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A Landscape Approach to Understanding Carbon Sequestration Assets at a State-Wide Scale for Sustainable Urban Planning

Siqi Lai [1,*], Le Zhang [2], Yijun Zeng [1] and Brian Deal [1]

[1] Department of Landscape Architecture, University of Illinois at Urbana-Champaign, 611 Taft Drive, Champaign, IL 61820, USA; yijunz4@illinois.edu (Y.Z.); deal@illinois.edu (B.D.)
[2] Center for Terrestrial Biodiversity of the South China Sea, Hainan University, Haikou 570228, China; lezhang3@hainanu.edu.cn
* Correspondence: siqilai2@illinois.edu

Abstract: This study presents a refined approach to spatially identify carbon sequestration assets, crucial for effective climate action planning in Illinois. By integrating landscape analytical methods with species-specific carbon assessment techniques, we deliver a nuanced evaluation of forest area sequestration potential. Our methodology employs a combination of landscape imagery, deep learning analytics, Kriging interpolation, and i-Tree Planting tools to process forest sample data. The results reveal a spatial variability in sequestration capacities, highlighting significant carbon sinks in southern Illinois. This region, known for its historical woodland richness, showcases the distinct carbon sequestration abilities of various tree species. Findings emphasize the role of biodiversity in the carbon cycle and provide actionable insights for forest management and carbon neutral strategies. This study demonstrates the utility of advanced spatial analysis in environmental research, underscoring its potential to enhance accuracy in ecological quantification and conservation efforts.

Keywords: carbon sequestration in Illinois; sustainable forest management; Kriging interpolation; deep learning

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Citation: Lai, S.; Zhang, L.; Zeng, Y.; Deal, B. A Landscape Approach to Understanding Carbon Sequestration Assets at a State-Wide Scale for Sustainable Urban Planning. *Sustainability* **2024**, *16*, 3779. https://doi.org/10.3390/su16093779

Academic Editors: Felicia Di Liddo, Pierluigi Morano, Francesco Tajani and Paola Amoruso

Received: 14 March 2024
Revised: 17 April 2024
Accepted: 25 April 2024
Published: 30 April 2024

1. Introduction

Concerns about global climate change are escalating, largely due to human-made carbon emissions. These emissions, which include large amounts of greenhouse gases such as carbon dioxide (CO_2), methane, and nitrous oxide, have been globally recognized as a serious environmental threat [1,2]. For this reason, international efforts such as the Paris Climate Agreement require participating countries to significantly reduce GHG emissions [3]. A key strategy for achieving these reductions is carbon sequestration, particularly in terrestrial ecosystems, which is an important countermeasure against global warming.

This paper explores the role of carbon sequestration in the Climate Action Plans (CAPs) adopted by governments and businesses. CAPs provide a strategic framework that includes a combination of sustainable energy strategies, transportation system improvements, land use planning, and renewable energy adoption, with a particular emphasis on carbon offsets. These offsets typically involve projects aimed at reducing emissions elsewhere, such as reforestation initiatives and methane capture programs, thus contributing to achieving carbon neutrality [4,5].

Terrestrial ecosystems, particularly forested areas, are natural carbon sinks and play an essential role in carbon storage and sequestration [6,7]. The accurate assessment of the carbon sequestration capacity of forests is essential for developing effective regional strategies, evaluating the benefits of ecosystem restoration, and establishing carbon trading mechanisms [6,8].

Recent advancements in measuring and estimating carbon storage in forest ecosystems have utilized a variety of methods—from sample plot measurements [9] and micrometeorological techniques [10] to advanced remote sensing technologies like LiDAR [11,12]. These methods provide critical data for understanding the health, amount, and distribution of our sequestration assets, which is indispensable for local and national entities aiming to achieve net-zero emissions.

Despite significant progress, challenges remain in accurately mapping the spatial distribution of carbon, particularly concerning species-specific, density, and size-related variations. This study aims to address these challenges by proposing refined methodologies that leverage both comprehensive field surveys and advanced remote sensing technologies, typically employed in urban green spaces, to enhance the spatial resolution and accuracy of forest carbon sequestration assessments. By integrating these techniques, this study seeks to bridge the existing granularity gap in current forest carbon sequestration methodologies, providing a more detailed and precise understanding of carbon distribution essential for effective climate action planning.

Given the identified gaps in current methodologies for assessing carbon sequestration, our research employs a novel approach that integrates landscape architecture methods with ecological data analysis. This interdisciplinary approach is designed to enhance the understanding and management of carbon sequestration assets in Illinois forests. Our primary research objectives are structured to address both the depth and scope of this challenge:

1. **Enhance methodological integration**: The first objective is synthesizing and enhancing diverse methodologies previously utilized for estimating carbon sinks. By integrating traditional ecological assessments with innovative spatial design principles, we aim to increase both the accuracy and comprehensiveness of carbon sequestration assessments. This objective involves a detailed analysis of specific tree data—focusing on quantity, species, and size—thereby providing a more granular view of carbon storage potentials than typically achieved in broader regional studies. This approach allows for a more targeted management strategy that can be tailored to specific forest types and conditions within Illinois.
2. **Refine spatial mapping techniques**: The second objective is to refine the spatial mapping of carbon assets across Illinois forests. Leveraging the precision of landscape architecture methods, particularly in spatial analysis, enables a more detailed and accurate mapping of carbon distributions. This innovative use of landscape methodologies in ecological research stands to significantly improve the spatial resolution of carbon sequestration data compared to traditional forestry assessments, which often lack detailed spatial differentiation.

These objectives are significant because they address critical weaknesses in current forest carbon sequestration assessments—namely, the general lack of detailed, localized data and the integration of robust spatial analytics with ecological metrics. By focusing on detailed tree data and integrating it with spatial design principles, our methodology enhances the accuracy and detail of carbon sequestration capacities, which is crucial for formulating effective conservation strategies and climate action plans. The application of landscape architecture methods provides an advanced toolset for spatially mapping carbon data, enabling the precise visualization of carbon distribution across varied forest compositions and conditions—an advancement over the more generalized, less localized approaches commonly used in the field.

This paper is structured as follows. Section 1 sets the context, establishing the significance of carbon assets and highlighting the research gap this study aims to address. Section 2 offers details about the geographical focus of the research and the data sources utilized, ensuring clarity regarding the empirical foundation of the analysis. We also elucidate the mixed methods (tree species identification, Kriging extrapolation, and i-Tree Planting tool) we adopted. Section 3 presents the outcomes of our analysis, laying out the data in a coherent manner to facilitate subsequent interpretation. Finally, in Section 4, we delve into the findings of our analysis and highlight the implications of our results for carbon sequestration analysis. We conclude our paper with a brief synopsis along with some thoughts on the approach and next steps.

2. Materials and Methods

In this section, we provided a detailed description of a deep learning-based analytical framework (Figure 1). We assessed carbon sequestration by integrating forest sample data from the Critical Trends Assessment Program (CTAP) [13], land use maps, and forest type maps [14] collected across Illinois. The validation of tree species is conducted through the analysis of Google Street View (GSV) 360 imagery coupled with computer vision techniques. Tree size distribution is measured using mean estimation. These parameters, including tree counts, species, and dimensions, feed into the i-Tree Planting (https://planting.itreetools.org/, accessed on 12 November 2023). We further employ Kriging interpolation technology [15] to elucidate the spatial variability patterns in carbon sequestration. Finally, we use the gain–loss method [16] to validate the results (see Appendix A for more details).

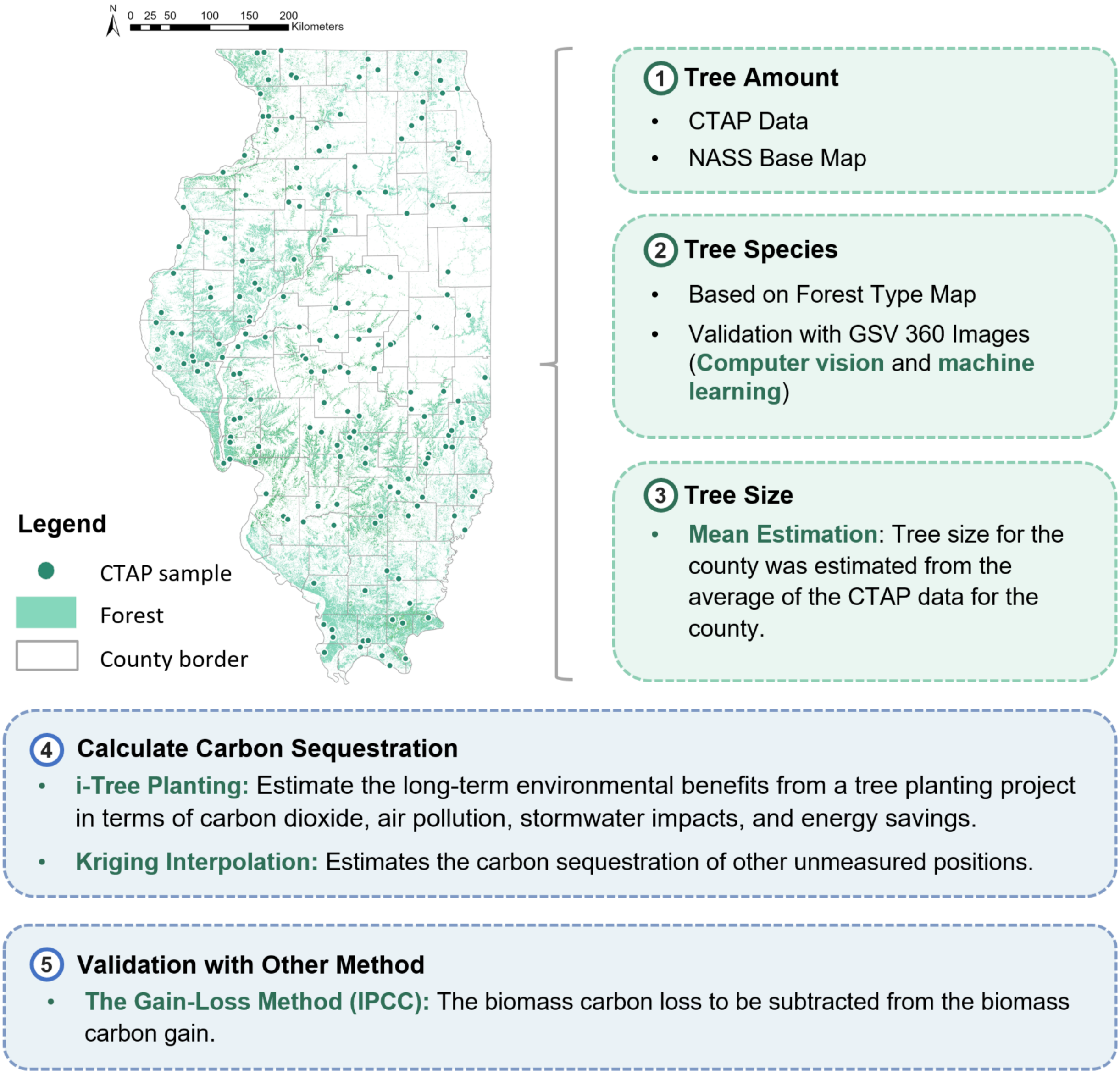

Figure 1. Conceptual framework for carbon sequestration calculation of Illinois forests.

2.1. Study Area

Illinois, the subject of this study, is predominantly an agricultural state with farms covering approximately 75% of its total land area (Figure 2). Alongside its agricultural prominence, Illinois experiences various environmental and ecological considerations, particularly in relation to land use and sustainability practices [17]. This agricultural dominance necessitates an incisive examination of the state's ecological strategies, particularly in the context of carbon sequestration and land stewardship. This involves assessing the spatial distribution of carbon sinks, strategically developing forests, and mitigating ecological deficits, in line with sustainable development goals (Illinois 30 by 30 Task Force) and initiatives specific to the state's climatic and ecological conditions [18]. Illinois has a temperate climate with broad-leaved deciduous trees. The most prevalent trees in Illinois are species such as the oak, hickory, gum, pine, cypress, elm, ash, cottonwood, maple, beech, and birch, which account for over 94% of the forest [18]. Therefore, these eleven species were chosen as the tested tree species in our study.

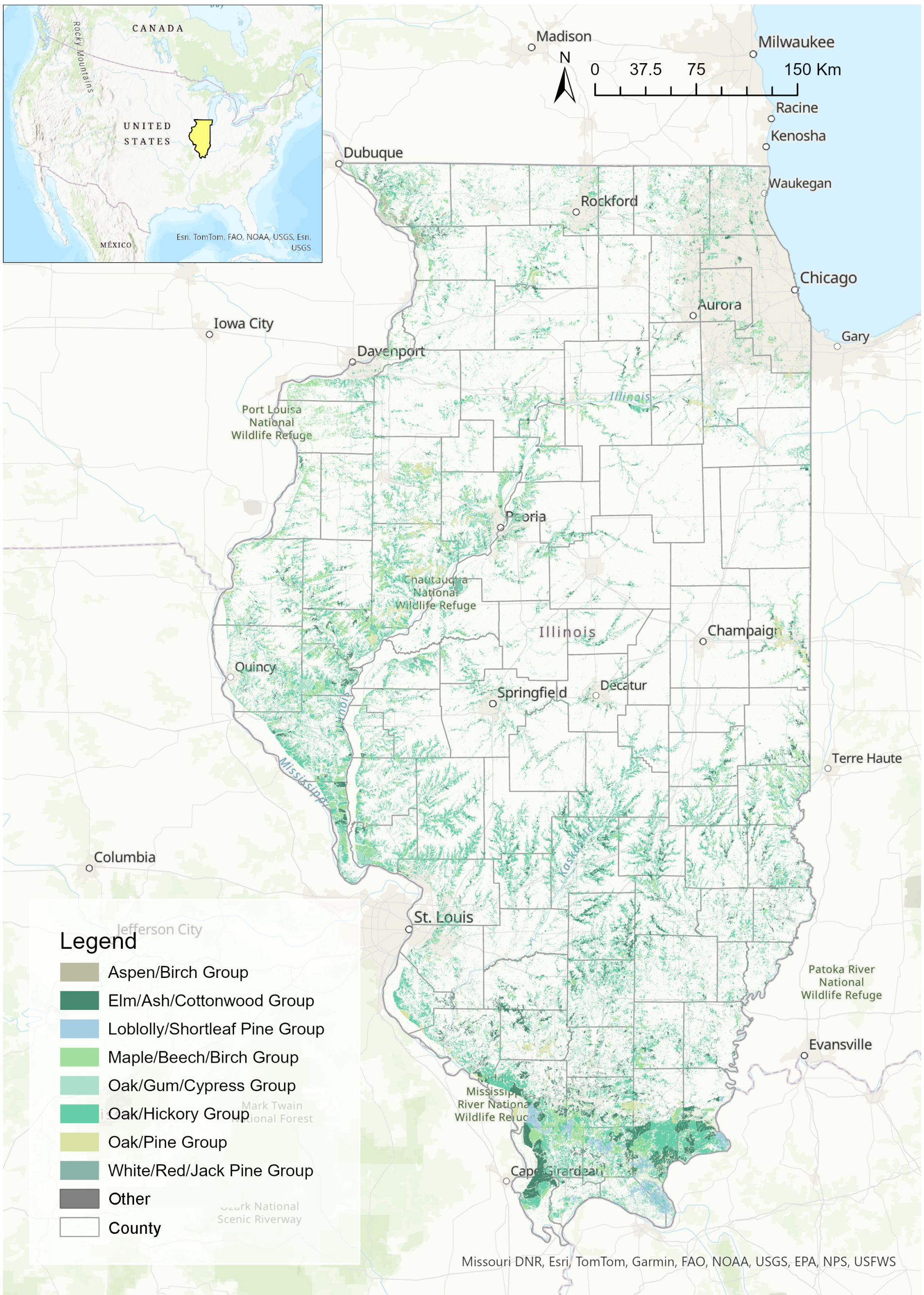

Figure 2. The location of Illinois and the locations of major forest tree species in Illinois based on US Forest Service (2003).

2.2. Data Sources and Processing

This study utilizes data from the Critical Trends Assessment Program (CTAP), an established monitoring program initiated in 1997 by the Illinois Department of Natural Resources to evaluate the ecological health of forests, wetlands, and grasslands across Illinois. CTAP has systematically examined nearly 200 randomly selected sites within Illinois forests to date. At each site, biological data are collected from three 50 m by 10 m rectangular transects extending from a central point, including the size and species of each tree within these areas (Table 1). Sites are revisited every five years to maintain and update the records, aligning with our study periods of 1997–2001, 2002–2006, 2007–2011, and 2012–2016. For this research, we analyzed data from 190 forest sites collected over two decades, from 1997 to 2016, obtained directly from the CTAP archives. Inclusion criteria for data analysis required consistent records across the specified intervals; therefore, sites with missed or duplicated visits were excluded, leaving 125 sites that met our rigorous standards for analysis (Figure 1).

Table 1. CTAP data samples.

Site ID	Number of Visit [1]	Genus	Species	Year	Size Classes [2]	Count
008203F	1	*Quercus*	*Rubra*	1997	H	1
015201F	3	*Acer*	*Saccharum*	2003	B	6
014504F	2	*Carya*	*Sp.*	2016	C	1
...	...	...	...	...	...	...

[1] Number of visits/revisits to a particular site in which the record was made. [2] Size classes of trees, based on diameter at breast height: A (5–9.9 cm), B (10–14.9 cm), C (15–19.9 cm), D (20–24.9 cm), E (25–29.9 cm), F (30–39.9 cm), G (40–49.9 cm), H (50–59.9 cm), I (>60 cm). For those >60 cm, DBH observers record the exact DBH measurements.

We chose specific streets in Illinois that were lined with the state's predominant forest tree species, making use of the available Google Street View (GSV) 360 imagery. Using the Street View Download 360 Pro 4.0.17 software, developed by Thomas Orlita in 2023, we were able to efficiently download batches of GSV images along with their associated metadata. These metadata included details such as the image's geographical coordinates, elevation, capture date, and the direction the camera was facing, all of which were embedded in the image file names. We gathered more than 30 GSV 360 images from each county for our validation efforts. In total, the collection process yielded over 5000 GSV 360 images across Illinois, as depicted in Figure 3. We then conducted a screening process to eliminate any images that featured indistinct trees, including those that were too young or bare of leaves. After this curation, a set of 3460 images remained and were deemed suitable for the study.

2.3. Methods

2.3.1. Tree Amount

In this study, we assessed the tree density within a defined unit area in Illinois by analyzing forest land coverage. The process began with the calculation of the total area of 125 CTAP sample sites. For each of the sites, the tree plot areas are defined by three 50 m-by-10 m rectangular transects that radiate out from the center point. Therefore, each site was measured to encompass an area of 1500 m^2, calculated as the product of the dimensions 3×50 m $\times$ 10 m. The total number of trees across all 125 sites was counted, amounting to 12,750 trees, with an average value of 102 for each site. To derive the average tree density, we divided the total tree count by the total area, yielding an approximate density of 0.068 trees per square meter. For a more granular analysis, we then divided the area into smaller units, each measuring 30 m × 30 m (900 m^2). The average tree density was applied to these units to estimate an average tree count, which resulted in approximately 61 trees per unit.

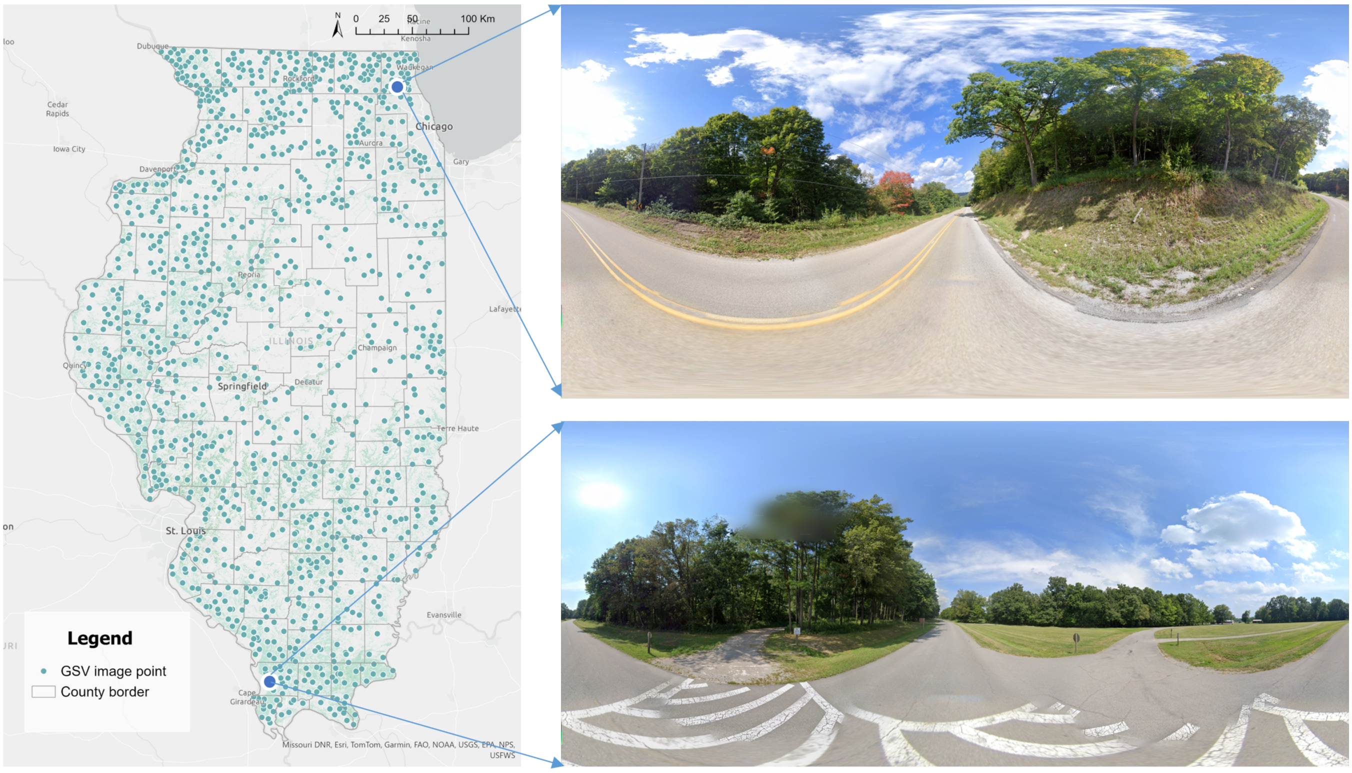

Figure 3. Spatial distribution and examples of GSV 360 images.

2.3.2. Image Recognition API for Tree Species Validation

Plant.id, created by the kindwise team, is designed to aid in the tracking of both invasive and endangered plant species, serving a variety of clients from commercial entities to individuals. Utilizing Python, TensorFlow, and AWS, the API delivers identifications of plant species from images, along with supplemental details such as common plant afflictions. The API's accuracy is enhanced by the inclusion of the plant's geographical coordinates. To further refine results, Plant.id enables the submission of multiple images for a single plant specimen. It provides both the scientific and common names of plants, attaching a confidence score to each suggested identification. The Python programming language, with the aid of libraries like requests, base64, and kindwise-api-client, is used to interact with the API, which has been tested with GSV 360 imagery. In assessing the API's precision in species identification, only the top-scoring suggestion is considered.

Our validation process of tree species identification is shown in Figure 4. Initially, a sample site was selected, highlighted on an aerial map to specify the study area. Subsequently, the tree types within this site were identified as belonging to the Maple/Beech/Birch Group based on the US Forest Service (2003) Tree Type Map. This preliminary identification was then corroborated with GSV 360 images, ensuring that the observed species corresponded with the tree type map data. To further refine our assessment, we utilized the Plant.id API, which confirmed the presence of Maple (Acer), corroborating our initial findings. The confluence of tree-type map data, GSV 360 images, and API-assisted identification forms a robust methodology for species verification.

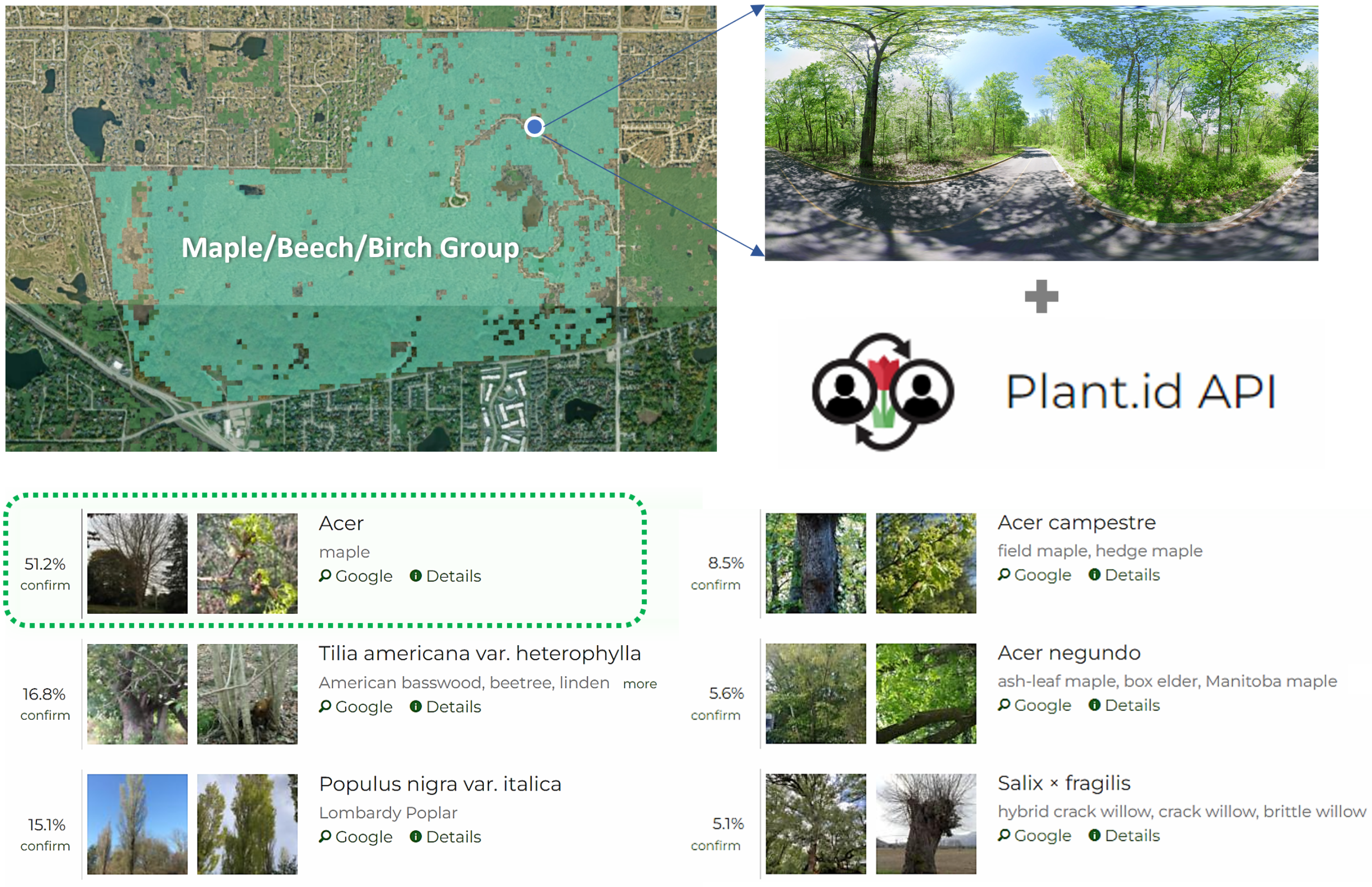

Figure 4. Descriptive flow of tree species identification process.

2.3.3. i-Tree Planting-Based Carbon Sequestration

In this research, we estimated the carbon sequestration capacity of Illinois forests using the i-Tree Planting tool, which calculates carbon sequestration for the whole tree (root and above-ground part). Carbon sequestration is identified as the annual amount of carbon, derived from atmospheric CO_2, absorbed and stored in the tissues of trees. The i-Tree planting tool computes forest carbon sequestration by employing a tree growth model and a biomass equation. This calculation is dependent on various factors including tree species, diameter at breast height (DBH), crown coverage, and geographic location [19–21]. The tool incorporates 150 allometric equations, each corresponding to a distinct tree species. In cases where a specific species lacks a dedicated equation, an aggregate equation at the genus level is utilized, if it exists. Should there be no genus level equation, the calculation defaults to using an equation at the family level. We list carbon sequestration values for this study in Table 2.

Table 2. Carbon sequestration value of a single tree.

Scientific Name	Common Name	Carbon Sequestration (kg CO_2/yr) by Size Group (DBH, cm)											
		5–9.9	**10–14.9**	**15–19.9**	**20–24.9**	**25–29.9**	**30–39.9**	**40–49.9**	**50–59.9**	**60–79.9**	**80–99.9**	**100–109.9**	**>110**
Fagus grandifolia	American beech	10.1	19.1	29.1	40.3	52.4	72.1	99.8	129.0	158.8	210.3	192.5	98.5
Ulmus americana	American Elm	11.1	21.6	33.9	47.6	62.5	87.0	122.9	162.1	204.2	290.6	289.4	201.4
Taxodium (Genus)	Bald Cypress spp. (Genus)	23.6	42.8	64.5	88.1	113.2	153.1	207.7	262.5	289.7	144.5	140.1	93.0
Populus grandidentata	Bigtooth aspen	20.1	41.1	67.3	98.0	132.6	192.6	282.1	383.5	437.1	336.3	343.0	242.8
Populus deltoides	Eastern Cottonwood	12.5	24.9	40.0	57.3	76.5	108.6	156.3	209.3	267.3	397.6	407.5	214.4
Fraxinus pennsylvanica	Green Ash	12.9	21.8	31.0	40.5	50.3	65.2	85.6	106.4	127.7	165.2	158.1	108.0
Carya (Genus)	Hickory spp. (Genus)	12.2	24.1	38.4	54.7	72.8	102.7	147.1	195.5	246.8	342.1	329.1	167.3
Ulmus (Genus)	Elm spp. (Genus)	18.0	35.4	55.8	78.6	103.4	144.1	203.9	269.2	339.3	264.7	263.8	183.7
Acer rubrum	Red Maple	16.0	30.6	47.8	67.2	88.6	123.8	175.8	232.9	294.0	412.6	401.2	206.3
Quercus rubra	Red Oak Group	10.5	21.0	33.4	47.4	62.8	88.1	125.6	166.8	211.3	304.2	304.5	159.2
Pinus resinosa	Red Pine	26.9	49.2	74.4	101.5	129.5	172.0	229.1	288.3	318.7	216.9	212.2	146.2
Betula nigra	River Birch	13.7	27.4	43.8	62.6	83.4	118.2	170.4	228.4	291.4	425.2	357.5	149.8
Acer saccharum	Sugar Maple	9.2	17.7	27.5	38.5	50.4	69.7	97.4	126.8	157.0	207.5	193.9	99.3
Liquidambar styraciflua	Sweetgum	16.9	32.6	51.6	73.5	98.0	139.4	200.0	266.8	301.6	218.3	214.6	144.5
Fraxinus americana	White Ash	11.5	22.3	34.9	48.9	64.1	88.8	124.9	164.1	206.1	291.7	289.7	151.9
Quercus alba	White Oak	7.1	14.4	23.1	33.2	44.4	63.4	92.0	124.1	159.2	234.6	237.7	123.4
Fraxinus americana	White Ash	11.5	22.3	34.9	48.9	64.1	88.8	124.9	164.1	206.1	291.7	289.7	151.9
Betula nigra	River Birch	13.7	27.4	43.8	62.6	83.4	118.2	170.4	228.4	291.4	425.2	357.5	149.8
Acer saccharinum	Silver Maple	19.9	33.4	47.3	61.6	76.1	98.4	128.7	159.6	191.0	246.0	233.9	157.6

2.3.4. Gain–Loss Method

The gain–loss method, as outlined by the Intergovernmental Panel on Climate Change [16], provides a systematic approach for calculating carbon sequestration in forest ecosystems. This method operates on the principle of balancing the carbon gains against the losses within specified carbon pools over a given time period. Gains in carbon are typically attributed to biomass growth and the expansion of forest areas, including both above-ground and below-ground biomass increases. Losses, conversely, account for carbon emitted due to forest degradation, deforestation, natural disturbances (such as fires), and human activities (like timber harvesting). In applying the gain–loss method, the calculation is initially confined to forest areas that have remained forests throughout the assessment period, focusing on distinct carbon pools. These pools commonly include living biomass (both above and below ground), deadwood, litter, and soil organic carbon. The gain–loss method can be encapsulated by the equation:

$$\Delta C_B = \Delta C_G - \Delta C_L \quad (1)$$

where ΔC_B = annual change in carbon stocks in biomass (the sum of above-ground and below-ground biomass terms in Equation (2)) for each land sub-category, considering the total area, tonnes C yr^{-1}; ΔC_G = annual increase in carbon stocks due to biomass growth for each land sub-category, considering the total area, tonnes C yr^{-1}; ΔC_L = annual decrease in carbon stocks due to biomass loss for each land sub-category, considering the total area, tonnes C yr^{-1}

$$\Delta C_{LUi} = \Delta C_{AB} + \Delta C_{BB} + \Delta C_{DW} + \Delta C_{LI} + \Delta C_{SO} + \Delta C_{HWP} \quad (2)$$

where ΔC_{LUi} = carbon stock changes for a stratum of a land-use category.

Subscripts denote the following carbon pools: AB = above-ground biomass; BB = below-ground biomass; DW = deadwood; LI = litter; SO = soils; HWP = harvested wood products.

2.3.5. Kriging Interpolation Method

Kriging interpolation, a potent tool for predicting environmental variables in uncharted areas, effectively utilizes the spatial autocorrelation found in ecological data [22]. It not only considers the distance between known data points but also models their spatial correlation, crucial for accurately depicting forest attributes [23]. The process of Kriging interpolation in this study involved three key phases:

Data exploration: The study began with a thorough examination of the spatial distribution of data. The suitability of Kriging interpolation is generally contingent upon the data exhibiting a normal distribution and possessing spatial autocorrelation [24]. To assess the distribution of our data, we employed histogram and Normal QQ plot tools. For data deviating from normal distribution, transformation techniques were applied to mitigate scaling effects [25,26]. Specifically, a log transformation, which utilizes the natural logarithm for data normalization, was employed for data exhibiting positive skewness with a limited presence of extreme values [27]. Outliers, both global and local, were identified using tools like histograms, semivariance/covariance clouds, and Voronoi mapping [28]. Global outliers are distinct from the overall dataset, while local outliers vary significantly from their immediate surroundings. Recognizing outliers is crucial, as they can indicate either real anomalies or errors. After identification, outliers resulting from errors were corrected or removed. Spatial autocorrelation, indicating that nearer points are more related than distant ones [29], was assessed. The degree of spatial dependency was categorized into high, moderate, or weak, based on the Nugget variance and Sill values [30].

Semivariogram modeling: Understanding the spatial correlation of the sample data was essential. We constructed empirical semivariograms for each model: spherical, Gaussian, and exponential [31]. The choice of model depended on how well each could capture the inherent spatial autocorrelation within the ecological data. The spherical model, typically preferred for its moderate assumption of spatial continuity, was compared against the Gaussian and exponential models, which assume smooth and rapid changes in spatial continuity, respectively. The best fit was determined by the least squares criterion, adjusted for the peculiarities of our dataset, which included varying densities of data points and differing degrees of spatial autocorrelation. The final model choice provided a robust framework for predicting environmental variables by effectively balancing the theoretical variances with empirical data observations.

Hotspot analysis: The final step was identifying statistically significant hot and cold spots in the spatial distribution of sequestration values using the Getis–Ord Gi* statistic [32]. This analysis helped in pinpointing areas with significant high or low values, thereby contributing to a deeper understanding of the spatial patterns in Carbon sequestration.

Throughout, the study employed ordinary Kriging, supported by rigorous testing for prediction accuracy at unknown locations, evaluating systematic bias and sensitivity using metrics like mean error (ME) and root mean square error (RMSE). The closer ME is to zero and the smaller the RMSE, the higher the accuracy of the Kriging model's predictions [33].

3. Results

This section presents the findings of our comprehensive analysis on the spatial distribution of tree species and forest carbon sequestration within the state of Illinois. The tree species distribution maps reveal how species prevalence correlates with environmental gradients and soil types, reflecting the diverse ecological niches in Illinois. Maps elucidate the spatial variation in sequestration rates across the state, with a marked carbon sink in the southern regions adjacent to Shawnee National Forest. Additionally, the hotspot map further distinguishes areas with the significant clustering of high and low carbon values, offering critical insights into the spatial patterns that may inform conservation efforts and policy making.

3.1. *Tree Species Distribution of Illinois' Forests*

Figure 5 presents the distribution of various tree species—oak, beech, cypress, hickory, elm, cottonwood, birch, gum, and a0sh—across the state, specifically illustrating the amount ratios of these species compared to the total tree amount in each area. A gradation of blue hues represents the density ratios, with the darker shades indicating regions of higher prevalence. In the illustrated maps, the spatial distribution of tree species is markedly varied, showcasing the ecological diversity of the region.

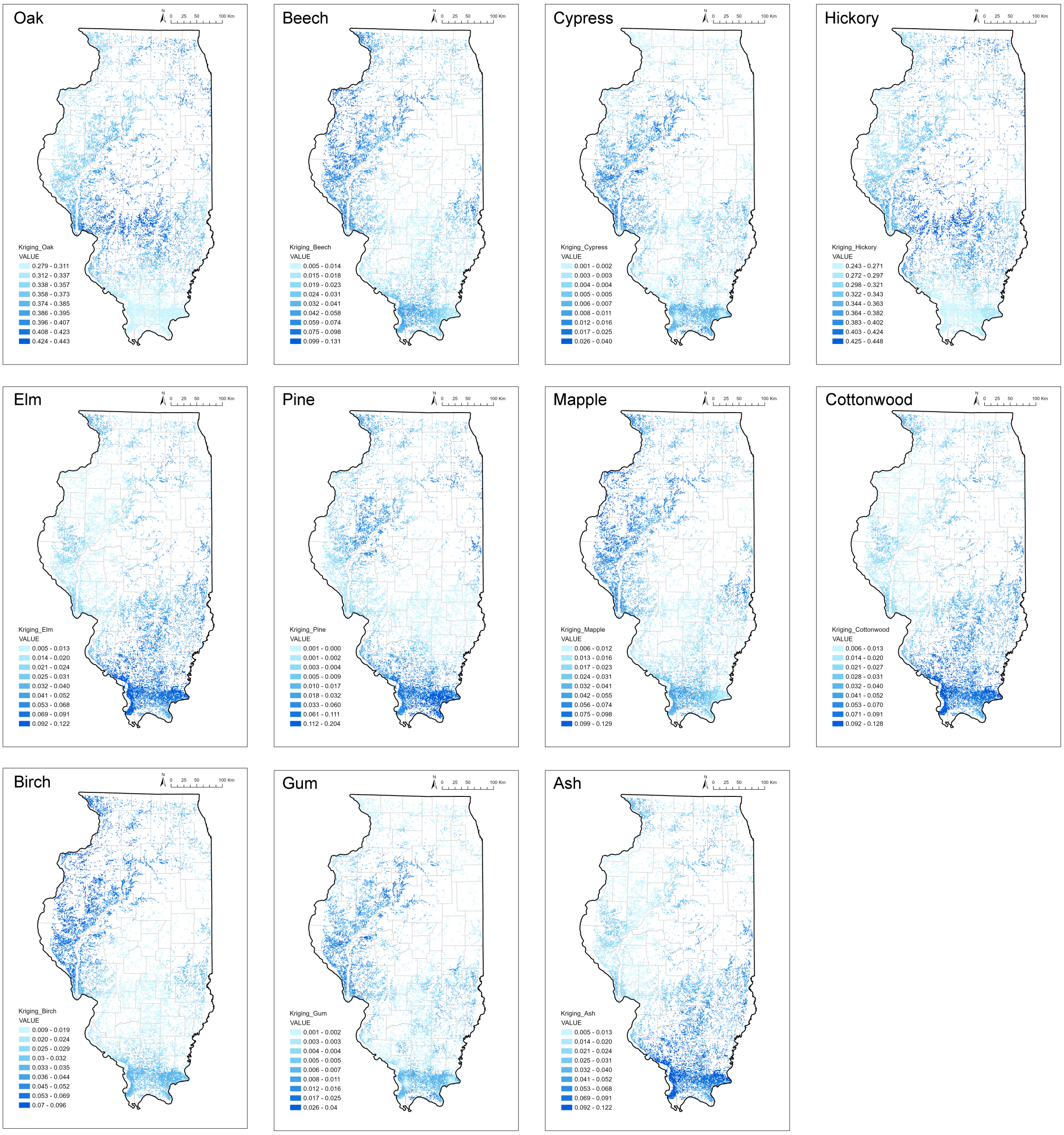

Figure 5. Spatial distribution of forest tree species.

Focusing on a selection of species, we observe distinct patterns of prevalence. The oak, for example, shows a robust presence with higher ratio values, particularly concentrated in the southern parts of the state, suggesting a preference for the warmer climate and soil types found in these areas. The beech trees display a more scattered distribution, with pockets of higher density in the northern region, indicating their adaption to cooler climates and possibly to specific soil conditions prevalent in those areas. Meanwhile, the cypress distribution is notably confined to the wetland areas along the Mississippi River, reflecting their ecological niche in wetter, swampy environments. In contrast, the hickory species exhibits a widespread distribution, albeit with moderate density ratios, implying a broad adaptability but less dominance in any specific region. The maples, which are known for their adaptability, show a relatively even distribution throughout the state, although with a slight increase in the northern regions, potentially due to the preference for cooler temperatures.

3.2. Sequestration Distribution of Illinois Forests

The results showed that the total sequestration potential was 5,377,200 t C/y within the Illinois forests, which is very close to the results 5,303,433 t C/y derived from IPCC gain–loss method. In Figure 6, (left), the Kriging interpolation map portrays the distribution of carbon sequestration, measured in kilograms of CO_2 per square meter per year. A palette of blues indicates varying intensities, with darker hues denoting higher sequestration values. Notably, the southern regions, particularly in areas adjacent to the Shawnee National Forest, exhibit the darkest blues, suggesting a significant carbon uptake, potentially due to the dense forest cover. Conversely, central areas around Springfield show lighter shades, implying lower carbon rates. The right map (Figure 6) highlights 'hotspots' of carbon sequestration using a Getis–Ord Gi* statistic, pinpointing areas with significant clustering of high and low carbon values. Here, the most intense hot spots, marked in deep red with 99% confidence, appear prominently along the southern tip of the state, near the confluence of the Mississippi and Ohio rivers, indicating robust sequestration likely influenced by the confluence of riverine and forest ecosystems. In contrast, the map reveals cold spots with a 90% confidence level, indicated in light blue, scattered throughout the central part of the state, including the region northwest of Decatur.

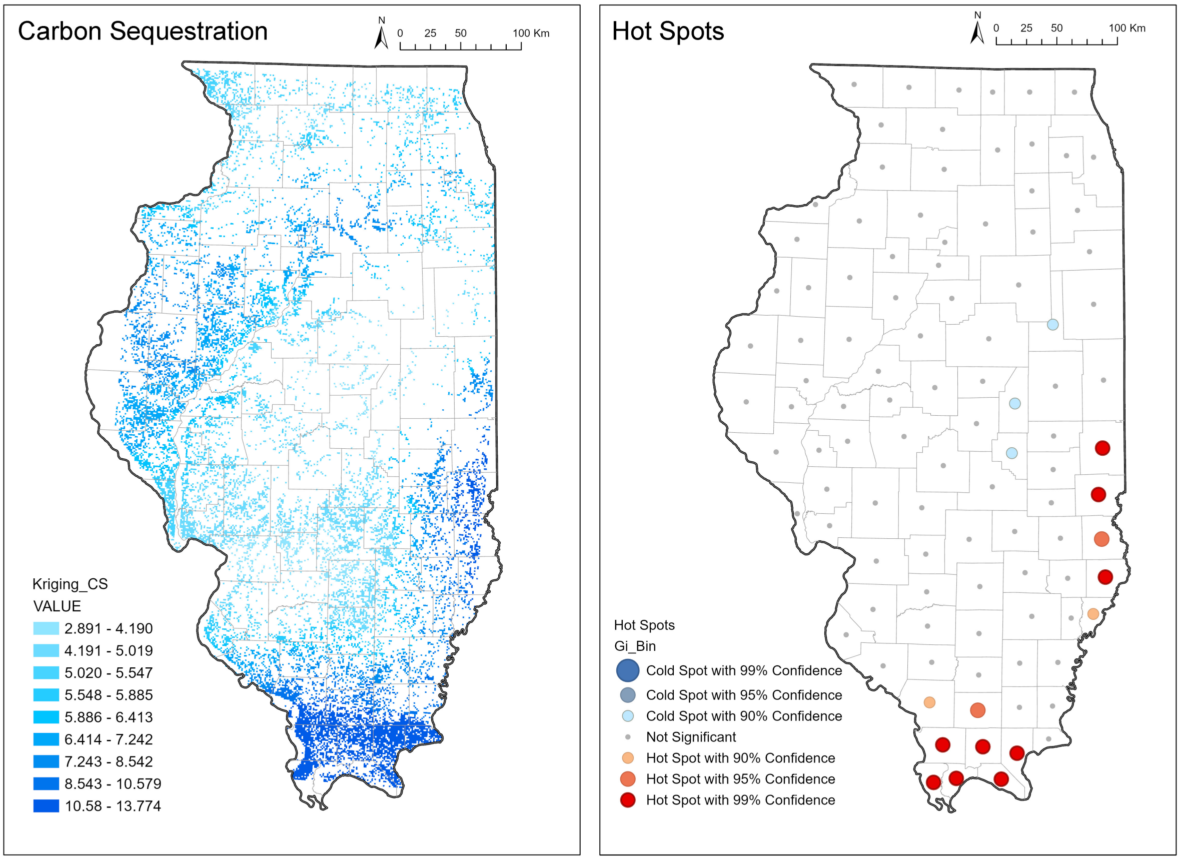

Figure 6. Spatial distribution of carbon sequestration (kg $CO_2/m^2/yr$) (**left**) and high/low value cluster areas (**right**).

4. Discussion

This discussion section will delve into the findings of our analysis, highlighting the implications of our results for carbon sequestration strategies and climate action planning at the state level.

4.1. Enhancing Carbon Sequestration Assessment: Comparing Landscape and Traditional Methods

Traditionally, forest carbon sequestration assessments have predominantly relied on inventory-based approaches [34]. These methods involve the direct measurements of tree attributes such as diameter at breast height (DBH), height, and wood density at sampled plots, which are then extrapolated to larger areas. While these methods are grounded in direct observations and provide reliable local data, their scalability to larger regions can be limited. Furthermore, traditional methods often overlook the spatial heterogeneity of forests, leading to a macroscopic view that might not capture the nuanced variations in carbon sequestration across different forest types and conditions.

In contrast, the landscape architecture method employed in our research incorporates advanced deep learning technologies and spatial analysis techniques. This approach leverages tools like computer vision and GSV 360 imagery, enabling us to capture a more detailed and comprehensive picture of the forest landscape. By integrating these technologies with Kriging interpolation and spatial analysis, our method provides a finer resolution of sequestration asset distribution, revealing the spatial variability and hotspots across the state of Illinois.

In the context of current advancements, our research distinguishes itself by offering a holistic evaluation of carbon stocks, encompassing both below- and above-ground reserves. This approach is in contrast to studies that typically emphasize aboveground biomass [35]. Our work advances the field by employing precise species-specific identification, thereby enhancing the granularity of carbon dynamic analysis. Each tree species possesses unique carbon storage capabilities, and our refined classification enables us to capture these variations accurately. This specificity in species analysis is not typically addressed in studies focused on temporal distribution, which may overlook the intricate differences at the species level [36].

Looking forward, the methodology developed in this study has promising implications for the broader field of environmental science and policy. Its ability to provide detailed spatial insights into carbon sequestration enhances its utility in strategic planning and management of forest resources, potentially informing national and global environmental policies. The adaptability of this method to other regions or ecosystems could be explored, offering a scalable model that integrates traditional ecological assessments with cutting-edge technology.

Moreover, as technology progresses, the integration of even more sophisticated analytical tools could further refine this methodology. Future research could focus on enhancing the accuracy of carbon stock estimation through the incorporation of real-time data acquisition and analysis. This could also facilitate the dynamic monitoring and management of forest resources, aligning closely with adaptive management strategies in conservation efforts.

4.2. Species-Specific Carbon Sequestration Dynamics in Illinois' Forests

To understand the complex mechanisms of carbon sequestration in Illinois' diverse forest ecosystems, it is imperative to examine the contribution of individual tree species to the state's carbon budget. Each species possesses intrinsic characteristics that influence its capacity to sequester carbon, and the spatial distribution of these species, as revealed in Figure 5, provides a nuanced understanding of their collective impact on the regional carbon cycle.

The focus of our detailed discussion is on three key species: oak (*Quercus* spp.), beech (*Fagus* spp.), and cypress (*Taxodium* spp.), chosen for their significant ecological roles and carbon sequestration capabilities:

- **Oak trees (*Quercus* spp.)**: Oak trees, with their substantial representation in the southern regions, exemplify the significant role of hardwood species. Their dense wood and extensive root systems allow them to store large amounts of carbon [37]. The concentration of oaks in the South correlates with their affinity for warmer temperatures and fertile soils, environments where they can grow robustly and thus enhance carbon uptake [38]. This suggests that conservation efforts in these areas could benefit from focusing on maintaining and expanding oak-dominated forest stands.
- **Beech trees (*Fagus* spp.)**: Located primarily in the cooler northern regions, Beech trees are adapted to environments that allow for high biomass accumulation, making them effective at long-term carbon storage. The patchy distribution of these trees indicates opportunities for targeted conservation strategies that leverage their carbon storage capabilities [39].
- **Cypress trees (*Taxodium* spp.)**: These trees thrive in the swampy areas along the Mississippi and Illinois Rivers and play a critical role in carbon sequestration within wetland ecosystems. Cypress trees are adept at capturing carbon in both their biomass and the surrounding water-logged soils, underscoring the need to protect and potentially expand these vital carbon sinks [40].

Other tree species also contribute to Illinois' forest carbon budget. These species include hickory (*Carya* spp.), gum (*Nyssa* spp.), pine (*Pinus* spp.), elm (*Ulmus* spp.), ash (*Fraxinus* spp.), cottonwood (*Populus* spp.), maple (*Acer* spp.), and birch (*Betula* spp.). Among them, Pine trees show a broader distribution which might reflect their use in reforestation efforts due to their fast growth rates and adaptability, indicating recent ecological succession or land-use changes. Maple trees appear widely distributed across the state. This could be because Maples are generally more adaptable to different environments, including urban settings. Cottonwood, another fast-growing species, appears to follow a pattern similar to pine, which might indicate its presence in areas of regrowth and active forest management. Elm, ash, gum, and birch have specific but less dense distributions. Elms and ashes might be undergoing recovery from diseases like Dutch elm disease and emerald ash borer infestations, which could explain their sparser presence. The Gum trees, typically found in wetlands similar to cypress, might indicate smaller, isolated wetland ecosystems that are vital to the state's carbon sequestration.

In summary, these species-specific analysis reveals that each tree species contributes uniquely to the carbon storage of Illinois' forests. Recognizing these dynamics is essential for developing strategic forest management practices that aim to maximize carbon sequestration.

4.3. Strategic Afforestation and Policy Implications for Illinois' Climate Action

The spatial analysis of forest carbon sequestration across Illinois is presented in Figure 6. It yields actionable insights that are pivotal for state-scale climate action planning. By identifying the distribution and intensity of sequestration assets, our findings can provide reference to strategic afforestation and reforestation efforts.

The significant sequestration potential of southern Illinois, especially in regions surrounding the Shawnee National Forest, indicates that these areas are prime candidates for targeted afforestation efforts. However, it is crucial to carefully assess and monitor these already dense carbon sinks to ensure that additional tree planting supports, rather than disrupts, their ecological balance and carbon sequestration efficiency. In contrast, areas with lower sequestration rates, such as those around Springfield, may greatly benefit from reforestation initiatives and the introduction of species known for high carbon uptake. Strategic planning in these regions could benefit from focusing on converting marginal or underutilized agricultural lands back into forested areas, thereby expanding the state's carbon sink capacity. Nevertheless, the proposal to convert marginal or underutilized agricultural lands into forested areas warrants a thoughtful consideration of the ecological suitability of these lands for forest regeneration. Marginal agricultural lands, characterized by limited soil depth, and suboptimal water and nutrient availability, may not inherently provide the conditions conducive to effective carbon sequestration or ecosystem support.

Therefore, our recommendations for strategic afforestation emphasize the importance of selecting native tree species that are inherently suited to Illinois' regional ecosystems over merely choosing species based on their carbon storage capacity. In addition, the dynamic nature of ecosystems and the impacts of climate change necessitates the ongoing monitoring of forest carbon stocks. The methods employed in this study provide a potential solution for establishing a monitoring system that can track changes over time and help adapt strategies as needed. Such a system would ensure that Illinois' climate action remains responsive to new data and continues to effectively capitalize on its carbon sequestration assets.

4.4. Limitations and Future Steps

The methodology implemented in our study, while innovative in its approach to assessing carbon sequestration in forest ecosystems, does possess certain limitations that warrant discussion.

Our study region is a complex array of terrestrial and aquatic ecosystems, each with distinct carbon flux dynamics. While forests are prominent carbon sinks, water bodies within these landscapes also play a critical role in the carbon cycle. However, the indirect effects of adjacent water bodies on the carbon sequestration potential of forests—a result of microclimatic changes and soil moisture dynamics—have not been explicitly modeled in this analysis. Future studies could incorporate these interactions by using more sophisticated spatial analyses that factor in the proximity of water bodies to forested areas and their resulting influence on carbon fluxes.

Kriging simulation's reliance on spatial autocorrelation presents limitations when applied to the varied topography and vegetation patterns of Illinois. In future iterations, integrating alternative spatial statistical methods that can accommodate irregularities in the data distribution may enhance accuracy. The mean estimation method for tree sizes, while useful for broad assessments, does not capture the full complexity of the spatial structure of the forests. Subsequent studies could employ more granular measurement techniques, such as individual tree crown analysis, which would enable a more precise understanding of carbon storage capacities across the landscape.

The next steps for this work include a more detailed look at the generalizability of the approach to other separate places. A broader view of sequestration is also needed so that similar approaches can be constructed for urban areas, wetlands, and agriculture-based assets.

5. Conclusions

This study has advanced the analysis of forest carbon sequestration in Illinois by merging the precision of landscape methodologies with established assessment techniques. The use of computer vision alongside spatial analysis tools like Kriging interpolation has unveiled a detailed map of the state's carbon assets.

While Kriging simulations have contributed to our understanding of carbon distribution, their accuracy is contingent upon the spatial autocorrelation present in the dataset. Acknowledging this, we recognize that further methodological advancements are necessary to enhance the precision of this tool for practical forestry management applications. Additionally, our average estimation approach to tree size determination, though useful for broad-scale analysis, may not fully capture the intricate spatial structure of forest data. Future research should aim to incorporate more sophisticated methods that preserve the complexity of spatial patterns, preventing potential oversimplification and loss of valuable information.

Despite these limitations, the methodology developed herein provides a framework for future ecological analysis. It sets a precedent for an acceptable uncertainty level in preliminary models, which can be rigorously tested and refined in subsequent research.

Author Contributions: Conceptualization, B.D. and S.L.; methodology, S.L. and L.Z.; software, S.L.; validation, S.L., Y.Z. and B.D.; formal analysis, S.L.; investigation, S.L.; resources, S.L., Y.Z. and L.Z.; data curation, S.L. and L.Z.; writing—original draft preparation, S.L.; writing—review and editing, B.D.; visualization, S.L.; supervision, B.D.; project administration, B.D.; funding acquisition, B.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

Acknowledgments: We appreciate the constructive suggestions from the anonymous reviewers.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The Appendix is a supplemental online repository that contains the intermediate dataset, as well as detailed descriptions and calculations related to the IPCC gain-loss methodology used in our study https://doi.org/10.6084/m9.figshare.25620855.v1.

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