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APPLICATION OF GIS AND REMOTE SENSING IN MAPPING AGROFORESTRY SYSTEMS AND HORTICULTURAL PRODUCTIVITY

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Abstract
The integration of Geographic Information Systems (GIS), Remote Sensing (RS), and Artificial Intelligence (AI) has revolutionized the mapping, monitoring, and management of complex agroforestry systems and horticultural production. This paper presents a comprehensive review of advanced geospatial frameworks that address the challenges of structural heterogeneity, tree-crop interactions, biomass estimation, and resource optimization in multifunctional landscapes. Key technologies discussed include spectral unmixing for mixed-pixel problems, multi-criteria decision making (MCDM) for land suitability mapping, vegetation indices (NDVI, EVI, NDRE, etc.) for crop health and phenology monitoring, machine learning algorithms for above-ground biomass and carbon stock estimation, thermal remote sensing for precision irrigation, and UAV-LiDAR combined with digital aerial photogrammetry for 3D canopy architecture and individual tree phenotyping. The study highlights the role of digital Monitoring, Reporting, and Verification (MRV) systems in carbon credit generation and emphasizes how these geospatial tools enhance biodiversity, soil health, water-use efficiency, and climate resilience. Despite existing barriers such as spatial resolution limitations in smallholder systems, emerging hyperspectral satellite missions and hybrid physics-informed models promise greater precision and scalability. This geospatial approach supports data-driven decision-making for sustainable food security and environmental conservation amid growing global population and climate pressures.

1. INTRODUCTION

The dual imperatives of achieving global food security for a population projected to reach 10.0 billion by 2050 and maintaining environmental sustainability have positioned agroforestry and precision horticulture as critical disciplines in modern land management (Islam & Karim, 2020). These systems represent a sophisticated departure from conventional monoculture by emphasizing structural complexity, biodiversity, and resource-use efficiency (Atzberger, 2013).

However, the inherent heterogeneity of these landscapes characterized by the multi-layered coexistence of trees, crops, and livestock presents significant monitoring and management challenges (Mmbando, 2025). Geographic Information Systems (GIS) and Remote Sensing (RS) have emerged as the primary technological pillars for overcoming these complexities, providing the spatial, spectral, and temporal data necessary for informed decision-making (Tsouros et al., 2019). By integrating space-borne sensors, unmanned aerial vehicles (UAVs), and advanced computational models, the scientific community can now map agroforestry suitability, estimate horticultural yields, and monitor carbon sequestration with a degree of precision previously unattainable (Remondino et al., 2011). This integrated GeoAI framework is visually summarized in Figure 1, which illustrates the flow of multi-source environmental data into AI-driven predictive systems.

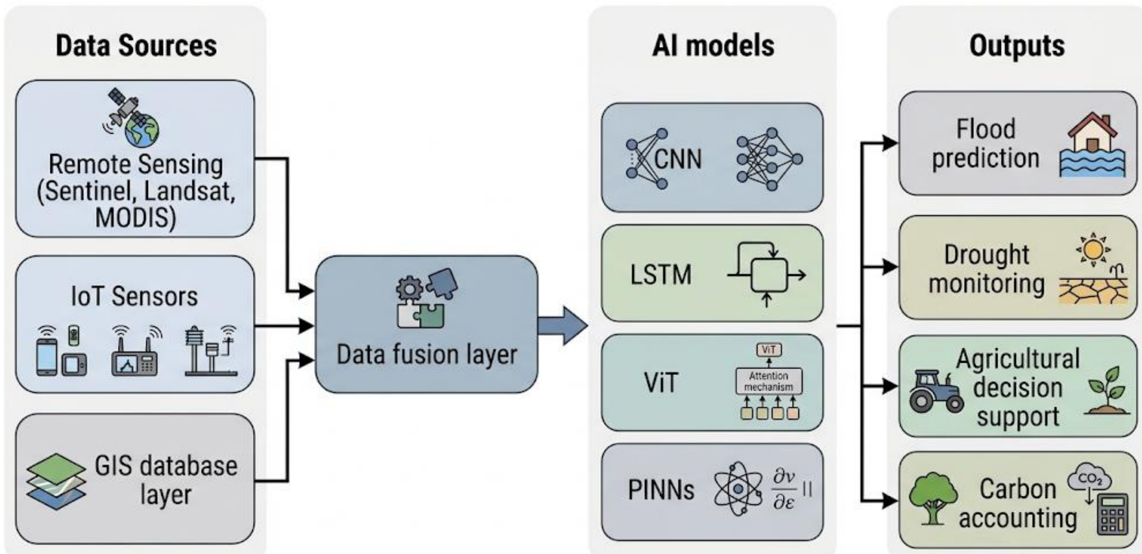


Figure 1: Conceptual Framework of GeoAI-Driven Environmental and Climate Predictive Modeling

2. Foundations of Geospatial Technology in Sustainable Land Management

The evolution of geospatial technology has fundamentally altered the perception, analysis, and management of crop systems and their surrounding environments (Dulam et al., 2025). The integration of GIS, RS, and the Global Positioning System (GPS) forms the basis of precision agriculture, enabling site-specific crop management (SSCM) that optimizes resource utilization while minimizing environmental degradation (Nandeha et al., 2025).

2.1 Principles of Remote Sensing and Spectral Analysis

Remote sensing for agricultural and horticultural purposes involves the acquisition of critical information from a distance, primarily through the identification of spectral signatures within the electromagnetic spectrum. The discipline has matured over nearly two centuries, with historical precedents for aerial imaging dating back to 1859 with balloon-mounted cameras, followed by the standardization of satellite-based sensing in the 1970s (Campbell & Wynne, 2011; Lillesand et al., 2015).

The effectiveness of remote sensing is determined by the characteristics of reflection, where different plant components and environmental features interact uniquely with various wavelengths. For example, the red region of the spectrum (0.62–0.75 μm) is characterized by the maximum absorption of solar radiation by chlorophyll, while the near-infrared (NIR) zone (0.75–1.3 μm) exhibits maximum energy reflection by the leaf cell structure (Jensen, 2007). This contrast allows for the calculation of various vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), which is pivotal for assessing plant vigor and biomass (Rouse et al., 1974; Tucker, 1979).

2.2 GIS as a Spatial Decision Support System

While remote sensing provides the data, Geographic Information Systems serve as the analytical engine designed to efficiently acquire, store, update, manipulate, analyze, and present geographically referenced information (SoftFarm, 2015).GIS facilitates a transition from conventional mapping to spatial reasoning, allowing users to overlay and contrast diverse datasets on a single platform (Agrospheres, 2025).

Table 1. Function and Data Types of GIS Components in Agroforestry and Horticulture

GIS Component	Function in Agroforestry/Horticulture	Data Types Integrated
Database Management	Storage and manipulation of digital climate and soil records	AGFORWEB database, Digital Climate Atlas
Spatial Analysis	Identifying interrelationships between environmental variables	Topography, slope, elevation, soil moisture
Visualization	Creating suitability and nutrient availability maps	Nutrient status, pest/weed intensity maps
Decision Support	Optimizing resource allocation and infrastructure planning	Cold store locations, market centers, transport routes

The application of GIS technology allows for the handling of geographical data with an accuracy rate of approximately 85%. Combined with the detection capabilities of remote sensing, which can achieve a 92% detection rate, the resulting framework provides a comprehensive approach to farming operations (Cureus, 2021).

3. Mapping Agroforestry Systems and Structural Complexity

Agroforestry systems are characterized by their spatial and temporal complexity, where trees and crops coexist simultaneously or sequentially. This complexity often limits the spatial extent to which traditional field surveys can be conducted, making geospatial technologies indispensable for large-scale assessments (Ahmed et al., 2023).

3.1 The Mixed Pixel Challenge and Spectral Unmixing

A persistent hurdle in remote sensing of agroforestry is the mixed pixel problem, where a single pixel contains reflectance values of multiple distinct materials. Spectral unmixing decomposes mixed pixels into their constituent materials, known as endmembers, and quantifies their fractional abundance within each pixel (MDPI, 2023).

Table 2. Categories and Applications of Spectral Unmixing Algorithms

Unmixing Algorithm Category	Technical Approach	Application Potential
Linear Spectral Unmixing (LSU)	Assumes pixel reflectance is a linear combination of endmembers	Mapping crop canopy and soil abundance variability
Non-negative Matrix Factorization (NMF)	Factorizes data into endmember and abundance matrices	Identifying minerals and species in complex environments
Manifold Learning-based NMF	Explores intrinsic data geometry and local windows	Preserving spatial/spectral info in multi-layered stands
Random Forest (RF) Regression	Supervised machine learning for abundance estimation	Predicting fractional cover of species in mixed dunes

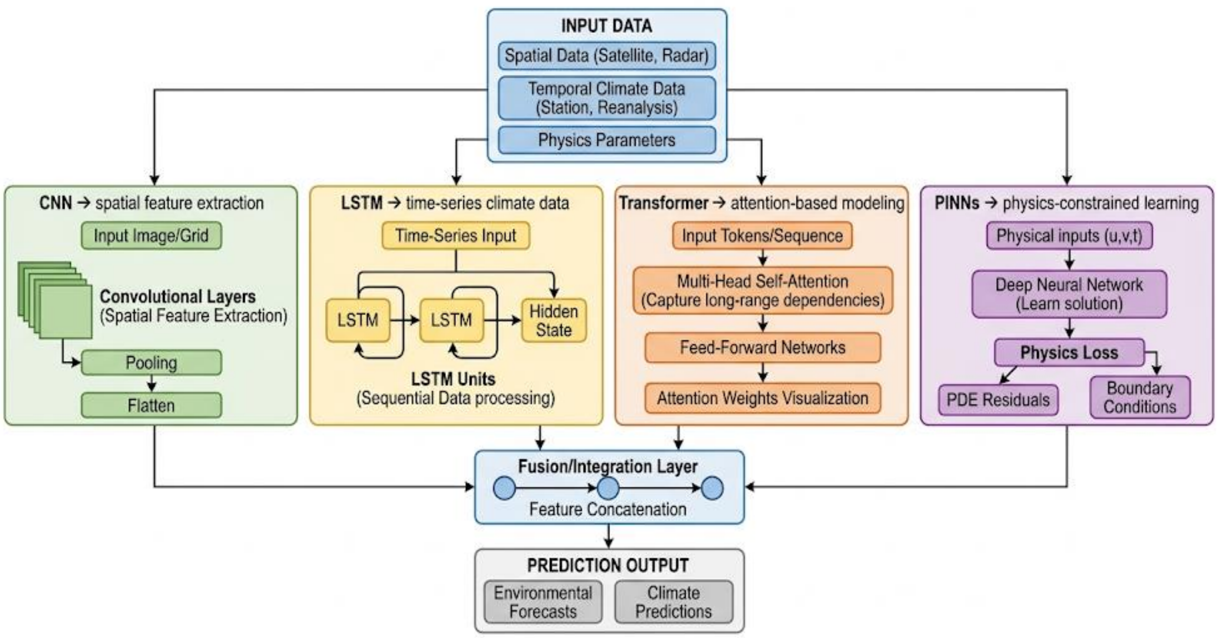
3.2 Agroforestry Suitability and Land Use Classification

The identification of land suitability for agroforestry involves analyzing multiple environmental and socio-economic factors. GIS-based methodologies often employ Multi-Criteria Decision Making (MCDM) methods, such as the Analytic Hierarchy Process (AHP) and Fuzzy AHP (Raihan, 2023). These models analyze spatial factors such as soil type, elevation, and climatic conditions to generate suitability maps (MDPI, 2024).

4. Deciphering Tree-Crop Interactions through Geospatial Analysis

The core of agroforestry productivity lies in the management of interactions between tree components and agricultural crops. These interactions impact productivity, biodiversity, and soil health through a complex interplay of positive and negative effects (Amn et al., 2026). The main AI architectures used in environmental modeling are summarized in Figure 2, showing their respective roles in spatial and temporal prediction tasks.

Figure 2: Machine Learning Architectures for Environmental and Climate Prediction



4.1 The Interaction Equation and Resource Competition

Researchers quantify these interactions using the fundamental equation:

I=F−C*I*=*F*−C

Where *I*I represents the overall interaction effect, *F*F denotes positive effects (e.g., soil fertility, microclimate), and CC denotes negative effects (e.g., competition for light, water, nutrients) (ICRAF, 2024).

Table 3. Biophysical Dimensions of Tree-Crop Interactions

Interaction Dimension	Promoting Factors (F)	Limiting Factors (C)
Above-ground	Microclimate improvement, shelter from wind/erosion	Competition for radiant energy, shading
Below-ground	Nutrient cycling, organic matter decomposition	Competition for water and nutrients, allelopathy
Atmospheric	Interception of radiant energy, rainfall	High vapor pressure deficit, temperature fluctuations

4.2 Ecosystem Services and Multi-functionality

Agroforestry systems are multifunctional objects providing numerous ecosystem services categorized into provisioning, regulatory, cultural, and support services. Protective Forest Belts (PFBs), for instance, serve as vital components in broader GIS-based ecological databases (AGFORWEB, 2023).

5. Biomass Estimation and Carbon Sequestration Modeling

Agroforestry plays a pivotal role in climate change mitigation by sequestering atmospheric carbon in biomass and soil organic matter. Unlike monocultures, agroforestry captures carbon more effectively over long periods (Beyer, 2025).

5.1 Machine Learning in Above-ground Biomass (AGB) Estimation

The estimation of carbon stocks requires the fusion of multi-source remote sensing data and advanced algorithms. Machine learning (ML) techniques have proven superior to traditional methods in terms of predictive accuracy (Zhao et al., 2024).

Table 4. Performance and Strengths of Machine Learning Algorithms in Biomass Estimation

ML Algorithm	Typical Performance (Accuracy/Kappa)	Key Strength
Random Forest (RF)	84.96% Accuracy / 0.76 Kappa	Robustness against noise, handles high-dimensional data
XGBoost	Variable (often highest accuracy)	Superior performance with optimized feature selection
Logistic Regression	65.43% (for distribution)	Simplicity, used for environmental factor evaluation
GIS Expert System	70.37% (for distribution)	Higher specificity in predicting species absence

5.2 Digital MRV and Carbon Credit Generation

To transform agroforestry into a climate solution, projects require a digital layer of Monitoring, Reporting, and Verification (MRV). Digital MRV (DMRV) uses satellite imagery, geotagged field data, and AI-driven analytics to track tree growth and soil carbon levels (TraceX, 2024).

6. Precision Horticulture: Productivity and Health Monitoring: Precision horticulture integrates remote sensing with GPS and GIS to optimize resource utilization and environmental sustainability (Nandeha et al., 2025).

6.1 Spectral Vegetation Indices for Crop Health

Vegetation indices (VIs) are critical parameters for crop development analytics. Most VIs are calculated from stable sections of the spectral reflectance curve (Agrospheres, 2025).

Table 5. Summary of Spectral Vegetation Indices for Horticultural Health Assessment

Vegetation Index	Simple / Professional Formula Format	Primary Application in Horticulture
NDVI (Normalized Difference Vegetation Index)	(NIR − RED) / (NIR + RED)	Broad assessment of plant vigor; tracks active crop growth
EVI (Enhanced Vegetation Index)	2.5 × (NIR − RED) / (NIR + 6 × RED − 7.5 × BLUE + 1)	Sensitive in dense vegetation; corrects atmospheric and soil noise
GNDVI (Green Normalized Difference Vegetation Index)	(NIR − GREEN) / (NIR + GREEN)	Measures nitrogen and chlorophyll content in plants
SAVI (Soil-Adjusted Vegetation Index)	(NIR − RED) × (1 + L) / (NIR + RED + L)	Isolates vegetation signal from soil; ideal for sparse crops
NDRE (Normalized Difference Red Edge Index)	(NIR − RED EDGE) / (NIR + RED EDGE)	Monitors crop health at maturity in dense canopies

6.2 Phenology and Yield Forecasting

Crop phenology provides vital information for management and yield estimation. The improved "SMF-S" method matches shape models to VI time series for each phenological stage in adaptive local windows. In winter wheat simulations, SMF-S achieved an average RMSE of 9.5 days (Zeng et al., 2023).

7. Advanced Water Management and Irrigation Optimization

Remote sensing offers non-invasive methods for monitoring soil and crop water status, enabling precision irrigation (Horticulturae, 2017).

7.1 Thermal Remote Sensing and the CWSI

Crop water status is monitored through thermal RS to detect canopy temperature (T_c) changes. The Crop Water Stress Index (CWSI) is highly sensitive to soil water variations. CWSI values above 0.6 are statistically linked to decreases in soil moisture (EOS, 2024).

7.2 Plant-Based Water Status Indicators

For deep-rooted woody crops, plant-based indicators are essential for scheduling deficit irrigation (DI) (Jose, 2009).

Table 6. Plant and Canopy-Based Water Stress Indicators

Water Stress Indicator	Measurement Method	Best Use Case
Ψ_{pd}	Pressure chamber (predawn)	Isohydric crops (some fruit trees)
Ψ_{st}	Pressure chamber (solar noon)	Anisohydric crops (grapevines)
MDS	LVDT sensors (continuous)	Automatable stress monitoring in woody crops
CWSI	Thermal cameras (remote)	Large-scale irrigation mapping

8. 3D Canopy Architecture and Individual Tree Phenotyping

The vertical complexity of agroforestry and orchards makes 3D structural analysis essential. Advancements enable extraction via LiDAR and Digital Aerial Photogrammetry (DAP) (MDPI, 2025).

8.1 UAV-LiDAR vs. Digital Aerial Photogrammetry

UAV-LiDAR outperformed DAP in individual tree segmentation (F-score 0.83 vs. 0.79), while DAP achieved higher pixel-level classification accuracy (73.83% vs. 57.32%) (MDPI, 2025). Mobile Laser Scanning (MLS) provides near-inventory-grade DBH accuracy (R^2 up to 0.98) (Atzberger, 2013).

8.2 High-Throughput Architectural Phenotyping

Architectural traits such as height, projected leaf area, and alpha volume are used to assess the intrinsic potential of cultivars. Indices obtained with UAV-LiDAR scans present values similar to those obtained with labor-intensive terrestrial LiDAR (Cureus, 2021).

9. Socio-Economic Frameworks and Digital Integration

Effective integration is often hindered by incompatible data formats and regulatory complexities. However, automation can lead to a 40% reduction in workforce expenses. Achieving resilience requires a structured approach emphasizing collaboration. Furthermore, the use of GIS in carbon markets carries significant ethical responsibilities regarding indigenous land rights (Ethical Geo, 2024).

10. Technical Barriers and Future Outlook

Primary limitations include insufficient spatial resolution for fragmented smallholder plots and a lack of intelligent predictive models (Mokhtar et al., 2025).

10.1 The Future of Hyperspectral Satellite Missions

Next-generation Earth Observation (EO) missions will provide unprecedented spectral resolution across hundreds of bands (DLR & ASI, 2025).

Table 7. Upcoming Hyperspectral Satellite Missions for Agricultural Monitoring

Mission	Agency	Primary Contribution to Agriculture/Forestry
EnMAP	DLR (Germany)	Global monitoring of biophysical and geochemical variables
PRISMA	ASI (Italy)	High-resolution hyperspectral imagery for crop classification
FLEX	ESA	Measuring chlorophyll fluorescence for vegetation status
CHIME	ESA/Copernicus	Sentinel expansion mission for hyperspectral mapping
Tanager	Planet	Frequent hyperspectral revisits for commercial applications

11. Conclusions

Advanced geospatial frameworks combining GIS, remote sensing, and AI-driven analytics provide a robust, scalable foundation for mapping, monitoring, and optimizing agroforestry systems and horticultural productivity in the face of climate variability and resource constraints. By enabling precise characterization of tree-crop interactions, biomass and carbon dynamics, phenological stages, and site-specific suitability, these technologies facilitate data-driven decision-making that enhances biodiversity, soil health, water-use efficiency, and overall system resilience. The integration of spectral unmixing, 3D structural modeling, digital twins, and machine learning supports real-time monitoring, early stress detection, and precision interventions, significantly reducing input waste while improving yields and ecosystem services. As global demands for sustainable food production and carbon sequestration intensify, continued advancements in hyperspectral missions, edge computing, and hybrid physics-informed models will further bridge the gap between research and on-farm application. Future efforts should prioritize open data sharing, capacity building for smallholders, and ethical governance to ensure equitable benefits. Ultimately, the widespread adoption of these geospatial innovations will be essential for building climate-resilient, multifunctional landscapes that simultaneously support agricultural productivity, environmental conservation, and rural livelihoods.

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