dynamics will enable researchers and policymakers to design interventions that support sustained AF integration. Expanding the geographic scope of our research to include additional Great Lakes or Upper Midwestern states—such as Minnesota, where recent studies indicate promising adoption potential (Benning 2024) — will further enhance our findings. A broader survey can capture regional variations in policy support, market conditions, and natural resource challenges, ultimately leading to more tailored and practical recommendations for increasing AF adoption across diverse settings.

Finally, integrating our survey data with complementary methodologies like remote sensing and geospatial analysis will yield a richer, multi-dimensional dataset. These techniques can provide spatially explicit insights into land use patterns and AF system distribution, refining our understanding of how physical and environmental factors interact with socioeconomic drivers.

4.5 Conclusion

This chapter has established a robust methodological framework for examining agroforestry adoption through the lens of landowner intentionality and management intensity. By detailing the development of a tailored survey instrument, along with the strategic use of parcel-specific identifiers and a stratified random sampling approach, we have laid the groundwork for nuanced data collection that captures both the quantitative and qualitative dimensions of AF practices across the Great Lakes region. The initial findings—illustrating consistent demographic trends, varied levels of AF engagement, and key relationships among landholding characteristics—demonstrate the potential of this instrument to yield insights that resonate with national and regional surveys.

Ultimately, these preliminary results underscore the multifaceted influences shaping AF adoption, from land tenure and off-farm income to education and local policy environments. As we prepare to incorporate additional data from the forthcoming Wave 2, future research will refine these trends and explore their implications for targeted outreach and policy design. This chapter validates our approach by aligning with previous studies and charts a course for ongoing investigations to inform sustainable agricultural practices and enhance support for AF integration in temperate regions.

REFERENCES

Agroforestry Strategic Framework: Fiscal Years 2019-2024. USDA-FS.

Amare, Dagninet, and Dietrich Darr. "Agroforestry Adoption as a Systems Concept: A Review." *Forest Policy and Economics*, vol. 120, Nov. 2020, p. 102299. *ScienceDirect*, https://doi.org/10.1016/j.forpol.2020.102299.

Arbuckle, J. Gordon, et al. "Non-Operator Landowner Interest in Agroforestry Practices in Two Missouri Watersheds." *Agroforestry Systems*, vol. 75, no. 1, Jan. 2009, pp. 73–82. *Springer Link*, https://doi.org/10.1007/s10457-008-9131-8.

Benning, Maxwell Healey. *Identifying the Factors That Constrain and Facilitate the Adoption of Agroforestry Practices by Minnesota and Wisconsin Agricultural Producers*. May 2024. *conservancy.umn.edu*, https://hdl.handle.net/11299/264278.

Bentrup, Gary, et al. "Supporting U.S. Agricultural Landscapes under Changing Conditions with Agroforestry: An Annotated Bibliography." *Bibliographies and Literature of Agriculture 137. Washington, DC: U.S. Department of Agriculture Forest Service. 63 p.*, vol. 137, 2018. *research.fs.usda.gov*, https://research.fs.usda.gov/treesearch/56389.

Carlisle, Liz. "Factors Influencing Farmer Adoption of Soil Health Practices in the United States: A Narrative Review." *Agroecology and Sustainable Food Systems*, vol. 40, no. 6, July 2016, pp. 583–613. *DOI.org (Crossref)*, https://doi.org/10.1080/21683565.2016.1156596.

Floress, Kristin, et al. "Factors Associated with Family Forest Owner Actions: A Vote-Count Meta-Analysis." *Landscape and Urban Planning*, vol. 188, Aug. 2019, pp. 19–29. *ScienceDirect*, https://doi.org/10.1016/j.landurbplan.2018.08.024.

Goldstein, Jenny E., et al. "Unlocking 'Lock-In' and Path Dependency: A Review across Disciplines and Socio-Environmental Contexts." *World Development*, vol. 161, Jan. 2023, Article 106116, pp. 1–22, doi:10.1016/j.worlddev.2022.106116.

Huff, Emily S., et al. "Where Farm and Forest Meet: Comparing National Woodland Owner Survey Respondents with and without Farmland." *Land Use Policy*, vol. 87, Sept. 2019, p. 104007. *ScienceDirect*, https://doi.org/10.1016/j.landusepol.2019.05.026.

Jose, Shibu. "Environmental Impacts and Benefits of Agroforestry." *Oxford Research Encyclopedia of Environmental Science*, 2019. *oxfordre.com*, https://doi.org/10.1093/acrefore/9780199389414.013.195.

Kellerman, Todd, et al. "Agroforestry across the United States: Results of the 2022 Census of Agriculture." *Agroforestry Systems*, vol. 99, no. 2, Feb. 2025, p. 34. *Springer Link*, https://doi.org/10.1007/s10457-024-01096-2.

Miller, Kristell A., et al. “An Assessment of Forest Landowner Interest in Selling Forest Carbon Credits in the Lake States, USA.” *Forest Policy and Economics. 25: 113-122.*, vol. 25, 2012, pp. 113–22. *research.fs.usda.gov*, https://doi.org/10.1016/j.forpol.2012.09.009.

Montambault, Jensen Reitz, and Janaki R. R. Alavalapati. “Socioeconomic Research in Agroforestry: A Decade in Review.” *Agroforestry Systems*, vol. 65, no. 2, Nov. 2005, pp. 151–61. *Springer Link*, https://doi.org/10.1007/s10457-005-0124-6.

Patel-Weynand, Toral, et al. *Agroforestry: Enhancing Resiliency in U.S. Agricultural Landscapes Under Changing Conditions*. WO-GTR-96, U.S. Department of Agriculture, Forest Service, 2017, p. WO-GTR-96. *DOI.org (Crossref)*, https://doi.org/10.2737/WO-GTR-96.

Prokopy, L. S., et al. “Adoption of Agricultural Conservation Practices in the United States: Evidence from 35 Years of Quantitative Literature.” *Journal of Soil and Water Conservation*, vol. 74, 2019, pp. 520–34. *research.fs.usda.gov*, https://doi.org/10.2489/jswc.74.5.520.

Smith, Matthew M., et al. “Windbreaks in the United States: A Systematic Review of Producer-Reported Benefits, Challenges, Management Activities and Drivers of Adoption.” *Agricultural Systems*, vol. 187, Feb. 2021, p. 103032. *ScienceDirect*, https://doi.org/10.1016/j.agsy.2020.103032.

Smith, Matthew M., et al. “Silvopasture in the USA: A Systematic Review of Natural Resource Professional and Producer-Reported Benefits, Challenges, and Management Activities.” *Agriculture, Ecosystems & Environment*, vol. 326, Mar. 2022, p. 107818. *ScienceDirect*, https://doi.org/10.1016/j.agee.2021.107818.

Strong, Nicole A., and Michael G. Jacobson. “Assessing Agroforestry Adoption Potential Utilising Market Segmentation: A Case Study in Pennsylvania.” *Small-Scale Forest Economics, Management and Policy*, vol. 4, no. 2, June 2005, pp. 215–28. *Springer Link*, https://doi.org/10.1007/s11842-005-0014-9.

Stubblefield, Kelsi Jordan. *Agroforestry Adoption: Influential Factors, Land Manager Perceptions, and Willingness-to-Accept Payments*. 2021. University of Missouri--Columbia, M.S. *DOI.org (Crossref)*, https://doi.org/10.32469/10355/90197.

Stubblefield, Kelsi, et al. “Factors Affecting Missouri Land Managers’ Willingness-to-Adopt Agroforestry Practices.” *Agroforestry Systems*, vol. 99, no. 1, Dec. 2024, p. 16. *Springer Link*, https://doi.org/10.1007/s10457-024-01117-0.

Trozzo, Katie E., et al. “Landowner Interest in Multifunctional Agroforestry Riparian Buffers.” *Agroforestry Systems*, vol. 88, no. 4, Aug. 2014, pp. 619–29. *DOI.org (Crossref)*, https://doi.org/10.1007/s10457-014-9678-5.

APPENDIX A - Additional Visualizations

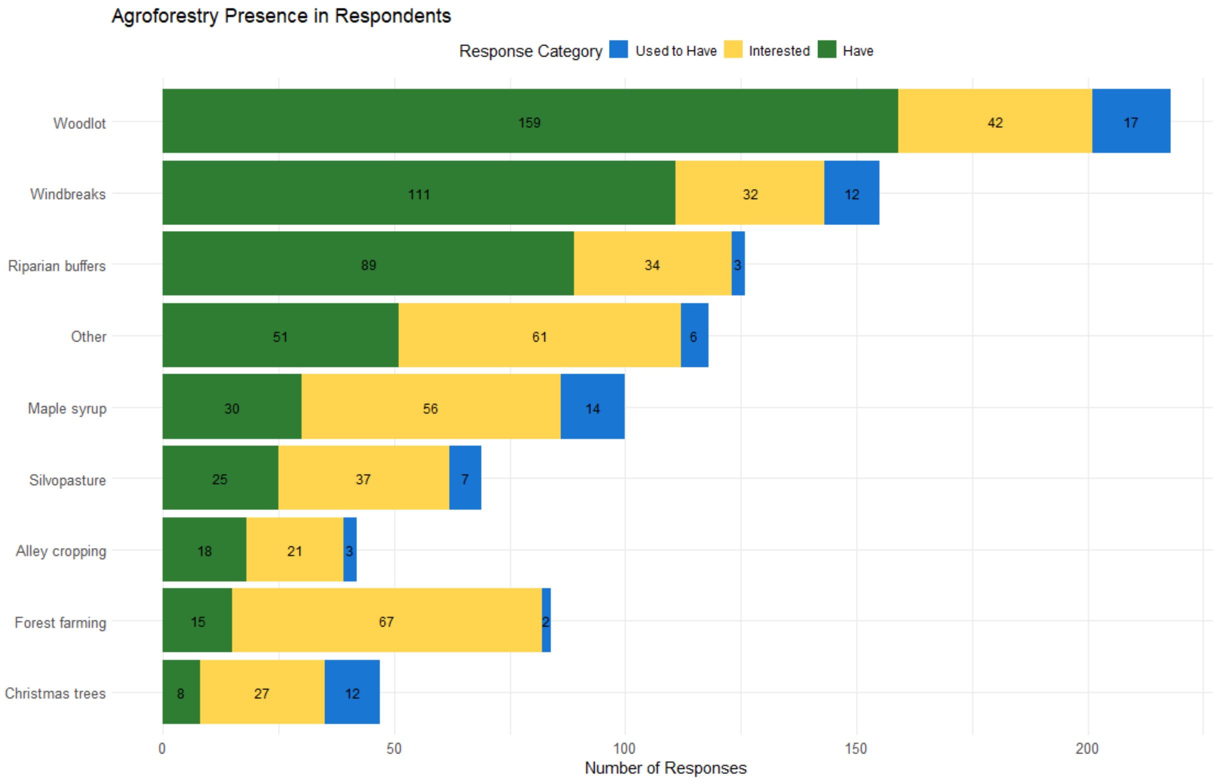

Fig 4.7.A1: Agroforestry presence among respondents. This bar chart illustrates the prevalence of different agroforestry practices reported by survey respondents. The responses are categorized into three groups: currently have the practice (green), used to have the practice (blue), and interested in adopting the practice (yellow). Woodlots and windbreaks are the most commonly maintained agroforestry features, while riparian buffers, maple syrup production, and forest farming show moderate levels of interest. Practices like alley cropping and Christmas tree production have lower overall adoption rates but still show some interest among respondents.

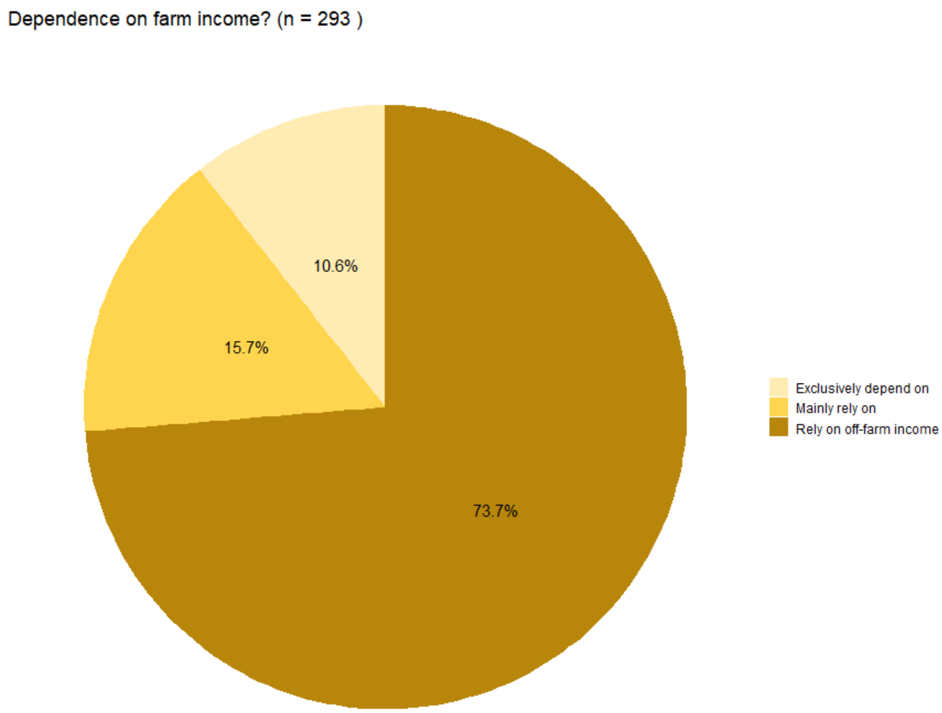

Figure 4.7.A2: Dependence on farm income among respondents. This pie chart illustrates the distribution of farm income reliance among survey respondents (n = 293). The majority (73.7%) rely primarily on off-farm income, while 15.7% report that they mainly rely on farm-generated revenue. Only 10.6% of respondents exclusively depend on farm income. These findings suggest that most landowners supplement their agricultural earnings with external income sources, which may influence their ability to invest in long-term land management practices such as agroforestry.

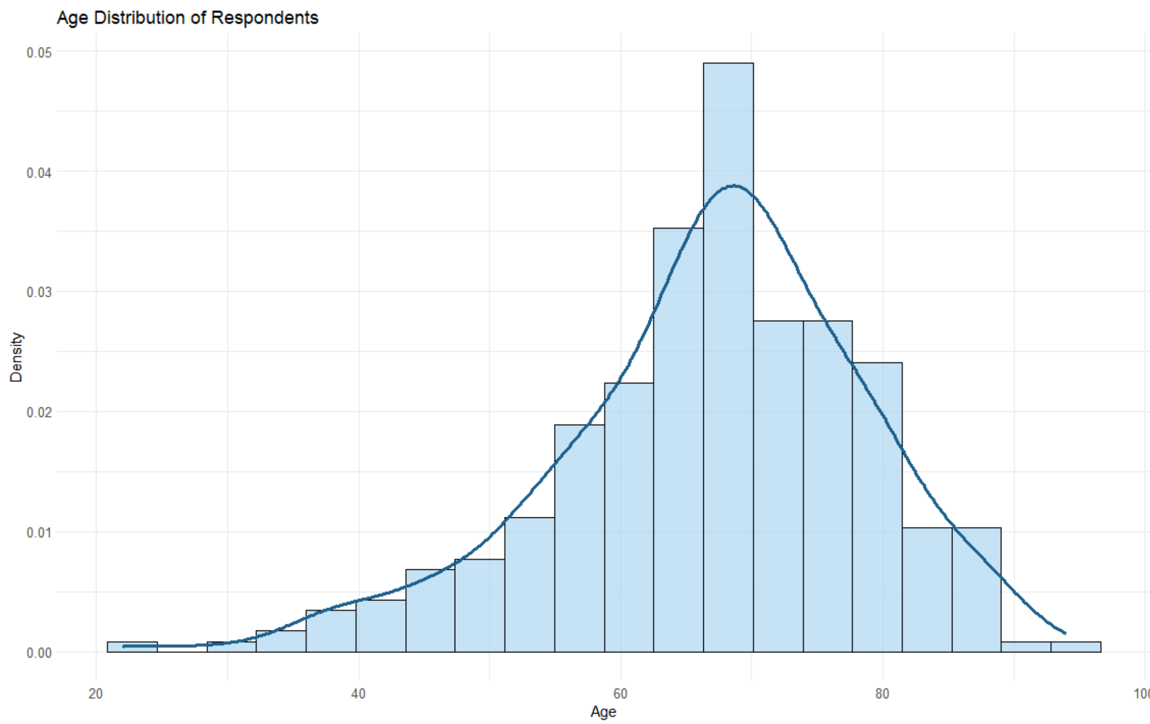

Figure 4.7.A3: Age distribution of 307 survey respondents. This histogram with a density curve illustrates the age distribution of landowner respondents. Most respondents are between 50 and 80 years old, peaking around the mid-60s. The average age was 66.9 years old. The distribution skews slightly older, suggesting that a significant portion of surveyed landowners are in or approaching retirement age, which may have implications for land management decisions and succession planning.

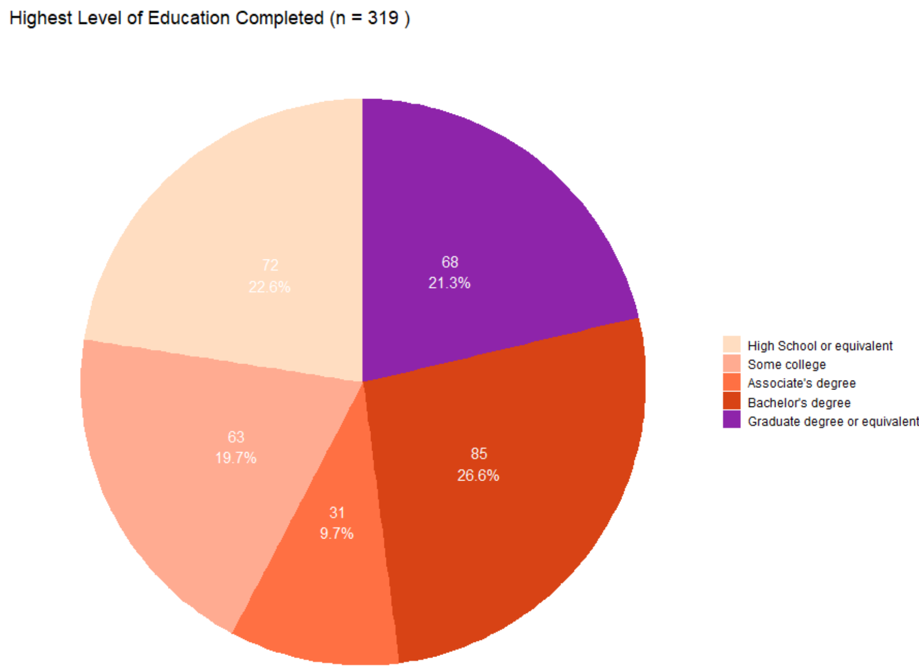

Figure 4.7.A4: Highest level of education completed by respondents. This pie chart illustrates the educational attainment of surveyed landowners (n = 319). The largest groups hold either a high school diploma or a bachelor's degree (26.6% each), followed by respondents with some college experience (19.7%), a graduate degree (21.3%), or an associate's degree (9.7%). These findings indicate a relatively high level of formal education among landowners, which may influence agroforestry knowledge and adoption.

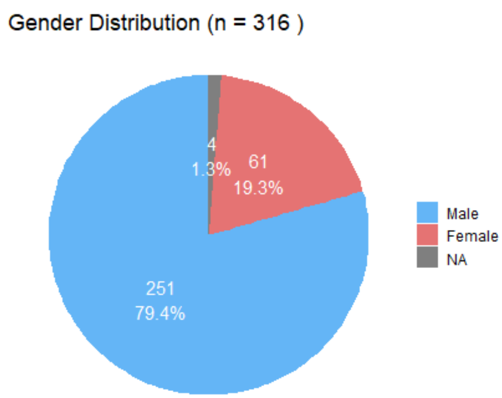

Figure 4.7.A5: Gender distribution of survey respondents. This pie chart displays the gender breakdown among respondents (n = 316). The majority (79.4%) identify as male, while 19.3% identify as female. A small percentage (1.3%) selected 'Other/Prefer not to say'. This distribution reflects common trends in land ownership and agricultural management demographics.

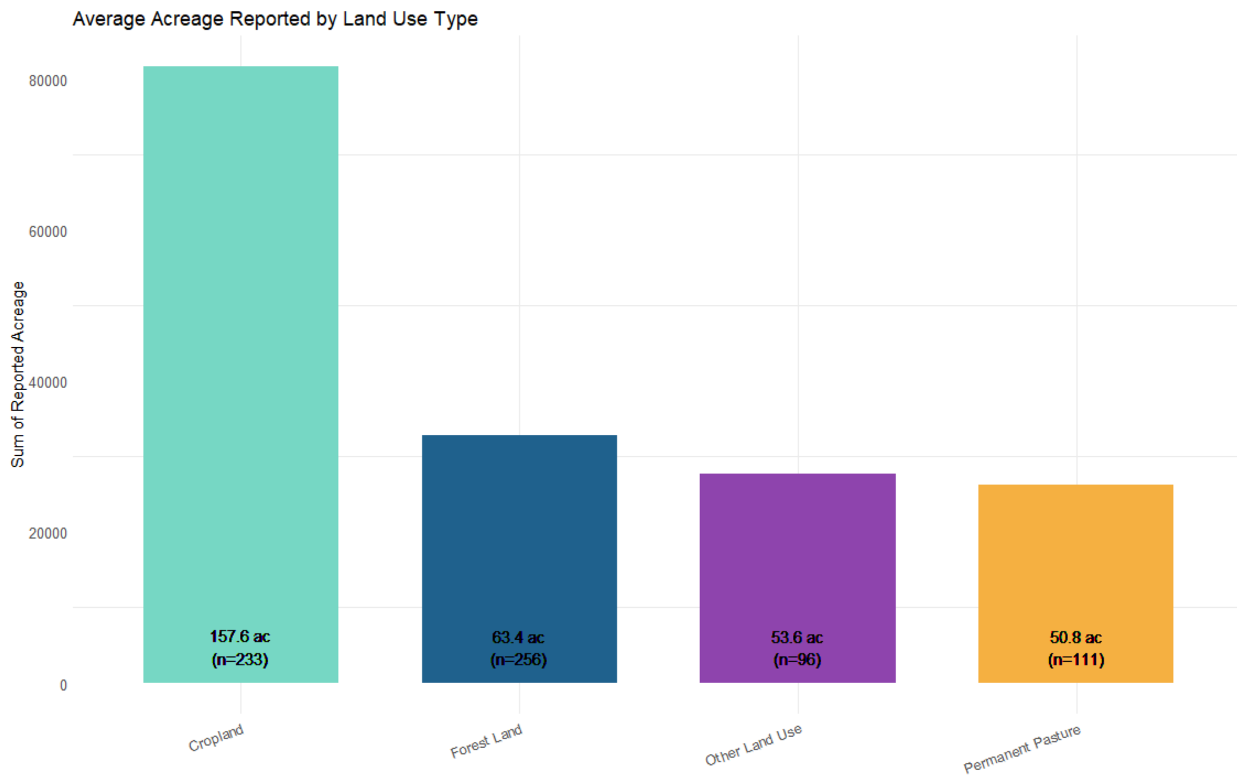

Figure 4.7.A6: Average acreage reported by land use type. This bar chart presents the average acreage managed by survey respondents (n varies by category) across four primary land use types: cropland, forest land, other land use, and permanent pasture. Cropland has the highest average acreage (157.6 acres), followed by forest land (63.4 acres), other land uses (53.6 acres), and permanent pasture (50.8 acres). The variation in land use categories highlights the diversity of land management approaches among respondents.

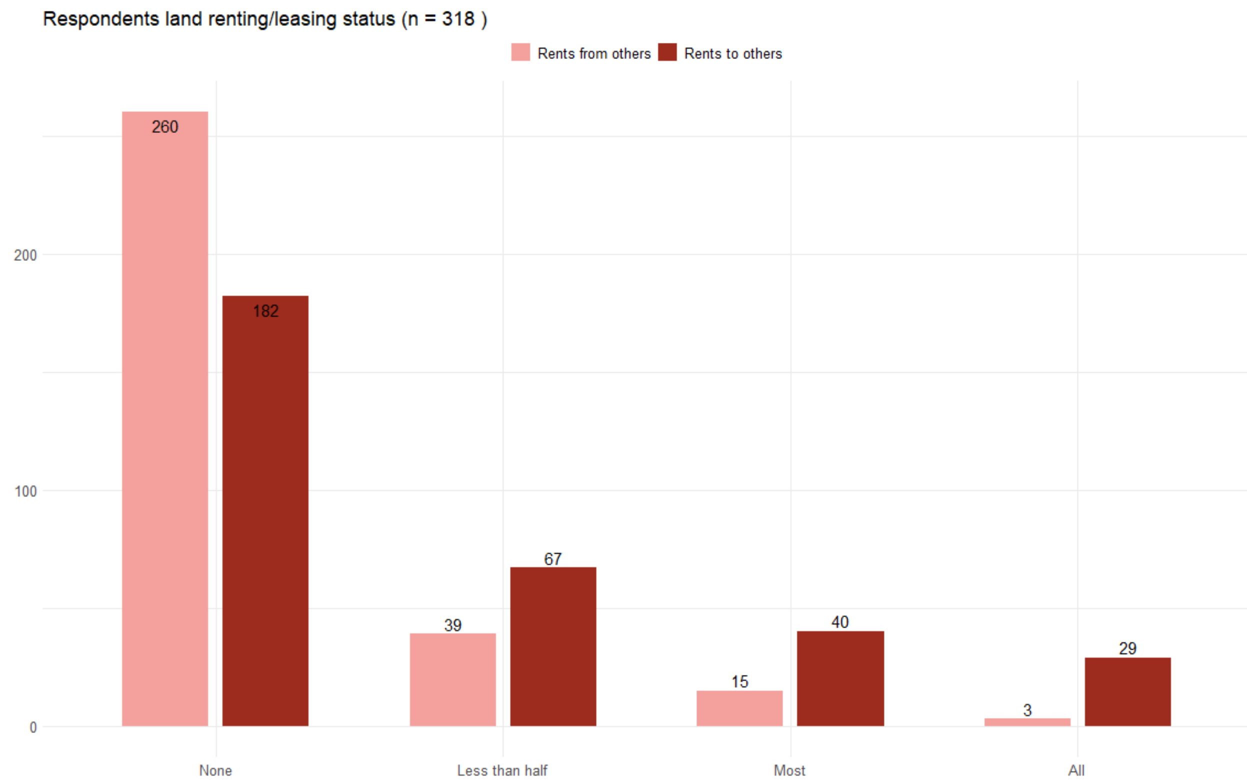

Figure 4.7.A7: Land renting and leasing status among respondents. This bar chart presents the distribution of land leasing practices among surveyed landowners (n = 318). The light pink bars represent respondents who rent land from others, while the dark red bars indicate those who rent land to others. The majority of respondents neither rent nor lease land, while a smaller subset participates in leasing arrangements to varying degrees. This data provides insight into land tenure dynamics within the surveyed population.

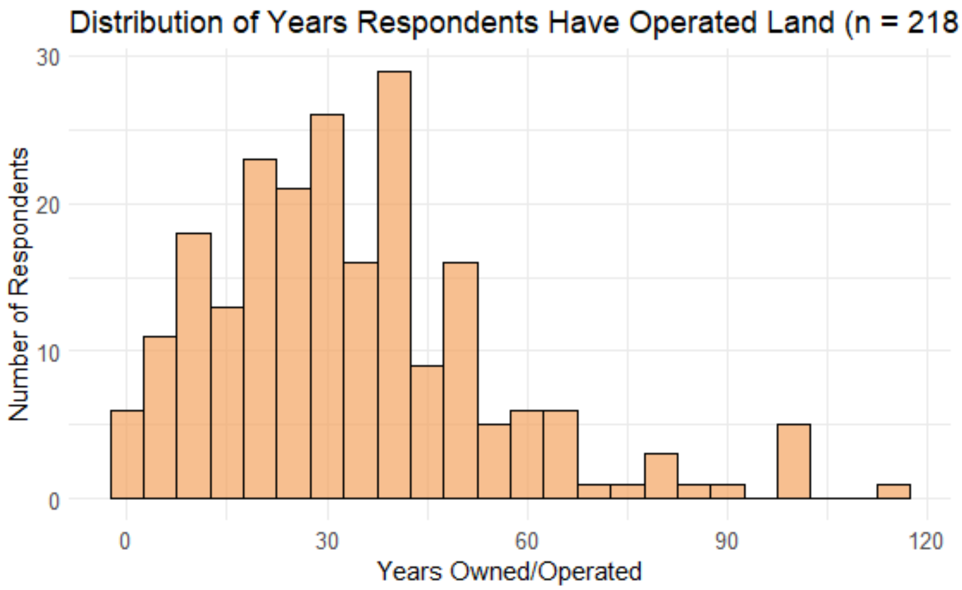

Figure 4.7.A8: Distribution of years respondents have operated land. This histogram displays the years survey respondents (n = 218) have owned or managed their land (only distribution 1 responses). Most respondents have operated their land for 10 to 40 years, with an average just over 30 years. A smaller subset reports ownership exceeding 60 years, with a few outliers managing land for over 90 years. This distribution suggests that many landowners have long-term land tenure through generations, which may influence agroforestry adoption and long-term management decisions.

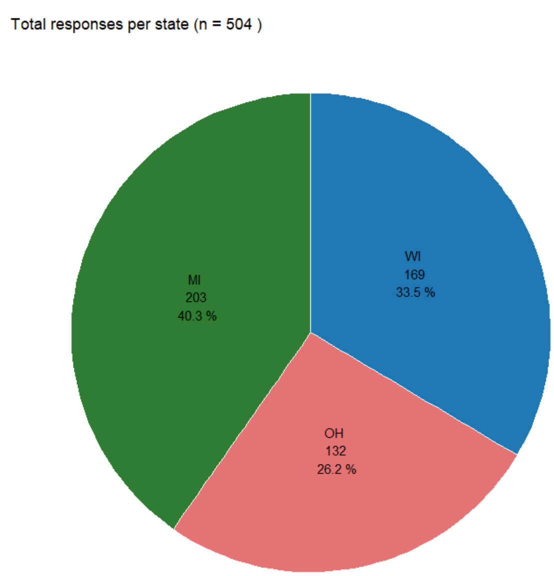

Figure 4.7.A9: Pie chart showing the total number of received, although not necessarily not usable survey responses by state (n = 504). Michigan (MI) accounts for the largest share of returns, followed by Wisconsin (WI) and Ohio (OH).

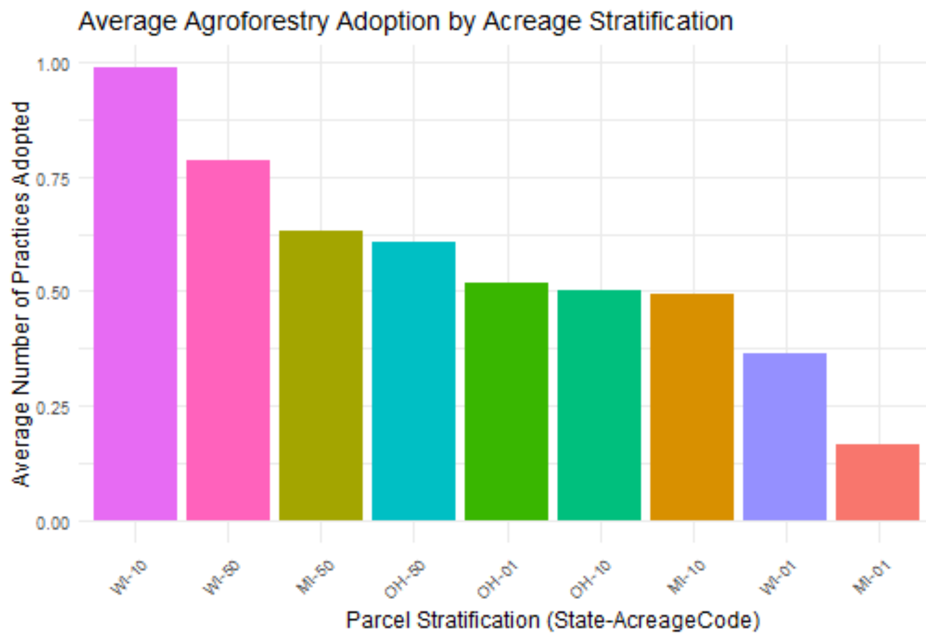

Figure 4.7.A10: Average number of agroforestry practices adopted by landowners, organized by each state and parcel acreage group. The bar heights indicate mean practice counts within each state-acreage stratification, highlighting differences in adoption across various landholding sizes.

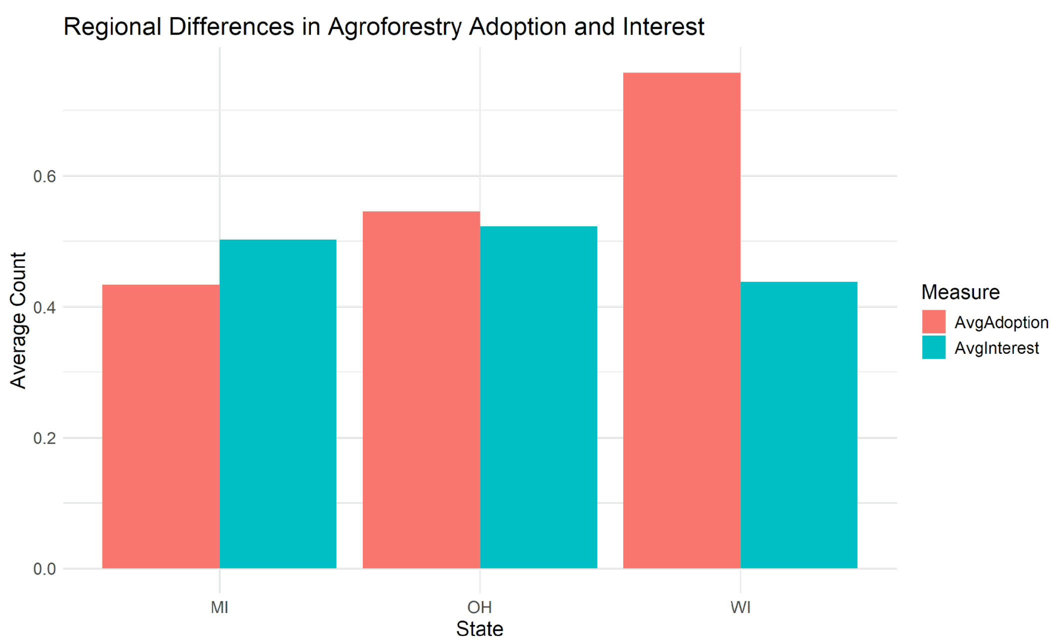

Figure 4.7.A11: Bar chart comparing the average number of agroforestry practices adopted ("AvgAdoption") and the average level of interest in additional practices ("AvgInterest") for Michigan (MI), Ohio (OH), and Wisconsin (WI). Wisconsin shows the highest overall adoption but a lower average interest than the other states, illustrating an inverse relationship between current adoption and future interest in agroforestry practices.

APPENDIX B - Survey Instruments

First Wave Cover Letter and Instrument

Welcome to the *Branching Out* Great Lakes Agroforestry Survey

We are a team of researchers from Michigan State University, the Ohio State University, and University of Wisconsin-Madison, interested in learning more about how landowners and farmers in Ohio, Michigan, and Wisconsin use trees or agroforestry practices as part of their operation. Agroforestry is the intentional integration of trees and crop or livestock production. If you are a woodland owner, and do not identify as a farmer or have any agriculture on your property, we hope you will still take this survey.

This study asks questions about your farm, your perspective on different on-farm conservation actions, and your network (e.g., of other farmers and professionals). Your participation in the study will consist of completing this survey. We will not use names, or other identifying information, in any reports of this research. We will report results at the state or regional level. All data will be treated with strict confidence, and your name will not be used in any report of the research findings. Your responses to questions are confidential. Your confidentiality will be protected to the maximum extent allowable by law.

If you would want to know the results of the study (within these restrictions) you should leave your name and contact information with us.

Your decision to participate or not participate in the research will have no effect on your professional activities. Participation is voluntary, you may choose not to participate at all, or you may refuse to participate in certain procedures or answer certain questions or discontinue your participation at any time without consequence. If at any point you feel any discomfort with the materials or questions, please do not hesitate to let us know. This short survey is intended to capture basic information about your on-farm practices. We will send a second wave survey to gather additional information, depending on your on-farm practices.

If you have any questions about this study or wish to be removed from the study after submitting a response, please contact: Emily Huff: ehuff@msu.edu. If you have questions or concerns about your role and rights as a research participant, would like to obtain information or offer input, or would like to register a complaint about this study, you may contact, anonymously if you wish, the Michigan State University's Human Research Protection Program at 517-355-2180, Fax 517-432-4503, or e-mail irb@msu.edu or regular mail at 4000 Collins Rd, Suite 136, Lansing, MI 48910.

Completing this survey indicates your consent to participate in this research.

Welcome to the *Branching Out* Great Lakes Agroforestry Survey

This short survey is intended to capture basic information about trees on your property. We anticipate that this survey will take approximately 10 minutes to complete. Questions about the survey can be directed to Amanda Curton, Project Manager (curtonam@msu.edu). We have enclosed a full consent form, including potential risks and benefits of participating in the study. By mailing back this survey, you agree to your anonymized responses being included in the dataset.

About Your Farm and/or Forest

1. Did you own or operate a farm or raise at least $1,000 worth of farm or forest products in 2023 (either to sell or for personal use)?

   ____ YES (please continue this survey) ____ NO (please mail back this survey in the envelope provided)

2. How many acres of the land you operated is in each of the following categories (please round up to the nearest whole number):

   ____ Cropland (row crops, hay, specialty crops, etc.) ____ Permanent pasture

   ____ Forest ____ Other (describe):

3. How long have you owned or operated this land? ____________ Years

4. What share of the land you **operate** do you rent **from** others?

   ___ None ___ Less than half ___ Most ___ All

5. What share of the land you **own** do you rent **to** others?

   ___ None ___ Less than half ___ Most ___ All

6. What is your most important source of farm income? (please select only one):

   ___ Crops ___ Livestock (animal products)___ Forest products ___ Other (please describe):

7. How much does your household rely on farm or forest income?

   ___ Exclusively depend on farm income ___ Mainly rely on farm income

   ___ Mainly rely on off-farm income

8. In the next five years do you plan to (please select only one):

   ___ Subdivide my property to sell
   ___ Subdivide my property for children/heirs
   ___ Sell my property
   ___ Give property to heirs
   ___ Keep my property

Current Practices

9. Please indicate if you currently do any of the following forestry or agroforestry practices:

Practice	Description	Yes, I do	No, but I used to	No, but I'm interested	No, and I'm not interested
Woodlot management	Intentionally using the woods on your land for timber or non-timber forest products (e.g., mushroom or berry gathering)	⬚	⬚	⬚	⬚
Windbreaks	Rows of trees or shrubs	⬚	⬚	⬚	⬚
Maple Syrup	Making maple or other syrup	⬚	⬚	⬚	⬚
Alley Cropping	Rows of trees or shrubs to create alleys between row crops	⬚	⬚	⬚	⬚
Silvopasture	The deliberate integration of trees and grazing livestock operations on the same land	⬚	⬚	⬚	⬚
Riparian forest buffers	An area of trees or shrubs next to a stream, lake, or wetland that is managed differently from the surrounding landscape	⬚	⬚	⬚	⬚
Forest Farming	Cultivation of high-value crops under the protection of a managed tree canopy	⬚	⬚	⬚	⬚
Christmas Trees	Cultivation of evergreen trees for sale	⬚	⬚	⬚	⬚
Other (e.g., nut crops or fruit trees)	Other practices that include woody perennials and their associated products	⬚	⬚	⬚	⬚

About You - Finally, we are interested in the characteristics of farmers and landowners who are currently using or interested in using agroforestry.

10. Age:_________
11. Check if any of the following apply:
    ___ Grew up on a farm
    ___ Grew up on land with woodlands
    ___ Prior farming experience before owning/operating on this land
    ___ Prior forestry experience before owning/operating on this land
    ___ Have a degree or training in agriculture, forestry, or a related field
12. Please indicate the highest level of education you have completed:
    ___ High school or equivalent ___ Some college ___ Associate's degree
    ___ Bachelor's degree ___ Graduate degree or equivalent (e.g., M.D., J.D., Ph.D., M.S.)
13. Which of the following best describes you:
    __ Male __ Female __ Non-binary __ I prefer not to answer

Second Wave Instrument

A: ABOUT YOU AND YOUR LAND

The next questions help us ensure we have heard from representative farmers in Michigan. They also allow us to compare how different sizes and kinds of farms are involved in agroforestry. This includes basic information about farm and household finances. Remember that your answers will be treated as confidential, and no information that personally identifies you will ever be released. If you are uncomfortable answering any question, you may leave it blank.

A1. Please indicate which of the following you grow, raise, or otherwise manage on your land? (Check all that apply)

- ☐ Row crops
- ☐ Hay/Alfalfa
- ☐ Specialty crops (including fruits/tree nuts, some vegetables, herbs/spices, flowers)
- ☐ Timber
- ☐ Other forest products (including firewood, Christmas trees, maple syrup, forest nuts/fruits)
- ☐ Dairy cattle, including heifers
- ☐ Beef cattle
- ☐ Sheep/Goats
- ☐ Hogs/Pigs
- ☐ Poultry
- ☐ Honey/honey bees/apiaries

  A1a. If you checked any of the livestock above, do you graze any of them? If you do not raise livestock, skip to Question A2.

  - ☐ Yes
  - ☐ No → if you do not raise livestock, skip to A2

  A1b. If you checked any of the livestock above - During the 2024 grazing season, how often did you move most of your livestock to new paddocks?

Daily	Every 2-3 days	Once a week	Less than once a week	Never
○	○	○	○	○

A2. **Which of the following represents the total operational receipts for business/revenue generated on your land in 2024?**

Please place a check beside the category that comes closest to your total gross farm receipts. Include all receipts from the sale of crops, livestock, milk and milk products, government payments and refunds, and income from custom farm work.

- ○ Under $10,000
- ○ $10,000 to $49,999
- ○ $50,000 to $99,999

- ◯ $100,000 to $249,999
- ◯ $250,000 to $999,999
- ◯ $1,000,000 or more

A3. Did you produce any of the following crops/products from forested lands you operated in 2024? (Check all that apply)

	Sold in 2024	Managed for in 2024	Used for personal or on-farm use in 2024
Firewood	☐	☐	☐
Trees for wood products (lumber, pulp, woodchips, etc.)	☐	☐	☐
Forages/hay/fodder for livestock	☐	☐	☐
Foods (berries, nuts, maple syrup, mushrooms, game, etc.)	☐	☐	☐
Medicinal plants and herbs (American ginseng, goldenseal, etc.)	☐	☐	☐
Decorative plants and/or materials for landscaping (e.g., flowers)	☐	☐	☐
Ecosystem services (e.g., carbon, water quality, air quality)	☐	☐	☐
Other crops/products - Specify:	☐	☐	☐

A4. In which year did you begin any farming or woods-related enterprises on your land? ______

A5. Did you produce and use/sell any of the following crops/products from forested lands land you operated in 2023? (Check all that apply)

	Sold in 2023	Used this for personal or on-farm use in 2023
Firewood	☐	☐
Trees for wood products (lumber, pulp, woodchips, etc.)	☐	☐
Forages/hay/fodder for livestock	☐	☐
Foods (raspberries, walnuts, maple syrup, mushrooms, game etc.)	☐	☐
Medicinal plants and herbs (American ginseng, goldenseal, etc.)	☐	☐
Decorative plants and/or materials for landscaping (e.g., flowers)	☐	☐
Ecosystem services (e.g., carbon, water quality, air quality)	☐	☐
Other crops/products - Specify:	☐	☐

A6. Have you used any of the following practices on your farmland or woodland? (Check all that apply)

	No	Yes, in the past year	Yes, in the past 2-5 years	Yes, 5 or more years ago
Pest and Weed Control:				
Cultivated for weed control (disking, plowing, mowing, etc.)	☐	☐	☐	☐
Made herbicide application for weed control	☐	☐	☐	☐
Put down barrier weed control (mulching/fabric/cover)	☐	☐	☐	☐
Used pesticides on cropland, pasture, or forested areas	☐	☐	☐	☐
Brush hogged or mowed for weed or invasive species control	☐	☐	☐	☐
Tree and Plant Management:				
Pruned tree branches and stems	☐	☐	☐	☐
Did root pruning (where applicable)	☐	☐	☐	☐
Replanted trees, windbreak vegetation, crops, or forages	☐	☐	☐	☐
Removed living or dead trees (thinning)	☐	☐	☐	☐
Removed undesirable understory vegetation or debris	☐	☐	☐	☐
Soil and Water Management:				
Irrigated trees, crops, or shrubs	☐	☐	☐	☐
Used fertilizer and/or soil amendments	☐	☐	☐	☐
Used practices to control/minimize nutrient or soil runoff	☐	☐	☐	☐
Wildlife and Livestock Management:				
Fencing or tree tubes to protect trees/crops from wildlife/livestock	☐	☐	☐	☐
Flash or short-duration grazing	☐	☐	☐	☐
Rotational grazing	☐	☐	☐	☐
Conservation and Habitat Enhancement:				
Adding pollinator habitat	☐	☐	☐	☐

Adding continuous living cover or perennial vegetation	☐	☐	☐	☐
Increasing carbon storage in plants and soil	☐	☐	☐	☐
Fire Management:				
Prescribed fire (where applicable)	☐	☐	☐	☐
Installation/maintenance of fire/fuel breaks	☐	☐	☐	☐
Other Management Activities:				
Other management activities - Specify:	☐	☐	☐	☐

A7. On a scale of 1-5, where 5 is "strongly agree" and 1 is "strongly disagree," **how strongly do you agree or disagree with each of the following statements?**

	Strongly Disagree	Disagree	Neither Agree Nor Disagree	Agree	Strongly Agree
I am optimistic about the future of my farm/land	○	○	○	○	○
Government should stop telling landowners how to manage their land	○	○	○	○	○
Government should do more to help farmers/landowners	○	○	○	○	○
In general, businesses can do things more efficiently than governments	○	○	○	○	○
I am concerned about the future of farming/woodlot management in this area	○	○	○	○	○
Agribusiness consolidations have helped my farm/land	○	○	○	○	○
Crop and revenue insurance is critical to my farm's survival	○	○	○	○	○
Business will harm society if it is not regulated by government	○	○	○	○	○
I am concerned governmental regulations will hurt my farm/land operations	○	○	○	○	○
Agribusinesses exert too much power in farm markets	○	○	○	○	○

B: GENERAL AGROFORESTRY QUESTIONS

In this survey, “agroforestry practices” is categorized as alley cropping, forest farming/maple syruping, riparian forest buffers, silvopasture, and windbreaks. Please reference the one-page sheet provided to provide examples of agroforestry practices you would see on your land.

B1. In your experience or opinion, to what extent do you think agroforestry practices provide (or would provide) any of the following benefits to your land/operation?

	No benefit	Some benefit	Significant benefit
Conservation Benefits:			
Improved soil health	◯	◯	◯
Improved soil erosion control	◯	◯	◯
Improved water quality (reducing nutrient runoff)	◯	◯	◯
Increased carbon storage in soils, trees, and vegetation	◯	◯	◯
Habitat for wildlife or pollinators	◯	◯	◯
Reduce pesticides and herbicides	◯	◯	◯
Increase biodiversity of plants, animals, or fungi	◯	◯	◯
Economic Benefits:			
Income diversification from multiple crops/products	◯	◯	◯
Crops/products for on-farm or personal use	◯	◯	◯
Increased land value	◯	◯	◯
Revenue from conservation program payments	◯	◯	◯
Revenue from hunting leases	◯	◯	◯
Improved farm resilience to weather extremes	◯	◯	◯
Other Benefits:			
Aesthetics/scenic beauty	◯	◯	◯
Hunting	◯	◯	◯
Recreation (other than hunting)	◯	◯	◯

B2. In your experience or opinion, how big of a barrier or challenge are each of the following to your ability to use agroforestry practices on your land/operation?

	Not a barrier or challenge	Minor barrier or challenge	Major barrier or challenge
Lack of information about establishing agroforestry practices	○	○	○
Difficulty establishing trees/shrubs or crops	○	○	○
High startup costs	○	○	○
Lack of information on management and maintenance	○	○	○
Expense of maintenance	○	○	○
Lack of information on recommended species (trees, shrubs, crops)	○	○	○
Lack of knowledge among technical assistance providers	○	○	○
Lack of examples or demonstration sites	○	○	○
Lack of financial assistance	○	○	○
Added labor and management complexity	○	○	○
Incompatible with current farm operations	○	○	○
Trees and crops compete for space, light, water, and nutrients	○	○	○
Tree/shrub pests and diseases	○	○	○

B3. Below are several statements on agroforestry systems. Please indicate the extent to which you agree with them:

I believe that agroforestry generally can…	Strongly Disagree	Disagree	Neither Agree Nor Disagree	Agree	Strongly Agree
Diversify products/income	○	○	○	○	○
Provide valuable crops/products for personal/on-farm use	○	○	○	○	○
Increase land value	○	○	○	○	○
Be costly to plant and maintain	○	○	○	○	○
Increase crop, livestock, and/or forage production	○	○	○	○	○
Improve crop and/or forage quality	○	○	○	○	○
Increase water use efficiency	○	○	○	○	○

Offer recreational opportunities	○	○	○	○	○
Improve marginal or unproductive land	○	○	○	○	○
Require more labor and inputs	○	○	○	○	○
Be difficult to manage	○	○	○	○	○
Promote wildlife habitat/biodiversity	○	○	○	○	○
Increase resilience to extreme weather	○	○	○	○	○
Improve soil health	○	○	○	○	○
Provide scenic beauty/pleasing aesthetics	○	○	○	○	○

B4. When considering whether to include or expand agroforestry practices on your land, how much would the following services help you implement agroforestry on your land?

	Not at all	Some	A lot
Labor assistance	○	○	○
Technical assistance for agricultural practices	○	○	○
Technical assistance for forestry practices	○	○	○
Access to high-quality seeds/starts	○	○	○
Access to equipment/planting materials	○	○	○
Government cost-share or incentives for installation	○	○	○
Peer support networks	○	○	○
Insurance programs	○	○	○
Credit/loan programs	○	○	○
Educational programs	○	○	○
Market access assistance	○	○	○
Policy and regulatory support	○	○	○
Monitoring and evaluation support	○	○	○
Long-term maintenance or technical support	○	○	○

B5. Do you currently use any of the agroforestry practices described on the one-page handout on your farmland/woodland?

- ○ Yes (**continue**)
- ○ No, I do not currently practice any of the described agroforestry practices (**Skip to 'C: Alley Cropping'**)

B6. Please estimate the total acres you used for each of the following agroforestry practices on your farm in 2024:

Total acres in windbreaks, shelterbelts and/or hedgerows: ___ acres
Total acres used for silvopasture: ___ acres
Total acres in a riparian forest buffer (buffers to waterways): ___ acres

Total acres in alley cropping and/or intercropping with trees/crops: ___ acres
Total acres used for forest farming, multi-story farming, and/or maple syruping/sugaring: ___ acres

PERCEPTIONS AND EXPERIENCES WITH SPECIFIC AGROFORESTRY PRACTICES

In the following sections, please offer your opinions on the likely benefits and challenges of individual agroforestry practices, indicate if you use each of these practices, and (if appropriate) answer a few questions about how you practice and experience that type of agroforestry. To revisit descriptions of agroforestry practices, please see the handout included with your survey.

C: ALLEY CROPPING

C1. Which best describes your interest in alley cropping?
- ○ I currently practice alley cropping.
- ○ No, I do not currently practice alley cropping, but I am **interested** in incorporating alley cropping into my operation.
- ○ No, I do not currently practice alley cropping, and I am **not interested** in alley cropping.
- ○ No, I do not currently practice alley cropping, but I have done so in the past.

C2. In addition to the possible generic benefits from agroforestry described above, do you believe alley cropping does or could provide any of the following benefits to your land/operation?

	Not a benefit	Slight benefit	Significant benefit
Economic Benefits:			
Income from sale of timber or forest products	○	○	○
Increased production/yield of crops or forage	○	○	○
Improved quality of crops, forage, and/or tree products	○	○	○
Increased crop water use efficiency and/or irrigation efficiency	○	○	○
Improved crop protection from insects and pests	○	○	○

C3. In addition to the possible challenges from agroforestry described above, do you believe alley cropping would add any additional barriers or challenges to your land/operation?

	Not a barrier or challenge	Minor barrier or challenge	Significant barrier or challenge
Increased wildlife damage to trees and crops	○	○	○
Risks of herbicide drift damaging trees/shrubs	○	○	○
Issues with snow drifts	○	○	○

The following questions apply to those currently practicing alley cropping or those who have tried but stopped using alley cropping. If you do not currently use or have not formerly used alley cropping, please skip to section **D: Forest Farming/Multi-story Farming/Maple Sugaring**.

C4. When were alley cropping practices first established on your land/this operation?
- ☐ Less than 5 years ago
- ☐ 5 - 10 years ago
- ☐ 10 - 20 years ago
- ☐ More than 20 years ago
- ☐ Don't know

C5. In the next five years, do you expect the area of your land used for alley cropping to increase, decrease, or stay the same? (Check one)
- ○ Increase
- ○ Decrease
- ○ Stay the same
- ○ Don't know

C6. How important are each of the following factors to your decision to stop using alley cropping?

	Not important	A little important	Important	Very important	N/A
Not profitable	○	○	○	○	○
Too much wildlife damage	○	○	○	○	○
Too much work/maintenance intensive	○	○	○	○	○
Does not produce/sustain additional yield	○	○	○	○	○
Lack of technical assistance/support to achieve goals	○	○	○	○	○
Other – please describe:____________________	○	○	○	○	○

D: FOREST FARMING/MULTI-STORY FARMING/MAPLE SUGARING

D1. Which best describes your interest in Forest Farming/Multi-story Farming/Maple Sugaring?
- ○ I currently practice forest farming, multi-story farming, and/or maple sugaring.
- ○ No, I do not currently practice forest farming, multi-story farming, and/or maple sugaring, but I am **interested** in adopting/incorporating forest farming, multi-story farming, and/or maple sugaring as a practice.
- ○ No, I do not currently practice forest farming, multi-story farming, and/or maple sugaring, and I am **not interested** in forest farming, multi-story farming, and/or maple sugaring.
- ○ No, I do not currently practice forest farming, multi-story farming, and/or maple sugaring, but I have done so in the past.

D2. In addition to the possible generic benefits from agroforestry described above, do you believe forest farming, multi-story farming, and/or maple sugaring could provide any of the following benefits to your land/operation?

	Not a benefit	Slight benefit	Significant benefit
Conservation Benefits:			
Invasive weed control	◯	◯	◯
Economic Benefits:			
Income from the sale of products (edibles, timber, etc.)	◯	◯	◯
Increased crop production/yield	◯	◯	◯
Improved crop quality	◯	◯	◯
Increased water-use efficiency	◯	◯	◯
Timber stand improvement	◯	◯	◯
Other Benefits:			
Cultural/family tradition	◯	◯	◯

D3. In addition to the possible challenges for agroforestry described above, do you believe forest farming, multi-story farming, and/or maple sugaring would add the following additional barrier or challenge to your land/operation?

	Not a barrier or challenge	Minor barrier or challenge	Major barrier or challenge
Theft of forest farming crops/products and equipment	◯	◯	◯

The following questions apply to those currently practicing Forest Farming/Multi-story Farming/Maple Sugaring or those who have tried but stopped practicing. *If you do not currently use or have not formerly used forest farming, please skip to section **E: Silvopasture**.*

D4. When were forest farming, multi-story farming, and/or maple sugaring practices first established on your land/this operation?

- ☐ Less than 5 years ago
- ☐ 5 years - less than 10 years ago
- ☐ 10 years - less than 15 years ago
- ☐ 15 years or more
- ☐ Don't know

D5. In the next five years, do you expect the area of your land in forest farming, multi-story farming, and/or maple sugaring to increase, decrease, or stay the same? (Check one)

- ◯ Increase
- ◯ Decrease

- ◯ Stay the same
- ◯ Don't know

D6. How important are each of the following factors to your decision to stop practicing forest farming, multi-story farming, and/or maple sugaring?

	Not important	A little important	Important	Very important	N/A
Not profitable	◯	◯	◯	◯	◯
No market for products	◯	◯	◯	◯	◯
Too much work/maintenance intensive	◯	◯	◯	◯	◯
Does not produce/sustain additional yield	◯	◯	◯	◯	◯
Lack of technical assistance/support to achieve goals	◯	◯	◯	◯	◯
Other – please describe:___________________	◯	◯	◯	◯	◯

E: SILVOPASTURE

E1. Which best describes your interest in silvopasture?

- ◯ I currently practice/use silvopasture.
- ◯ No, I do not currently practice/use silvopasture, but I am **interested** in adopting/incorporating silvopasture as a practice.
- ◯ No, I do not currently practice/use silvopasture, and I am **not interested** in silvopasture.
- ◯ No, I do not currently practice/use silvopasture, but I have done so in the past.

E2. In addition to the possible generic benefits from agroforestry described above, do you believe silvopasture could provide any of the following benefits to your land/operation?

	Not a benefit	Slight benefit	Significant benefit
Conservation Benefits:			
Invasive/noxious plant control	◯	◯	◯
Expansion of pasture acreage	◯	◯	◯
Economic Benefits:			
Income from the sale of products (meat, eggs, stockers, timber, etc.)	◯	◯	◯
Improved animal welfare and health	◯	◯	◯
Increased forage quality	◯	◯	◯
Increased forage availability throughout the year	◯	◯	◯
Increased forage production on a per acre basis	◯	◯	◯
Reduction in feed purchases	◯	◯	◯

Timber stand improvement	◯	◯	◯
Wildfire fuel reduction	◯	◯	◯

E3. In addition to the possible challenges from agroforestry described above, do you believe silvopasture would add any of the following additional barriers or challenges to your land/operation?

	Not a barrier or challenge	Minor barrier or challenge	Major barrier or challenge
Windthrow (trees falling over after thinning)	◯	◯	◯
Livestock poisoning from foraging on toxic plants	◯	◯	◯
Soil compaction from livestock	◯	◯	◯

The following questions apply to those currently practicing silvopasture or those who have tried but stopped using silvopasture. *If you do not currently use or have not formerly used silvopasture, please skip to section **F: Riparian Forest Buffers**.*

E4. When were silvopasture practices first established on your land/this operation?

- ☐ Less than 5 years ago
- ☐ 5 years - less than 10 years ago
- ☐ 10 years - less than 15 years ago
- ☐ 15 years or more
- ☐ Don't know

E5. In the next five years, do you expect the area of your land in silvopasture to increase, decrease, or stay the same? (Check one)

- ◯ Increase
- ◯ Decrease
- ◯ Stay the same
- ◯ Don't know

E6. How important are each of the following factors to your decision to stop using silvopasture?

	Not important	A little important	Important	Very important	N/A
Not profitable	◯	◯	◯	◯	◯
Lack of stand regeneration	◯	◯	◯	◯	◯
Too much work/maintenance intensive	◯	◯	◯	◯	◯
Does not produce/sustain additional yield	◯	◯	◯	◯	◯
Lack of technical assistance/support to achieve goals	◯	◯	◯	◯	◯
Not an efficient use of acreage for pasture	◯	◯	◯	◯	◯
No improvement in livestock wellbeing	◯	◯	◯	◯	◯
Other – please describe:___________________	◯	◯	◯	◯	◯

F: RIPARIAN FOREST BUFFERS

F1. Which best describes your interest in riparian forest buffers?

- ◯ I currently maintain/have riparian forest buffers.
- ◯ No, I do not currently maintain/have riparian forest buffers, but I am **interested** in adopting/incorporating riparian forest buffers as a practice.
- ◯ No, I do not currently maintain/have riparian forest buffers, and I am **not interested** in riparian forest buffers.
- ◯ No, I do not currently maintain/have riparian forest buffers, but I have in the past.

F2. In addition to the possible generic benefits from agroforestry described above, do you believe riparian forest buffers could provide any of the following benefits to your land/operation?

	Not a benefit	Slight benefit	Significant benefit
Conservation Benefits:			
Bank stabilization	◯	◯	◯
Shade for aquatic environment	◯	◯	◯
Traps debris during flooding	◯	◯	◯
Economic Benefits:			
Income from buffer trees/shrubs	◯	◯	◯
Crop protection	◯	◯	◯

F3. In addition to the possible challenges for agroforestry described above, do you believe riparian forest buffers would add any of the following additional barriers or challenges to your land/operation?

	Not a barrier or challenge	Minor barrier or challenge	Major barrier or challenge
Loss of cropland	○	○	○
Trees falling into waterways/fields	○	○	○
Damage to buffer trees/vegetation from flooding	○	○	○
Herbicide drift damaging trees/shrubs	○	○	○
Issues with subsurface drainage tiles	○	○	○
Damage to buffer trees/vegetation from livestock	○	○	○
Damage to buffer trees/vegetation from wildlife	○	○	○

The following questions apply to those currently using riparian forest buffers or those who have tried, but stopped using riparian forest buffers. *If you do not currently use or have not formerly used riparian forest buffers, please skip to section **G: Windbreaks**.*

F4. When were riparian forest buffers first established on the land/this operation?

☐ Less than 5 years ago
☐ 5 years - less than 10 years ago
☐ 10 years - less than 15 years ago
☐ 15 years or more
☐ Don't know

F5. How often do you monitor your riparian buffer zones?

○ Periodic assessments (i.e., monthly, seasonally, annually) for bank integrity
○ Non-periodically, but as needed for reporting or for alignment with land management
○ Sporadically, spending on resource/time availability
○ Rarely, only when there is a noticeable problem
○ Never

F6. How do you maintain your riparian forest buffers? (Check all that apply)

☐ Periodic planting or replanting of buffer vegetation
☐ Regular pruning or thinning of vegetation
☐ Monitoring and managing for pests, invasive species, and disease
☐ Natural growth with no specific interventions

F7. In the next five years, do you intend to increase, decrease, or maintain the area in riparian forest buffers? (Check one)

○ Increase
○ Decrease
○ Stay the same
○ Don't know

F8. How important are each of the following factors to your decision to stop using riparian forest buffers?

	Not important	A little important	Important	Very important	N/A
Not profitable	○	○	○	○	○
Invasive species concerns	○	○	○	○	○
Too much work/maintenance intensive	○	○	○	○	○
Does not produce/sustain additional yield	○	○	○	○	○
Lack of technical assistance/support to achieve goals	○	○	○	○	○
Not effective for erosion control	○	○	○	○	○
Other – please describe:___________________	○	○	○	○	○

G: WINDBREAKS (also called SHELTER BELTS/HEDGEROWS)

G1. Which best describes your interest in windbreaks?

- ○ I currently maintain/have windbreaks.
- ○ No, I do not currently maintain/have windbreaks, but I am **interested** in adopting/incorporating windbreaks as a practice.
- ○ No, I do not currently maintain/have windbreaks, and I am **not interested** in windbreaks.
- ○ No, I do not currently maintain/have windbreaks, but I have in the past.

G2. In addition to the possible generic benefits from agroforestry described above, do you believe windbreaks could provide any of the following additional benefits to your land/operation?

	Not a benefit	Slight benefit	Significant benefit
Conservation Benefits:			
Dust mitigation	○	○	○
Economic Benefits:			
Increased crop production/yield	○	○	○
Improved crop quality	○	○	○
Income from windbreak trees/shrubs (firewood, timber, nuts, etc.)	○	○	○
Improved welfare of livestock	○	○	○
Increased livestock production	○	○	○
Snow management	○	○	○
Protection of farm buildings, home, and other structures	○	○	○

Farmstead energy conservation	○	○	○
Increased crop water use efficiency and/or irrigation efficiency	○	○	○
Reduced spread of tree diseases (canker, citrus greening, etc.)	○	○	○
Other Benefits:			
Improved working or living environment from less intense wind	○	○	○
Privacy/visual screening	○	○	○
Odor reduction	○	○	○
Noise reduction	○	○	○

G3. In addition to the possible challenges for agroforestry described above, do you believe windbreaks would add any additional barriers or challenges to your land/operation?

	Not a barrier or challenge	Minor barrier or challenge	Major barrier or challenge
Difficulty regrowing trees within an established windbreak	○	○	○
Lack of markets for products from windbreak	○	○	○
Loss of cropland	○	○	○
Harbors harmful crop pests (wildlife, insects, weeds, etc.)	○	○	○
Trees and crops compete for space, light, water, and nutrients	○	○	○
Livestock damage to trees	○	○	○
Wildlife damage to trees	○	○	○
Snow drift issues	○	○	○

The following questions apply to those currently using windbreaks or those who have tried but stopped using windbreaks. *If you do not currently use or have not formerly used windbreaks, please skip to **H: Incentives And Program Participation**.*

G4. When were windbreaks first established on the land/this operation?

- ☐ Less than 5 years ago
- ☐ 5 years - less than 10 years ago
- ☐ 10 years - less than 15 years ago
- ☐ 15 years or more
- ☐ Don't know

G5. How often do you monitor your windbreaks?

- ○ Periodic assessments (ie, monthly, seasonally, annually) for integrity
- ○ Non-periodically, but as needed for reporting or for alignment with land management
- ○ Sporadically, spending on resource/time availability
- ○ Rarely, only when there is a noticeable problem

○ Never

G6. How do you maintain your windbreaks? (Check all that apply)

☐ Periodic planting or replanting of buffer vegetation
☐ Regular pruning or thinning of vegetation
☐ Monitoring and managing for pests, invasive species, and disease
☐ Natural growth with no specific interventions

G7. In the next five years, will the area of the land in windbreaks increase, decrease, or stay the same? (Check one)

○ Increase
○ Decrease
○ Stay the same
○ Don't know

G8. How important are each of the following factors to your decision to stop using windbreaks?

	Not important	A little important	Important	Very important	N/A
Not profitable	○	○	○	○	○
Invasive species concerns	○	○	○	○	○
Too much work/maintenance intensive	○	○	○	○	○
Does not produce/sustain additional yield	○	○	○	○	○
Lack of technical assistance/support to achieve goals	○	○	○	○	○
Not effective for erosion control	○	○	○	○	○
Other – please describe:____________________	○	○	○	○	○

H: INCENTIVES AND PROGRAM PARTICIPATION

H1. Did you participate in or benefit from the following programs between 2022-2024?
(Check all that apply)

- Federal crop insurance (e.g., yield or revenue loss programs)
- Federal ag commodity programs (e.g., PLC, ARC, MAL, or DMC programs)
- Federal conservation programs (e.g., EQIP, CRP, etc.)
- State or local conservation programs (e.g., SWCD programs)
- USDA Trade Assistance program payments
- State property tax reduction programs for agriculture or forestry
- A carbon market (e.g., Family Forest Carbon Program, Michigan Forest Carbon Project)

H2. Have you previously participated in any <u>cost-share or incentive programs</u> to support **agroforestry** practices on your land? Please select one of the following options:

- ◯ Yes, I have participated in cost-share programs. (Continue to Question H2a)
- ◯ No, I have not participated, but **am interested**. (Skip to Question H3)
- ◯ No, I have not participated and am **not interested**. (Skip to Qustion H3)

H2a. Which agency, group, or program did you participate in?

- Federal crop insurance (e.g., yield or revenue loss programs)
- Federal ag commodity programs (e.g., PLC, ARC, MAL, or DMC programs)
- Federal conservation programs (e.g., EQIP, CRP, etc.)
- State or local conservation programs (e.g., SWCD programs)
- USDA Trade Assistance program payments
- State property tax reduction programs for agriculture or forestry
- A carbon market (e.g., Family Forest Carbon Program, Michigan Forest Carbon Project)

H2b. What percent of the total costs of implementing your agroforestry practices were covered by the cost-share program?

- ◯ Less than 50%
- ◯ 50%
- ◯ 51-75%
- ◯ More than 75%

H3. What barriers have you faced or would you expect to face in participating in cost-share programs for agroforestry? (Check all that apply)

- ☐ Lack of information
- ☐ Paperwork load
- ☐ Inadequate funding amount
- ☐ Restrictions on land use under program conditions
- ☐ Wait time
- ☐ Limited upfront capital
- ☐ Challenges with program staff
- ☐ Other (please specify):

H4. In the future - which type of organization would you <u>prefer</u> to administer cost-share programs for agroforestry on your land? Rank the following options from most preferred (1) to least preferred (5):

___ Local government agency (e.g., county, conservation district/council, municipalities)
___ State agency (e.g., Michigan Department of Natural Resources, Michigan Department of Agriculture and Rural Development, Michigan EGLE)
___ Federal agency (e.g., Natural Resources Conservation Service (NRCS), Farm Service Agency)
___ Non-governmental organization (NGO) (e.g., The Nature Conservancy, American Forest Foundation, or other Environmental/Conservation Foundations and Organizations)
___ Private company (e.g., TruTerra, FarmRaise, Farm Credit Services)
___ University Extension
Other (please specify) ________________________

H5. In the future, how would you prefer to receive incentive payments?

- ◯ One-time payment before establishment
- ◯ One-time payment after establishment
- ◯ Installments over multiple years
- ◯ I am not interested in receiving incentive payments

I: SCENARIOS: Incentive Programs for Agroforestry

You are considering participating in an incentive program that will reimburse a portion of the expenses associated with creating or expanding an agroforestry system on your land. Establishment costs for expanding or creating your system total $1,500 per acre. Two assistance options are presented to you, but they vary across two factors:

- **Payment:** Choices will reflect reimbursement payment rates to help establish agroforestry practices. The rates represent the portion of establishment costs the program will pay, with you being responsible for the remainder.
  - Choice options: (1)$750/acre payment, (2) $1,125/acre payment, (3) $1,500/acre payment
- **Technical Assistance:** Choices will either offer a personalized distant or in-person consultation with a natural resources specialist working in forestry, agricultural systems, and agroforestry. An in-person consultation involves the specialist traveling to your property, whereas a distant consultation involves the specialist communicating with you through phone and email conversations and/or video-conferencing. In addition to a consultation, you will also receive educational resources such as fact sheets and other informational publications.
  - Choice options: (1) resources + distant communication, (2) resources + in-person communication

Based upon these varying factors, you make a decision about whether to participate in the program or not.

EXAMPLE: When presented with the following question, you would select the choice that sounds most appealing to you. If “Program 2” sounds the most preferable, then you would indicate this choice by marking the bubble under the respective column (as shown below).

If neither option sounds appealing, then you would select the “Neither” option.

	Program 1	Program 2	
Incentive Rate →	$1,500 per acre	$1,125 per acre	Neither - Will not participate
Technical Assistance →	Resources + Distant	Resources + In-person	
	○	●	○

Before proceeding, please read the following carefully:

Hypothetical bias occurs when a respondent’s preferences under hypothetical conditions differ from their actual decisions in real life situations. This happens because people generally exhibit higher willingness to participate when their choices do not have actual consequences.

Please select your preference for each of the following comparisons. Within each choice set, please indicate the option that is most appealing to you assuming an establishment cost of $1,500 per acre. Keep in mind that you may select the “Neither” option. Treat each choice set as a stand-alone decision. Please try to base your choices on how you may behave in reality.

Choice Set 1

	Program 1	Program 2	Neither
Incentive Rate →	$1,125 per acre	$750 per acre	Neither - Will not participate
Technical Assistance →	Resources + Distant	Resources + In-person	
	○	○	○

Choice Set 2

	Program 1	Program 2	Neither
Incentive Rate →	$750 per acre	$1,500 per acre	Neither - Will not participate
Technical Assistance →	Resources + In-person	Resources + Distant	
	○	○	○

Choice Set 3

	Program 1	Program 2	Neither
Incentive Rate →	$1,500 per acre	$1,125 per acre	Neither - Will not participate
Technical Assistance →	Resources + Distant	Resources + In-person	
	○	○	○

Choice Set 4

	Program 1	Program 2	Neither
Incentive Rate →	$750 per acre	$1,500 per acre	Neither - Will not participate
Technical Assistance →	Resources + Distant	Resources + In-person	
	○	○	○

J: COMMUNICATION AND INFORMATION

J1. Please think about the farmers in your community with whom you communicate about farm or forest management practices. About how many think **you** should incorporate agroforestry practices into your operation? Please select only one:

- Very few, less than 15%
- Some, more than 15% but less than 50%
- Most, more than 50%

J2. Please think again about the farmers in your community with whom you communicate about farm or forest management practices. About how many of **them** do you believe incorporate one or more agroforestry practices into their operation? Please select only one:

☐ Very few, less than 15%
☐ Some, more than 15% but less than 50%
☐ Most, more than 50%

J3. How useful are the following sources of information for you when you want to learn about farm or forest land management and related topics?

	Not at all useful	Somewhat useful	Very useful	Never used
Advice/information from my paid agricultural advisors (crop advisor, seed dealer, fertilizer dealer, etc.)	○	○	○	○
Advice/information from professional foresters	○	○	○	○
Beginning farmer support programs	○	○	○	○
Conferences	○	○	○	○
Farm or Forestry financial management training	○	○	○	○
Farm stress or crisis hotlines	○	○	○	○
Land transition or Estate planning programs	○	○	○	○
Field days or demonstration sites	○	○	○	○
Forest landowner associations or cooperatives	○	○	○	○
Other farmers or landowners I communicate with	○	○	○	○
Programs sponsored by farm organizations (e.g., Farm Bureau, OSA, ODPA, OEFFA, etc.)	○	○	○	○
Publications from forestry research institutes	○	○	○	○
Reading information on the internet	○	○	○	○
Reading printed farm/forest magazines and books	○	○	○	○
State farm/forestry agency resources and programs	○	○	○	○

Technical assistance from forestry extension service	○	○	○	○
Trial and error on my land	○	○	○	○
University Extension programs (MSU)	○	○	○	○
USDA Natural Resources Conservation Service (NRCS) programs	○	○	○	○
Workshops or training sessions on forest management	○	○	○	○

J4. Have you attended any agroforestry events, trainings, or conferences?
- ○ Yes (continue)
- ○ No (**Skip** to Question J5)

J4a. What are the greatest benefits you expect or have experienced from participating in agroforestry events, trainings, or conferences?

	Not a benefit (1)	(2)	(3)	(4)	Great benefit (5)
Advocate for farmers' interests	○	○	○	○	○
Learn about new farm management practices	○	○	○	○	○
Learn about soil and water conservation issues	○	○	○	○	○
Teach others about farm management practices	○	○	○	○	○
Teach others about soil and water conservation issues	○	○	○	○	○
Meet with other farmers or forest landowners	○	○	○	○	○

J5. What organizations are you a member of? Please add any formal or informal (e.g., Facebook groups like Michigan Farm Families) groups you belong to. (Check all that apply)
- ☐ Farm Groups (e.g., Farm Bureau, Farmers Union)
- ☐ A Growers or Landowner Association (e.g., Michigan Corn Growers Association, Michigan Forest Association)
- ☐ Conservation District
- ☐ Farm or Forestry-related Facebook Group (e.g., Michigan Forest Association, Michigan Farms)
- ☐ Other Social media group, please list: ________________________________
- ☐ Other: ____
- ☐ None of the above

Chapter 5: Integration of Parcel-Level Data with Survey Results to Perform Spatial Estimation of LSWFs Associated with Agroforestry in the Lake States

Objectives:

- Describe integrating parcel-level survey data with high-resolution spatial analyses to validate LSWF identification as intentional agroforestry practices.
- Link landowner responses with remotely sensed LSWF features to assess the presence of windbreaks and riparian buffers at the parcel scale.
- Examine case studies and aggregate trends to identify agreements and discrepancies between survey reports and spatial outputs.
- Recommend refining agroforestry mapping methodologies and improving national inventory accuracy through similar integrated analysis.

5.0 Abstract

Integrating parcel-level survey data with spatial datasets offers an innovative approach to refining the identification and characterization of linear and small-scale woody features (LSWFs) as agroforestry (AF) practices. This study synthesizes survey data collected from stratified random parcels across three states in the Great Lakes region with high-resolution geospatial analyses of LSWFs to evaluate their presence, management intentionality, and correspondence to agroforestry practices such as windbreaks and riparian buffers. By leveraging advancements in remote sensing, including machine-learning classification and 1-meter resolution aerial imagery, the study examines the spatial alignment of LSWF features with survey-derived reports from landowners. Key findings address the extent to which LSWFs identified through remote sensing methodologies can be validated as AF practices compared to ground-truth data derived from parcel-level surveys. Metrics were developed to assess the consistency between observed LSWFs and self-reported agroforestry features, with an emphasis on distinguishing intentional agroforestry from unmanaged woody vegetation. Case studies of LSWF presence and absence were evaluated to identify broader spatial trends in agroforestry adoption and management across the landscape. The results highlight regional patterns of LSWF intentionality, particularly within the Great Lakes region, providing insights into the relationship between reported land use practices and spatially inferred LSWF configurations. The study addresses significant gaps in

national AF mapping efforts by demonstrating how parcel-level surveys can enhance the resolution and accuracy of agroforestry assessments. It further offers practical recommendations for improving future methodologies, including the integration of geospatial technologies and producer-based surveys. These findings contribute to a more nuanced understanding of the distribution, adoption, and management of LSWFs as agroforestry practices, facilitating the development of more effective strategies for promoting agroforestry at regional and national scales.

5.1 Introduction/Background

5.1.1 Contextualizing Agroforestry Mapping and Classification

Nationwide efforts to map agroforestry (AF) features have historically relied on datasets like the U.S. Census of Agriculture, which could capture only a fraction of actual AF usage due to inconsistent awareness of AF terminology and limited survey result detail (Smith et al. 2022). Simultaneously, response rates to traditional surveys are continuously declining (USDA, 2021; Eggleston et al., 2024), offering stakeholders less insight on apparent trends in land management among private landholders, who in the United States make autonomous decisions on sustainable and/or resilient land use practices for most of the country's land area. While some regions outside the US maintain inventories of identifiable AF practices—for example, windbreaks or riparian buffers—these assessments often do not adequately account for the impacts and factors that influence management intensity and intent. Farmers may plant trees to address a specific agronomic goal, yet without clear records of management objectives, even robust mapping tools risk conflating actively managed AF with unmanaged woody cover (Sharma et al. 2022; Ahmad et al. 2016).

Another major limitation arises from the challenge of detecting small-scale or linear small woody features (LSWFs) with existing methods and datasets. Typical remote sensing approaches have become adept at identifying large forest patches but struggle to classify slender tree rows or narrow vegetative buffers (Meneguzzo et al. 2013; Liknes et al. 2017; Burke et al., 2019). Where LSWFs run along field boundaries, rivers, or roads, they may appear similar to naturally occurring vegetation, diminishing the ability of standard classification algorithms to distinguish intentional AF practices from incidental tree growth. Consequently, small-scale AF elements such as windbreaks or riparian buffers are frequently overlooked, creating underestimates of genuine AF adoption (Begue et al. 2018).

These difficulties underscore the strong reliance of AF classification on clear management definitions. A row of trees planted to reduce erosion or protect crops exemplifies AF yet can visually resemble a line of unmanaged shrubs. Likewise, from imagery, a row of trees can look very neatly managed and, on ground-truthing evaluation, be a very ineffective windbreak if at all. Even advanced mapping platforms encounter substantial obstacles without explicit ground truth data on why trees are planted and how they are maintained. This blurred boundary between managed and unmanaged vegetation illustrates the complexity of interpreting AF features solely from aerial or satellite imagery.

5.1.2 Importance of Ground-Truthing for Accurate Classification

Smith et al. (2022) emphasize that national-level remote sensing assessments must be paired with “ground truth” data to avoid misclassifying AF features. Ground-truthing entails verifying the management goals and maintenance of a given woody feature, ensuring that identified trees reflect an intentional AF system rather than spontaneous or minimally managed growth. Such verification is critical for refining existing national estimates, given how AF practice's “4 Is” (intent, inputs, integration, and impacts) are often invisible from imagery alone.

Current mapping approaches rely heavily on shape- or pixel-based classifications that cannot capture the nuanced objectives behind tree establishment (Sharma et al., 2022; Pirbasti et al., 2024). Indeed, there is a fundamental gap between estimates of LSWFs, realized values of LSWFs through exhaustive remote sensing, and actual validation of AF practices on the ground. Relying on remote sensing or survey-based methods in isolation to quantify the presence of AF will always have numerous inherent imperfections. Therefore, it is essential to combine producer surveys with these spatial methods. Many studies demonstrate that high-resolution imagery can detect linear features effectively (Ahmad et al., 2016; Burke et al., 2019; Sarti et al 2021; Luscombe et al., 2023; Patriarca et al., 2024). Yet, producer interviews or questionnaires are needed to confirm whether these features are managed for wind protection, riparian buffering, or other AF practices. This synergy between remotely sensed data and on-the-ground perspectives fills the informational gap on management intensity, a decisive factor in AF classification.

By incorporating landowner-reported details—such as maintenance frequency, monitoring, or planning frameworks—researchers can refine AF maps and better align them with how farmers or landowners actually steward their landscapes. This integrative approach confirms the presence of AF systems and allows for an improved understanding of their ecological roles, management variations, and adoption patterns (Romanova et al., 2022; Stubblefield 2021). Consequently, ground-truthed data can help address the systematic undercounting of AF features and lay a more robust foundation for nationwide AF assessments.

5.1.3 Leveraging Remote Sensing for LSWF Identification

Recent advances in remote sensing have considerably enhanced our capacity to identify and map linear and small-scale woody features (LSWFs) associated with AF practices. In particular, the previously described integration of machine-learning classification techniques with 1-meter resolution aerial imagery has enabled the production of detailed tree cover maps that capture even subtle vegetative features outside conventional forest boundaries (Meneguzzo et al. 2013; Liknes et al. 2017; Burke et al. 2019; Chapter 1 and 2). Complementary to these advances, shape-based metrics have been effectively employed to detect windbreaks and riparian forest buffers by quantifying geometric attributes such as linearity and sinuosity, thereby facilitating the semi-automated identification of these AF elements (Liknes et al. 2017; Chapter 1). Luscombe et al. (2023) demonstrated that integrating airborne LiDAR (~2 m resolution) can accurately resolve fine-scale tree lines and hedgerows with over 90% positional precision. Patriarca et al. (2024) propose an object-oriented classification workflow using freely available high-resolution orthophotos similar to NAIP, facilitating the automated mapping of hedgerows and woody strips at a large scale. Despite these promising advancements, challenges remain in distinguishing unmanaged tree features from those intentionally integrated into AF systems, a distinction that is critical for accurate classification and subsequent policy and management decisions (Begue et al. 2018).

Smith et al. (2022) encapsulate the potential of remote sensing in augmenting national AF assessments by stating:

"With advances in spatial assessment technologies, remote sensing offers potential opportunities to supplement survey methodologies in developing national estimates of agroforestry use. In the U.S., high-resolution aerial imagery and machine-learning classification systems are being used to develop 1 m resolution maps of tree cover, which can then be used to identify windbreaks and riparian forest buffers based on their shape. This approach can be used to estimate land area and locations for these types of linear agroforestry practices and may be a way to cross check numbers derived from survey methods. Challenges remain in accurately identifying forest farming, silvopasture, and similar block-type agroforestry practices from other forest land covers and uses. Remotely sensed data will need to be augmented with producer-based surveys that can provide key information, including number of adopters and their demographics as well as practice implementation and management factors."

Integrating high-resolution remote sensing with ground-truthing via producer surveys is essential to refining LSWF inventories and ensuring that AF mapping efforts accurately reflect the actual AF practices employed on the landscape.

5.1.4 Rationale for Parcel-stratified, Random Surveys in the Lake States

Identifying AF features on a larger landscape scale requires robust remote sensing analysis and a ground-truth element that situates detected tree cover within the context of deliberate management decisions. In the Lake States region (Minnesota, Wisconsin, and Michigan), recent advances in high-resolution imagery and shape-based classification (e.g., Liknes et al. 2017) provide greater specificity in locating linear woody features. However, these tools alone cannot fully distinguish intentionally managed windbreaks or riparian forest buffers from incidental tree rows, abandoned shelterbelts, or other unmanaged features (Begue et al. 2018). Consequently, there is a pressing need to complement these spatial datasets with wholistic and spatially random surveys that capture local landowners' nuanced objectives and stewardship practices. Parcel-level data offer the granular insight to confirm whether identified LSWFs fulfill established AF definitions involving purposeful design and management intensity (Smith et al. 2022). Additionally, distributing a survey randomly to private landholders allows for a greater meta-analysis of trends in land management beyond the traditional silos of agricultural and forestry producers and practitioners. Indeed, a parcel-scale questionnaire or interview with the landowner can clarify whether a visually identified buffer was planted for wind protection, water filtration, or wildlife habitat rather than simply arising from natural succession. By integrating local landowner perspectives with high-resolution imagery, researchers and policymakers in the Lake States can more accurately map the distribution of windbreaks, riparian buffers, and similar AF features, thereby guiding targeted outreach, financial incentives, and technical assistance to sustain and expand AF practices across the region.

5.2 Research Objectives

5.2.1 Clarifying LSWF Presence and Intentionality

The primary objective is to clarify the presence and intentionality of linear and small-scale woody features (LSWFs) as agroforestry (AF) practices in the Lake States. By examining case studies at the parcel level, this research seeks to fill existing gaps in national-scale AF assessments that can conflate unmanaged tree cover with intentionally managed windbreaks and riparian buffers, or generally underestimate the presence and importance of AF features on landscapes (Begue et al. 2018). In doing so, the study will measure how landowners perceive and manage these features, thereby assessing whether the spatially detected LSWFs align with established AF definitions and management standards (Smith et al. 2022).

5.2.2 Evaluating Landscape Trends in the Great Lakes Region

A second objective is to evaluate the broader landscape trends of LSWF adoption and intentionality across 35 counties in Michigan, Ohio, and Wisconsin. Integrating parcel-level survey data with high-resolution remote sensing analyses will allow for identifying regional hotspots and areas where AF practices could be under- or over-represented. This spatial evaluation aims to reveal patterns in the distribution of managed windbreaks and riparian buffers that can inform both regional planning and policy development (Ahmad et al. 2016; Meneguzzo et al. 2013).

5.2.3 Providing Recommendations for Improved Estimations

The final objective is to offer practical recommendations for refining AF mapping methodologies or broader estimations. This research intends to develop guidance on distinguishing intentionally managed AF features from unmanaged woody vegetation by integrating remote sensing data with detailed producer surveys. By establishing best data calibration and integration practices, the study aims to enhance the accuracy of future national assessments of AF practices, thereby supporting more effective conservation and management strategies (Liknes et al. 2017; Smith et al. 2022).

5.3 Data and Methods

5.3.1 Data

5.3.1.1 Exhaustive LSWF Dataset

The exhaustive LSWF dataset for this study was developed through machine-learning classifications applied to 1-meter resolution aerial imagery spanning 35 counties in Michigan, Ohio, and Wisconsin. Convolutional Neural Networks (CNNs) were used to process large volumes of imagery, and their outputs generated high-resolution delineations of woody features along agricultural fields, waterways, and property boundaries. LSWF identification from a very high-resolution tree canopy class involved shape metrics, segmentation, and filtering steps to isolate relatively narrow or linear tree stands. These classification rules aimed to avoid mislabeling broader forest patches or incidental clusters of shrubs, thereby delivering a dataset of plausible agroforestry-related features across the region.

A separate methods paper (see Chapter 1) provides in-depth detail on the neural network architecture, training procedures, and performance evaluations. The present work relies on that foundational process for its analyses, integrating the LSWF classifications with survey data. Previous chapters provide a map of the study areas.

5.3.1.2 Parcel-referenced Survey Data

The parcel-referenced survey data were collected by drawing a stratified random sample of parcels from each state, with acreage-based categories of 1–10 acres, 10–50 acres, and 50+ acres. This sampling extended to all counties in each state and was not limited to the 35 counties covered by the LSWF dataset. ReGRID served as the source for parcel information in Michigan and Ohio. At the same time, the Statewide Parcel Map Initiative (coordinated by the State Cartographer's Office and the Wisconsin Land Information Program) provided analogous data in Wisconsin.

Using R, a random set of parcels was pulled, generating 333 parcels per stratification group. For the smallest category (1 to 10 acres), 334 parcels were selected to maintain a balanced representation. The final mailing list was refined to give precedence to private landowners through a data cleaning process. Public entities and larger industrial or infrastructural corporations were removed from the final dataset to target individuals with direct decision-making authority over land management.

This broad geographic coverage supports additional analyses related to AF in the study states. Wave 1 of the survey emphasized the presence or absence of windbreaks, riparian buffers, or other woody features, along with basic demographic information on land operators and tenure. This initial questionnaire was designed to capture a straightforward inventory of landowner practices, establishing a baseline for further assessment.

Each surveyed parcel was assigned a unique identification code that linked the mail responses to the relevant geospatial data. Chapter 4 provides a more detailed overview of how the survey instruments captured landowner intentionality and expands on the discussion of how parcel-level data can be integrated with remote sensing outputs to clarify management objectives for LSWFs.

5.3.2 Methods

5.3.2.1 Linking Parcel Survey Data to LSWF Spatial Information

The first step in integrating landowner-reported agroforestry (AF) features with remotely detected LSWFs was establishing an apparent geospatial reference for each parcel. Unique parcel identification codes were matched to the LSWF dataset through spatial overlays, linking the location of windbreaks, riparian buffers, or other linear woody features to the reported attributes from the survey. This allowed for direct association between each surveyed parcel and any corresponding LSWF polygons identified via machine-learning.

Once parcels and LSWF records were linked, presence/absence matrices were constructed to capture agreement or discrepancy between landowner survey responses and observed LSWFs. Landowners who indicated having windbreaks or riparian buffers were matched with corresponding features in the spatial dataset. Parcels where owners indicated no relevant woody features were similarly reviewed for any LSWFs that might be false positives. These matrices represented an essential mechanism for systematically comparing ground-reported AF practices with spatial detections.

Analyses focused on whether each feature labeled as a windbreak or buffer in the LSWF dataset aligned with self-identified management practices. Parcels where the LSWF dataset identified probable AF elements, yet the owner’s survey response showed no such features, were flagged for further scrutiny. Conversely, situations where the survey reported AF features but the spatial detection missed those features were also noted, creating a framework to guide more detailed case study evaluations.

5.3.2.2 Examining Case Studies for Agreement/Discrepancy

The described cases were drawn from parcels that exhibited high alignment between the survey responses and model outputs and instances where notable discrepancies arose. These case studies focused on potential reasons for agreement, such as clearly defined windbreak rows, and for discrepancy, such as canopy misclassification or overlooked features along shared boundaries.

The evaluation of each case considered that the survey instrument asked landowners to characterize their land operations broadly rather than the specific parcel pulled for sampling. For that reason, the final analysis included the selected parcels and adjacent parcels belonging to the same respondent. This approach accurately assessed potential AF features extending beyond a single parcel boundary. To protect anonymity, individual parcel maps or imagery are not published. Instead, aggregated or generalized descriptions and illustrations convey patterns and outcomes relating to ownership structure, tree-cover layout, and on-ground management.

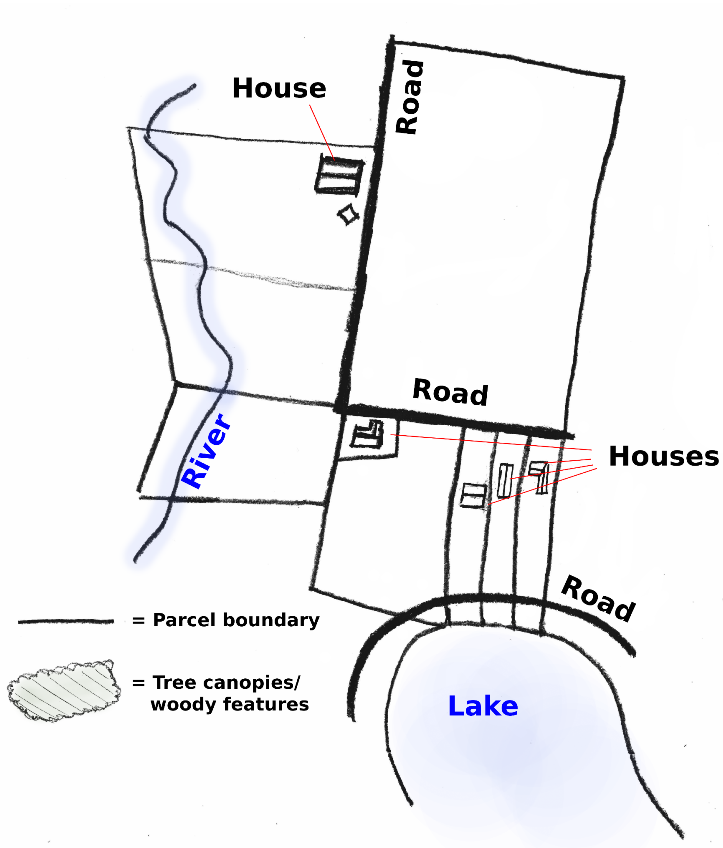

Figure 2: Reference figure displaying a generalized, hypothetical parcel map of a region in the study area to demonstrate survey response overlap with LSWF survey results while protecting respondent anonymity. This sample landscape includes a mixture of parcel sizes, residential and non-residential parcels, as well as some reference features such as roads, a lake, and a river. This version does not include any woody features on the landscape for demonstration purposes.

Anticipated factors causing mismatches included abandoned windbreaks overgrown with volunteer species, unreported woody strips along property edges, and survey responses referring to larger non-adjacent operational holdings where the sampled parcel did not contain an active AF practice. Unrecognized or fully forested riparian zones presented another explanation for divergence, particularly when high tree density obscured the linearity or intentional/unintentional structure of buffers. These case study findings guided refinements in data cleaning and classification, highlighting the importance of verifying whether detected features indeed reflected managed AF practices.

5.3.2.3 Assessing Landscape-Level Trends

Insights from the case studies were aggregated to identify spatial patterns of LSWF presence and AF adoption across the study area. Instances where survey data and model outputs agreed helped delineate counties or regions that appeared more likely to host intentionally managed woody buffers or windbreaks. Areas with higher frequencies of discrepancies prompted further consideration of local land-use practices, data collection methods, and possible misclassification in the LSWF dataset.

Drawing on these aggregated observations, the analysis compared LSWF densities with known AF adoption hotspots and regions where uptake may be minimal. This comparison offered preliminary indicators of whether certain landscape features, climatic conditions, or policy influences correlated with higher incidences of managed woody features. Data at this stage remained preliminary due to the limited information on management intensity, making it challenging to reach definitive conclusions on how different owners approach AF practices. These landscape-level assessments established a foundation for more detailed studies in later chapters. The absence of thorough data on landowner intent and the degree of active management underscored the need for a more comprehensive investigation. Follow-up survey waves and additional datasets are intended to refine the overall picture of AF adoption, shedding light on the motivations behind establishing LSWFs and the roles these features play in supporting broader conservation or economic objectives.

5.4 Results

5.4.1 Presence/Absence Across Surveyed Parcels

The survey responses collected from parcels within the study counties offer a foundational perspective on the presence or absence of windbreaks and riparian buffers. Wave 1 results compiled on February 22, 2024, indicate that seven respondents in each state, for a total of 21 across Michigan, Ohio, and Wisconsin, reported having windbreaks and/or riparian buffers on their land. These reported features were then cross-referenced with the spatial dataset of linear and small-scale woody features (LSWFs) to gauge how effectively remote sensing classification aligned with landowner observations. Overall, the patterns suggest a generally consistent match between survey responses and mapped LSWFs, although the data reveal cases where certain AF elements were either completely and clearly overlooked by the model or went unreported by landowners.

The assessment of windbreaks showed that nine of the twelve surveyed parcels in the study counties included model-derived LSWFs in areas where the respondents had indicated windbreaks in their survey answers. One respondent reported a windbreak, which in imagery was visually along a lakeshore, yet the classification model did not detect any corresponding feature. Two other respondents managed land spanning hundreds of acres in scattered, non-adjacent parcels beyond the surveyed parcel, and no windbreaks were mapped within the parcels selected for the survey or their immediate neighbors. An additional respondent described a missed windbreak on a smaller holding within a larger, possibly rented, non-adjacent tract, suggesting that the complexities of tenure and management can lead to gaps in the alignment of survey findings and spatial/survey data.

Riparian buffers exhibited a similar pattern, with nine of twelve surveyed parcels showing an LSWF that aligned with the riparian buffers stated in the survey responses. Two respondents indicated the presence of riparian forest buffers on parcels that were primarily forested outside of the waterway corridors. These extensive tree stands did not register as LSWFs in the classification because the model filtered out broader forest areas (see Figure 4). After removing the parcels where the canopy was contiguous and fully wooded, nine of ten surveyed parcels in the study counties contained riparian buffers that matched the spatial outputs. These findings illustrate that the model performed well when buffers conformed to narrower, linear shapes along riparian areas, though fully forested situations required additional scrutiny.

When the presence of windbreaks and riparian buffers was combined, 17 out of 19 surveyed parcels that reported either practice had spatially detected LSWFs within the same parcel or on adjacent parcels controlled by the same landowner. These results support the observation that many recognized agroforestry (AF) features, particularly when they adhere to distinct linear forms, can be identified using the methods described in Chapter 1. Nevertheless, the few missed detections emphasize the need to pay close attention to management scenarios where AF practices occur on fragmented holdings or are integrated into more extensive swaths of forested land.

A parallel priority of this assessment was to verify the absence of LSWFs for respondents who indicated no windbreaks or riparian buffers on their parcels. A total of 42 respondents across the study counties reported having none of these AF practices, prompting a comparison of survey statements with LSWF classifications. Twelve of these 42 parcels, along with adjacent parcels owned by the same individuals, showed model-detected features that were potentially inconsistent with the reported absence. This discrepancy highlights false positives ranging from marginal spillover effects at boundary edges to trees that formed urban-like canopies misclassified as LSWFs (see Figure 4).

False positives warrant a more detailed look at how the classification processes handle small clusters of canopy and how remote sensing boundaries are drawn. Five cases featured LSWFs that marginally spilled across a parcel boundary from a neighboring tract where the adjacent landowner presumably managed the trees. Two smaller parcels showed linear stands of urban trees, which suggests that the classification process would benefit from a systematic urban reclassification step, following the strategies described in Chapter 3. One elongated residential parcel by a lake contained a strip of LSWF across multiple lakefront ‘front yards’, though the respondent did not consider those trees a managed AF practice (as other respondents classified similar features as windbreaks or riparian buffers). These instances underscore the complexity of distinguishing intentional AF features in densely settled landscapes and raise questions about how to interpret ownership boundaries when evaluating the presence of AF practices.

5.4.2 Summary Agreement Between Survey Data and LSWF Detection

A concise comparison of survey-based presence/absence data and spatially mapped linear and small-scale woody features (LSWFs) revealed moderate to high consistency. Table 4.1 (below) illustrates this relationship by categorizing surveyed parcels into four categories: true positives, true negatives, false positives, and false negatives. Of the 19 parcels where landowners reported windbreaks or riparian buffers, 17 contained corresponding features in the spatial dataset, suggesting a relatively low rate of missed detections (2 false negatives). Conversely, 42 surveyed parcels indicated no AF features, yet 12 of those showed LSWFs in the classification, generating a cluster of false positives. These discrepancies appear to stem from classification challenges at property boundaries and confusion around forested parcels that might be interpreted differently by respondents and the machine-learning model, detailed further in 5.5.2.

Table 1: Survey vs. LSWF spatial outputs confusion matrix for agreement.

	Survey Presence	**Survey Absence**
LSWF Spatial Presence	17 (True Pos.)	12 (False Pos.)
LSWF Spatial Absence	2 (False Neg.)	30 (True Neg.)

The resulting agreement rate for parcels that either had both a self-reported feature and a spatially detected LSWF (true positives), or indicated none both in the survey and the spatial output (true negatives), was sufficient to reinforce the utility of combining these datasets. At the same time, the presence of false positives and false negatives underscores the importance of iterative refinements. The overall accuracy for identifying windbreaks or riparian buffers approached roughly three-quarters of the surveyed sample (see Table 2). This figure is encouraging for a first-wave approach that hinges on basic parcel attributes and classification metrics, yet it indicates room for improved discrimination of sparse woodlands, boundary-adjacent tree stands, and occasionally overlooked linear features. As further discussed in 5.5.2, modifying the criteria for inclusion of LSWFs on a property would significantly improve our overall agreement metric, as many LSWFs that did not agree with survey results were only incidentally related to parcels responding to the survey, on adjacent land holdings.

Table 2: Agreement rate calculation between survey and LSWF dataset.

Metric	**Value**
Total Surveyed Parcels	61
Surveyed Parcels Reporting Windbreaks/Buffers	19 (31.1% of responding parcels in spatial study counties)
Surveyed Parcels Indicating No Windbreaks/Buffers	42 (68.9% of responding parcels in spatial study counties)
Spatially Mapped Parcels with LSWFs	29 (47.5%)
Spatially Mapped Parcels without LSWFs	32 (52.5%)
True Positives (TP) Count	17
False Positives (FP) Count	12
False Negatives (FN) Count	2
True Negatives (TN) Count	30
Overall Agreement Rate (%)	(TP + TN) / 61 → 47/61 ≈ 77.0%

It is essential to note that the survey instrument in Wave 1 was limited to whether landowners perceived a windbreak or riparian buffer on any portion of their holdings without accounting for the nuances of maintenance, planting history, or management intensity. The classification likewise targeted the presence of woody configurations matching shape-based metrics, rather than parsing the degree to which these features might be actively stewarded. Subsequent survey waves and expanded datasets are thus anticipated to better capture the intentionality and intensity of AF practices, refining the accuracy metrics beyond the basic presence/absence framework.

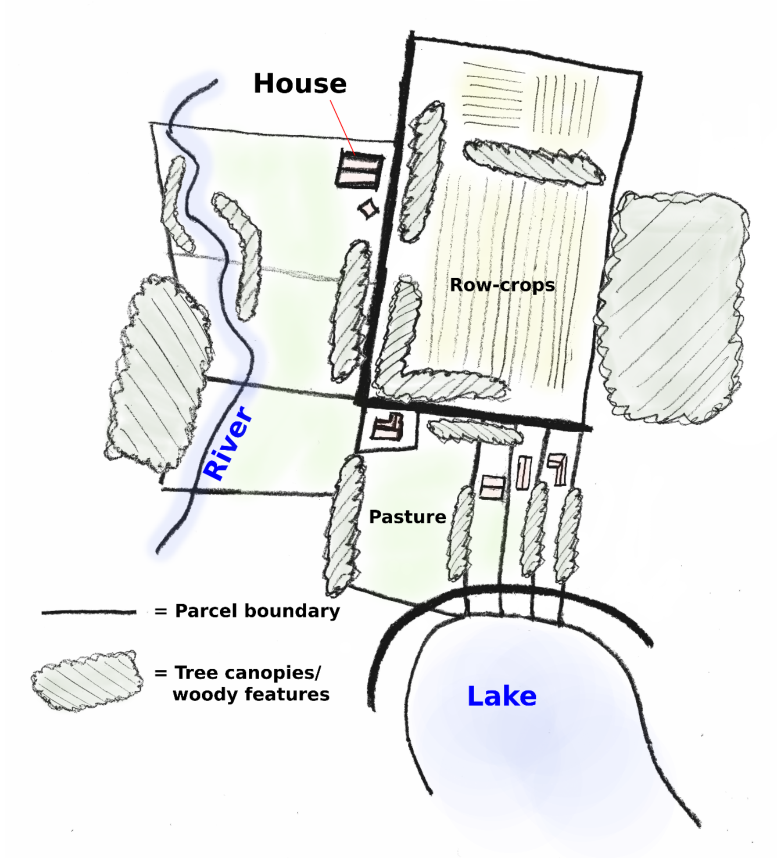

Figure 3: View of our hypothetical landscape with scenarios found in true-positive responses. Typically, true positive responses reporting a windbreak or riparian buffer AF practice very clearly had a whole or significant portion of an LSWF on their parcel pulled for the survey or for an adjacent parcel where there was the same land tenure and land management practice as indicated visually through imagery (e.g., a tilled field where the tilling operation clearly ran directly across a parcel boundary). Along the river, typical examples for a riparian forest buffer are shown which would have been included in the final LSWF dataset, and other examples show typical hedgerows or windbreaks as would have been seen on imagery. On the hypothetical area's left- and rightmost sides are two 'forest' patches or woodlots, which would not be counted as LSWFs in our spatial results.

5.4.3 Spatial Patterns of LSWF Presence

Patterns in the spatial occurrence of linear and small-scale woody features (LSWFs) largely reflect the land use and cover types within the study counties. Most true positives, where landowner-reported agroforestry (AF) features aligned with remote sensing detections, fell along field edges and property boundaries in active agricultural areas. These sites frequently encompassed vegetation rows that shielded crops from wind or paralleled waterways for erosion control, mirroring the findings of Chapter 2 regarding the shape-based attributes of windbreaks and riparian buffers. Because these boundary-oriented tree stands generally form narrower configurations distinct from the surrounding landscape, they were more reliably captured by the model.

Urban contexts, residential parcels, and lakefront properties presented greater challenges for accurate classification. Trees in these locations often formed fragmented or irregular canopies, and some parcels exhibited extensive ornamental or incidental vegetation. Although these elements sometimes appeared as linear clusters in aerial imagery, landowners did not recognize or report them as intentional AF practices. Similarly, the classification approach filtered out denser woodland patches and large contiguous tree cover in northern counties dominated by forested landscapes. Survey responses from these heavily forested areas frequently indicated no managed AF features, further illustrating how environmental context influenced both detection and self-reporting of potential LSWFs.

Concentrations of LSWFs were highest in mid-sized agricultural operations, where farmers often seek to enhance crop productivity or protect water resources without the scale or intensity of more extensive, industrialized operations. Preliminary observations suggest that industrial-scale farms, frequently characterized by extensive row-crop acreage and limited field margins, reported fewer AF practices and exhibited fewer mappable LSWFs. This trend may reflect distinct management styles in heavily mechanized systems, though further evidence is needed to confirm the correlation between operational size and the likelihood of maintaining windbreaks or riparian buffers.

Last, it is important to consider that the analyses in this chapter rely on survey responses drawn only from 35 counties. These counties, distributed across three states, do not represent the total jurisdictional areas, or even a fully representative portion of survey responses. Patterns of LSWF adoption and detection discussed here may, therefore, be distinct from what might be observed in the remaining counties. Additional data will further refine an understanding of how regional variations in land use, ownership structure, and environmental factors influence the presence, accuracy, and classification of agroforestry-related woody features.

5.5 Discussion

5.5.1 Validating Remote Sensing for Agroforestry Classification

The results described in Chapter 4 point to a strong alignment between remote sensing outputs and survey-confirmed agroforestry (AF) features, particularly windbreaks and riparian buffers. Parcels where landowners reported linear woody features generally matched the model's detections, suggesting that high-resolution imagery and shape-based classification can be reliable for identifying smaller-scale linear tree features. This correlation was highest in actively managed agricultural regions where boundary-oriented vegetation fits the model's windbreak and/or riparian corridor criteria.

A few cases revealed that some LSWFs were unmanaged or overlooked by landowners in their survey responses. Some respondents possessed wooded strips that fell within the model's thresholds for AF-like features, yet they did not recognize these strips as intentional plantings. In other scenarios, landowners described "wild" or spontaneously regenerated vegetation, which does not necessarily align with AF definitions even if it appears structurally similar. These examples highlight how classification methods can identify woody features that are functionally akin to windbreaks or buffers but may not reflect the deliberate management behaviors often associated with AF systems.

These findings suggest the need for continued refinements in remote sensing approaches to further distinguish intentionally managed vegetation. Gathering additional information on management inputs—whether pruning, planting, or planned rotations—could help refine algorithms that currently rely on shape metrics alone. Future classification efforts should incorporate higher-resolution imagery or multi-temporal data to track planting activities over time. This type of iterative improvement is key for enhancing the consistency and accuracy of

AF detection, particularly in landscapes where farmers might allow natural regeneration or sporadic tree growth at field edges.

5.5.2 Common Discrepancies

Aligning self-reported survey data with remotely sensed LSWF detections is inherently challenging due to variations in land ownership, parcel boundaries, and differing interpretations of management practices. Discrepancies between survey data and the model's spatial inferences often arose from issues related to land ownership and management boundaries. In some instances, landowners described their land operations holistically, spanning multiple parcels, while our study framework sampled individual parcels. This mismatch occasionally created confusion over which property a landowner's reported windbreak or buffer might actually occupy. Similarly, certain parcels can be nominally owned by one party yet were farmed or maintained by another, leading to uncertainty regarding who was responsible for planting or managing linear woody features.

Land tenure complexities became clear when a single row-crop field extended across multiple parcel boundaries. The imagery consistently depicted a unified field or contiguous LSWF, yet the legal ownership might vary from one parcel to the next. Determining whether a windbreak extending across multiple boundary lines should be credited to one landowner or several could challenge survey-based methods. When the classification model accurately identified LSWFs in such scenarios, there was still ambiguity in assigning management responsibility to an individual respondent.

These challenges also applied to riparian buffers in agrarian settings. Many buffers detected in the southern regions of the study area in Michigan and Wisconsin were narrow and clearly demarcated, standing out as individual features. However, riparian buffers can blend seamlessly into larger woodland patches in the northern sections dominated by extensive forests. The classification model typically filtered out large areas of forest cover, meaning such contiguous forested riparian zones did not appear in LSWF outputs. Some landowners from those areas still reported buffers in the survey, reflecting a belief that any wooded strip near a stream qualified as a “riparian buffer,” regardless of whether the trees were intentionally planted or integrated.

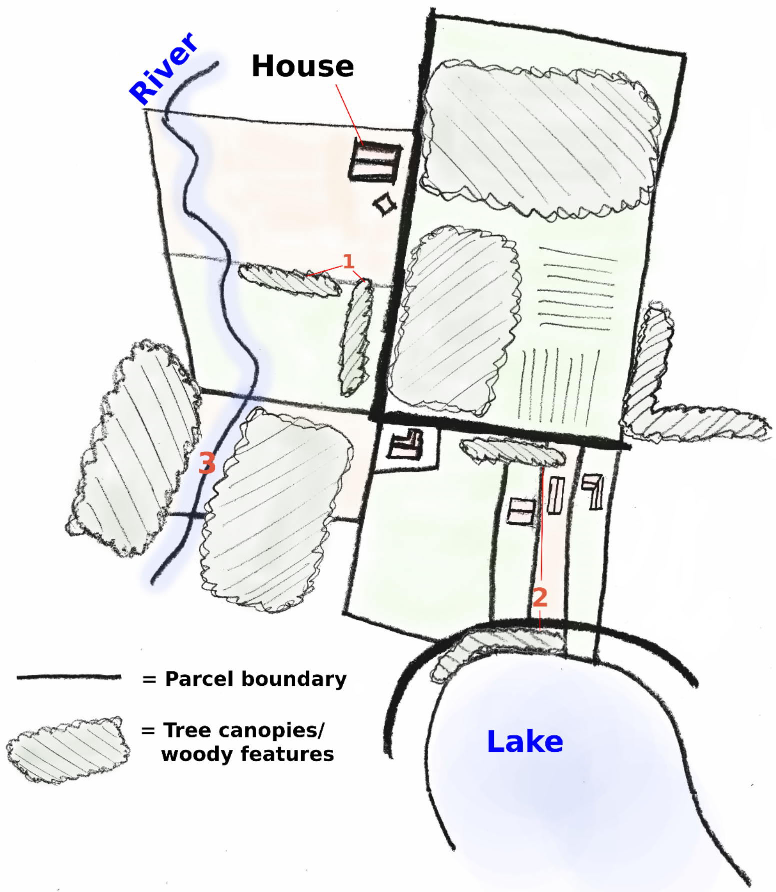

Figure 4: Common cases where false-positive LSWFs were recorded on properties not indicating an AF practice (numbers 1 and 2), or false-negative LSWF reporting of survey-positive riparian buffers (number 3). Respondent parcels indicating a discrepancy in the data presented are shaded light orange. Typically errors arose from 1) marginal sections of LSWFs on adjacent properties crossing over to a respondent’s parcel, 2) portions or ends of full LSWF features which cross over two or more parcels, although the full feature considered my constitute a LSWF, or 3) AF features such as riparian buffers masked by a continuous connection to a larger woody feature (forest/woodlot).

Taken together, these discrepancies underscore the influence of land tenure configurations and varying land cover types on the classification’s ability to align with landowner-reported AF practices. Parcel-specific ownership records do not always account for shared operations or fluid management boundaries, and a one-size-fits-all approach to identifying riparian buffers may overlook important distinctions in tree cover density. Future refinements in both survey instruments and classification methods should address these nuances, ensuring that reported AF features are more accurately attributed to the individuals responsible for their establishment and upkeep.

5.5.3 Necessity of Two-Wave Surveying and Further Analysis

The first wave of surveys was limited to gathering basic presence/absence data on windbreaks and riparian buffers, which provided a foundational layer of understanding but did not fully capture the depth of landowner intentions or management regimes. Farmers and other landowners may have planted trees for varied objectives—soil conservation, wildlife habitat, or erosion control—yet these goals remain unverified when the survey instrument only asks whether specific practices exist. This incomplete view can lead to ambiguity regarding how actively these features are maintained or whether they truly align with established agroforestry (AF) principles.

A second wave of surveys will address this gap by probing deeper into the intensity and objectives of management. Questions aimed at clarifying maintenance practices, planting motivations, and resource inputs (e.g., pruning schedules, manure application, or selective thinning) will offer critical insights into the level of intention behind each woody feature. These data will help distinguish deliberately managed AF systems from incidental or minimally maintained vegetation, providing a more comprehensive evaluation of how farmers engage in AF.

Such detail on management intensity can refine the broader conversation around AF adoption. Participants who confirm active establishment, regular upkeep, and targeted design for wind or water filtration underscore the degree to which these features serve strategic land-use objectives. At the same time, reporting that certain stands remain unmanaged or are spontaneously regenerating challenges the assumption that all woody vegetation in agricultural settings is being stewarded as AF. This deeper information, combined with remote sensing outputs, will clarify whether the model's detections align with genuine AF practices or if recalibrations are needed to account for passive forms of tree growth.

5.5.4 Broader Implications for National AF Mapping, Augmenting National Statistics

Parcel-level surveys, although resource-intensive, carry considerable potential for boosting the reliability of large-scale AF inventories, especially when integrated with remote sensing methods. They provide ground-truth data on management goals, ownership structures, and agricultural practices, all of which help distinguish actively tended AF features from other woody vegetation. This approach can strengthen national estimates that rely solely on broad survey datasets or structural analyses using more spatially coarse data, which could either underestimate AF practice presence for the most common practices or risk overestimating managed AF practices, conflating it with unmanaged woody fragments.

Generating consistent, high-resolution woody feature datasets is similarly resource-intensive, underscoring the value of targeted surveying in pilot areas before expanding to a larger scale. In many cases, conducting a detailed pilot study in counties or regions representative of diverse land-use patterns is more feasible. Researchers can extract generalized statistics on AF presence and absence by combining these smaller-scale yet in-depth surveys with spatial analysis. Regional estimates on the most common AF practices (windbreaks, riparian buffers) could be estimated more thoroughly without relying on resource-intensive efforts to increase survey response rates, by generating estimates of LSWFs and referencing that with a percentage of LSWFs 'likely' to be AF practices. As an example of how to conduct a cost-effective mailing to a focused study area, the United States Postal Service (USPS) Every Door Direct Mail (EDDM) service offers a low-cost distribution option for mailed survey forms, potentially streamlining outreach to specific rural communities to confirm a presence of LSWFs.

Scaling this integrated approach to broader initiatives requires following methods that adapt well to varied landscapes and policies. Chapter 1 laid out a methodology for deriving LSWFs in any county with sufficiently high-resolution imagery. Through parallel landowner surveys, each region can be assessed for levels of AF adoption, yielding more precise statistics to guide conservation incentives or land-use planning. Policies encouraging windbreak establishment, riparian protection, and AF expansion could thus rest on evidence showing how these features manifest differently in distinct agricultural and environmental contexts.

Future remote sensing efforts should incorporate more extensive landowner engagement to refine classification parameters. Survey responses indicating why trees were planted or how often they are maintained can help train models to detect nuanced patterns of vegetation arrangement or growth. In turn, this feedback loop between ground-based surveys and spatial analysis allows policymakers and researchers to track the efficacy of AF promotion campaigns, revealing whether local or federal programs truly incentivize the adoption and careful stewardship of trees on agricultural lands, or the incorporation of agricultural practices in wooded settings.

5.6 Conclusions and Recommendations

Wave 1 data reveal that linear and small-scale woody features (LSWFs) derived from high-resolution spatial analyses largely aligned with landowners' reported agroforestry (AF) practices, particularly for windbreaks and riparian buffers. Survey results showed an agreement rate of nearly three-quarters, highlighting the utility of combining remote sensing with parcel-referenced data. However, the presence of false positives and false negatives underscores the necessity for validating features on the ground. These discrepancies confirm that a multi-step approach—integrating multiple lines of evidence, including more detailed surveys and iterative feedback—is essential for capturing the full spectrum of management intentions.

Advancements in remote sensing algorithms should focus on distinguishing actively managed woody features from those that emerge without deliberate planning, drawing on the methodological recommendations outlined in Chapter 1. Refined shape metrics and the incorporation of temporal data may help differentiate planted windbreaks or buffers from unmanaged vegetation, while multi-season imagery can capture changes resulting from pruning, strategic planting, or tree removal. Parallel improvements in survey design could include more targeted questions about the intensity and frequency of management practices, ensuring that the next wave of landowner data captures crucial details of AF stewardship. This dual refinement of spatial detection and survey instruments will provide a more substantial basis for identifying AF systems at scale.

Scaling the integrated survey and remote sensing approach requires systematic producer outreach and rigorous geospatial analyses. Future initiatives can benefit from practical measures such as two-wave survey methods (presence/absence, followed by detailed management queries) to gather more accurate, layered data, and from leveraging higher-resolution imagery where feasible. Policy support would also strengthen the viability of this work: financial incentives or technical assistance programs could encourage landowners to adopt and maintain AF features. At the same time, direct engagement—through mailers or cooperative extension networks—might improve response rates and data quality. Over time, these strategies will help refine national and regional AF inventories, creating better-informed conservation and land-use planning frameworks.

REFERENCES

Ahmad, Tauqueer, et al. "Estimation of Area under Agroforestry Using High Resolution Satellite Data." *Agroforestry Systems*, vol. 90, no. 2, Apr. 2016, pp. 289–303. *Springer Link*, https://doi.org/10.1007/s10457-015-9854-2.

Bégué, Agnès, et al. "Remote Sensing and Cropping Practices: A Review." *Remote Sensing*, vol. 10, no. 1, 1, Jan. 2018, p. 99. *www.mdpi.com*, https://doi.org/10.3390/rs10010099.

Burke, Morgen W. V., et al. "Detection of Shelterbelt Density Change Using Historic APFO and NAIP Aerial Imagery." *Remote Sensing*, vol. 11, no. 3, 3, Jan. 2019, p. 218. *www.mdpi.com*, https://doi.org/10.3390/rs11030218.

Eggleston, Jonathan. "Frequent Survey Requests and Declining Response Rates: Evidence from the 2020 Census and Household Surveys." *Journal of Survey Statistics and Methodology*, vol. 12, no. 5, Nov. 2024, pp. 1138–56. *Silverchair*, https://doi.org/10.1093/jssam/smae022.

Garrett, Harold E., et al., editors. *North American Agroforestry*. 3rd edition, Wiley, 2022. *K10plus ISBN*, https://doi.org/10.1002/9780891183785.

Liknes, Greg C., et al. "Shape Indexes for Semi-Automated Detection of Windbreaks in Thematic Tree Cover Maps from the Central United States." *International Journal of Applied Earth Observation and Geoinformation*, vol. 59, July 2017, pp. 167–74. *DOI.org (Crossref)*, https://doi.org/10.1016/j.jag.2017.03.005.

Luscombe, David J., et al. "Rapid, Repeatable Landscape-scale Mapping of Tree, Hedgerow, and Woodland Habitats (THaW), Using Airborne LiDAR and Spaceborne SAR Data." *Ecology and Evolution*, vol. 13, no. 5, May 2023, p. e10103. *PubMed Central*, https://doi.org/10.1002/ece3.10103.

Meneguzzo, Dacia M., et al. "Mapping Trees Outside Forests Using High-Resolution Aerial Imagery: A Comparison of Pixel- and Object-Based Classification Approaches." *Environmental Monitoring and Assessment*, vol. 185, no. 8, Aug. 2013, pp. 6261–75. *Springer Link*, https://doi.org/10.1007/s10661-012-3022-1.

Patriarca, Alessio, et al. "Wide-Scale Identification of Small Woody Features of Landscape from Remote Sensing." *Land*, vol. 13, no. 8, 8, Aug. 2024, p. 1128. *www.mdpi.com*, https://doi.org/10.3390/land13081128.

Pirbasti, Mehran Alizadeh, et al. "Hedgerows Monitoring in Remote Sensing: A Comprehensive Review." *IEEE Access*, vol. 12, 2024, pp. 156184–207. *DOI.org (Crossref)*, https://doi.org/10.1109/ACCESS.2024.3485512.

Romanova, Olga, et al. “Perspectives of Agroforestry Practitioners on Agroforestry Adoption: Case Study of Selected SARE Participants☆.” *Rural Sociology*, vol. 87, no. 4, Dec. 2022, pp. 1401–31. *DOI.org (Crossref)*, https://doi.org/10.1111/ruso.12463.

Sharma, Prashant, et al. “Geospatial Technology in Agroforestry: Status, Prospects, and Constraints.” *Environmental Science and Pollution Research*, vol. 30, no. 55, Nov. 2023, pp. 116459–87. *Springer Link*, https://doi.org/10.1007/s11356-022-20305-y.

Smith, M. M., et al. “Agroforestry Extent in the United States: A Review of National Datasets and Inventory Efforts.” *Agriculture (Switzerland)*, vol. 12, no. 5, 2022. Scopus, *Scopus*, https://doi.org/10.3390/agriculture12050726.

Stubblefield, Kelsi Jordan. *Agroforestry Adoption: Influential Factors, Land Manager Perceptions, and Willingness-to-Accept Payments*. 2021. University of Missouri--Columbia, M.S. *DOI.org (Crossref)*, https://doi.org/10.32469/10355/90197.

USDA. *The Drop in Farmer Response Rates to USDA Surveys Has Leveled Off*. 1 Feb. 2021, https://www.usda.gov/about-usda/news/radio/daily-newsline/2021-02-01/drop-farmer-response-rates-usda-surveys-has-leveled.