Climate-Resilient Agroecosystem Design through Integration of Artificial Intelligence, Remote Sensing, and GIS

Dr. Zhang Ming [1*], Dr. Liu Fang [2], Dr. Chen Hao [3], Dr. Mehmet Yildiz [4], Dr. Ahmet Demir [5]

[1-5] Faculty of Plant Protection, South China Agricultural University, Guangzhou, China

*Corresponding author: **Dr. Zhang Ming**

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ABSTRACT

Climate change alters the circumstances under which crops are produced, increasing the need for agroecosystem management that accomplishes several goals: high productivity, efficient use of precious resources, and the ability to adapt to changing and extreme climate conditions. In this paper, we summarize the findings of research articles on the combination of AI (artificia l intelligence), RS (remote sensing), and GIS (geographic information systems) technology in the planning of climate-friendly agroecosystems. We aim to illustrate the contribution of these technology fields to four main functions of agroecosystems: crop and environmental monitoring, climate impact and yield forecasts, assessment of the suitability of lands and resources, and carbon and biodiversity assessments. Artificial intelligence approaches such as ML (machine learning) and DL (deep Learning) are highly efficient and capable of forecasting crop yields and drought consequences based on agricultural, meteorological, and climate data. AI technologies are constantly developing and achieving very high results concerning crop yield forecasting. Suitability maps, and vulnerability assessments that support field- and landscape-scale decision-making. The literature further shows growing application of these integrated technologies to soil organic carbon monitoring, carbon stock assessment, and biodiversity-relevant land-cover characterization, extending their relevance beyond productivity toward broader ecosystem-service outcomes. Despite this progress, we identify persistent constraints, including fragmented data interoperability, limited model transferability across agroecological zones, uneven ground-truth validation, and barriers to adoption among smallholder and resource-constrained farming systems. We conclude that AI–RS–GIS integration constitutes a scientifically active and increasingly synergistic foundation for climate-resilient agroecosystem design, and we outline research priorities needed to move from demonstrated technical performance toward equitable, operational deployment.

Keywords: agroecosystem management; climate-smart farming; geospatial decision support; land suitability analysis; machine learning; predictive analytics; satellite and UAV monitoring; sustainability indicators

1. Introduction

Agriculture has an ambivalent and under scrutiny role in climate change. On the one hand, it greatly contributes to greenhouse gas emissions via land use modification, fertilizer application, and livestock farming. And at the same time, among other sectors agriculture is one of the most vulnerable sectors exposed to the impacts of climate change represented in changes in temperature and precipitation patterns, increased frequency of extreme events, and changes in pest and diseases pressure [6]. Because of this situation, more and more attention is paid in research and practice in agriculture to such approaches as climate-resilient (CRA) and climate-smart agriculture (CSA) that imply increasing productivity and ability to adapt to climate changes and at the same time reducing or sequestering emissions.

Three fields of digital technologies have come to play an important role in the realization of CRA and CSA from local to global levels. Among them, artificial intelligence, which comprises both traditional machine learning and deep learning methodologies, makes it possible to process big heterogeneous agricultural and environmental databases in order to find patterns and forecast future trends [1, 2, 4, 32]. Remote sensing, which is currently based on the use of both satellites and drones, can be used in order to obtain data about the condition of vegetation and soil in space and over time [3, 27, 29, 34]. Finally, geographic information systems collect all available information collected by remote sensing and other sources, such as soils, topography, climate, and many others, in order to convert it into maps that can be used by scientists as well as agriculturalists [6, 17]. Convolutional neural networks and, more recently, attention and transformer models have been displaying better performance at multi-temporal and multi-spectral yield and stress prediction tasks. Applications of remote sensing for agriculture have also been reviewed in regard to crop monitoring, water and irrigation management, and food security in a broader sense. GIS-based spatial analysis has played a long-time part in precision agriculture in the form of land evaluation and management zones delineation.

In literature, there is little acknowledgment of the integration of these 3 areas of knowledge into one functional whole rather than running parallel to each other in supporting climate-resilient agroecosystems. This review aims to fill that void by putting together recent peer-reviewed research on (i) AI technologies applied to climate risks and yield forecasting; (ii) remote sensing technologies applied to crop and environmental monitoring; (iii) GIS-based spatial analysis applied to land suitability and vulnerability assessment; (iv) practical applications of the integrated approach to carbon and biodiversity assessment, and finding out the echoed areas of synergy, as well as those where evidence is scarce with the future research agenda outlined.

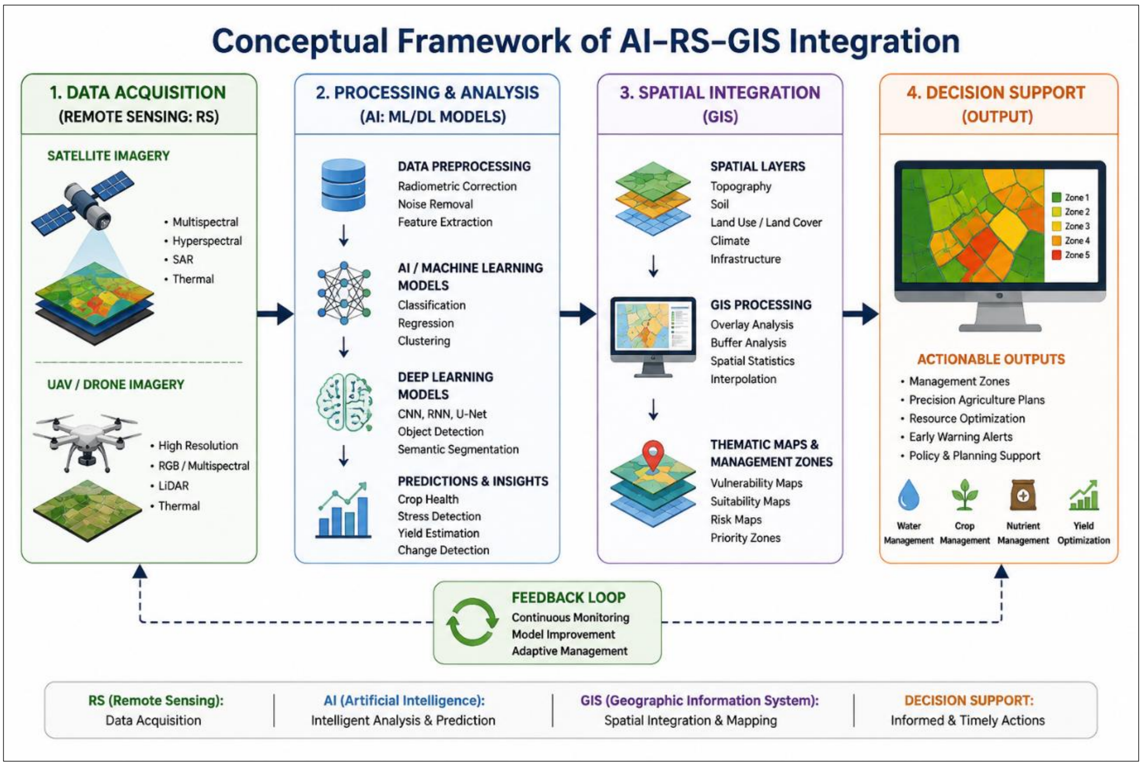

Fig 1: Conceptual Framework of AI–RS–GIS Integration

Table 1: Comparison of AI, RS, and GIS Contributions to Agroecosystem Design

Domain	Key Capability	Role in Climate Resilience	Data Inputs
Remote Sensing	High-res spatial coverage	Real-time monitoring of crop/soil	Multispectral, Radar, Thermal
Artificial Intelligence	Pattern & Trend recognition	Predictive modeling & stress detection	Time-series, Tabular, Image data
GIS	Spatial integration	Site-specific decision making	Land-use, Topography, Soil maps

2. Artificial Intelligence for Climate Risk and Agroecosystem Prediction

2.1. Machine learning and deep learning foundations

Reviews of machine learning in agriculture consistently identify crop yield prediction, disease and pest detection, weed identification, and water and nutrient management as the dominant application areas, with tree-based ensemble methods, support vector machines, and neural networks among the most frequently applied algorithm classes [1, 2, 32]. Comparative work has shown that gradient-boosted tree methods such as XGBoost can match or exceed the accuracy of deep learning approaches for tabular or moderately dimensioned agricultural datasets, while deep learning architectures tend to show a comparative advantage when the underlying data are high-dimensional and spatially or temporally structured, such as multi-temporal satellite image stacks [11, 12]. Chlingaryan and colleagues, reviewing machine learning approaches specifically for yield prediction and nitrogen status estimation, similarly emphasize that model choice should be matched to data structure and scale rather than treated as universally superior across contexts [4].

2.2. Deep learning architectures for multi-source prediction

More recent work has moved toward architectures explicitly designed to fuse multiple data modalities and temporal scales. Attention-augmented convolutional neural networks combined with contrastive learning have been proposed to integrate multi-temporal, multi-spectral satellite imagery for yield prediction, with attention mechanisms used to weight phenologically important observation periods more heavily than agronomically less informative ones [13]. Related multi-modal frameworks combine satellite imagery, soil properties, and climate time series within convolutional and temporal-attention architectures, reporting that the inclusion of soil and climate covariates alongside spectral data materially improves predictive skill relative to spectral data alone, while also highlighting the continued need for model interpretability given the high-stakes nature of agricultural planning decisions [14]. Explainable AI (XAI) techniques have accordingly been applied to yield-prediction models — for example, to interpret which spatial regions and spectral bands a convolutional model relies on when predicting soybean yield from Sentinel-2 imagery — reflecting a broader recognition that predictive accuracy alone is insufficient for models intended to inform really agronomic and policy decisions [15, 16, 56].

Machine learning-based yield and drought forecasting has also been demonstrated at national and regional scales using satellite drought indices combined with weather and climate-index data, illustrating the applicability of these methods beyond field-level prediction to food-security-relevant regional forecasting [9]. Hybrid approaches that combine physically based dynamical climate models with machine learning post-processing have likewise been used to improve seasonal yield forecasts, suggesting that the most robust operational systems are likely to combine, rather than replace, process-based agronomic and climate models with data-driven learning [10].

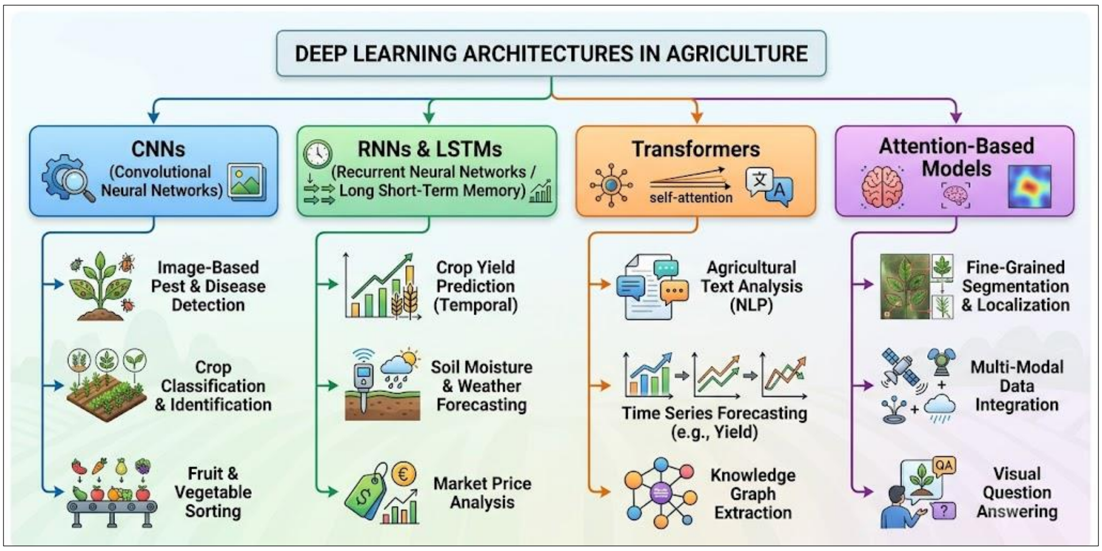

Fig 2: Taxonomy of Deep Learning Architectures in Agriculture

2.3. Crop water stress and physiological risk prediction

A parallel and increasingly convergent literature applies AI techniques to non-destructive detection of crop water stress from RGB, thermal, and hyperspectral imagery, using both classical machine learning and deep learning, including generative adversarial network-based data augmentation and explainable AI methods, to address the data-limited conditions that are common in field-scale agricultural monitoring [16]. This body of work is methodologically continuous with the yield-prediction literature but focused on earlier-stage, sub-lethal physiological stress detection, which is of particular relevance to climate risk assessment because it allows anticipatory rather than purely retrospective characterization of climate-related agroecosystem stress.

3. Remote Sensing for Agroecosystem and Environmental Monitoring

Satellite remote sensing remains the primary data source underpinning large-area agroecosystem monitoring, owing to its consistent revisit frequency, growing spatial resolution, and free availability of major missions such as Sentinel-2 and Landsat [3, 29, 34]. Reviews of remote sensing applications in agriculture identify crop growth and yield monitoring, irrigation and water management, and crop loss assessment as core use cases, and note that the meta-analytic evidence base has grown substantially as sensor archives have lengthened and computational capacity for large-scale image processing has increased [3, 29]. UAV-based remote sensing complements satellite observation by providing centimeter-scale spatial resolution and flexible revisit timing tied to specific management or phenological events, and has been reviewed extensively with respect to platform types, sensor payloads, and data-processing approaches relevant to precision and climate-smart agriculture [27, 28].

High-throughput phenotyping platforms that combine ground-based, UAV, and satellite sensors have been reviewed as a means of scaling trait measurement — including canopy structure, biomass, and stress indicators — from individual plots to breeding trial and landscape scales, which is directly relevant to identifying and characterizing climate-resilient genotypes and cropping systems [30]. Vegetation indices derived from UAV multispectral imagery have also been used to differentiate management practices such as tillage regime, illustrating the sensitivity of remote sensing indicators not only to crop status but to underlying agroecosystem management decisions relevant to climate resilience and soil conservation [28].

A growing sub-literature applies deep learning directly to multi-source remote sensing fusion for yield estimation, including architectures that combine convolutional and recurrent or attention-based components to integrate optical, radar, and solar-induced fluorescence data for winter wheat yield estimation, with authors noting that fusion generally improves robustness under variable cloud cover and canopy conditions relative to single-sensor approaches. This fusion-oriented direction parallels the sensor-fusion trend identified for water-stress detection and underscores a broader methodological convergence across the remote sensing and AI literatures toward multi-source, rather than single-source, agroecosystem characterization.

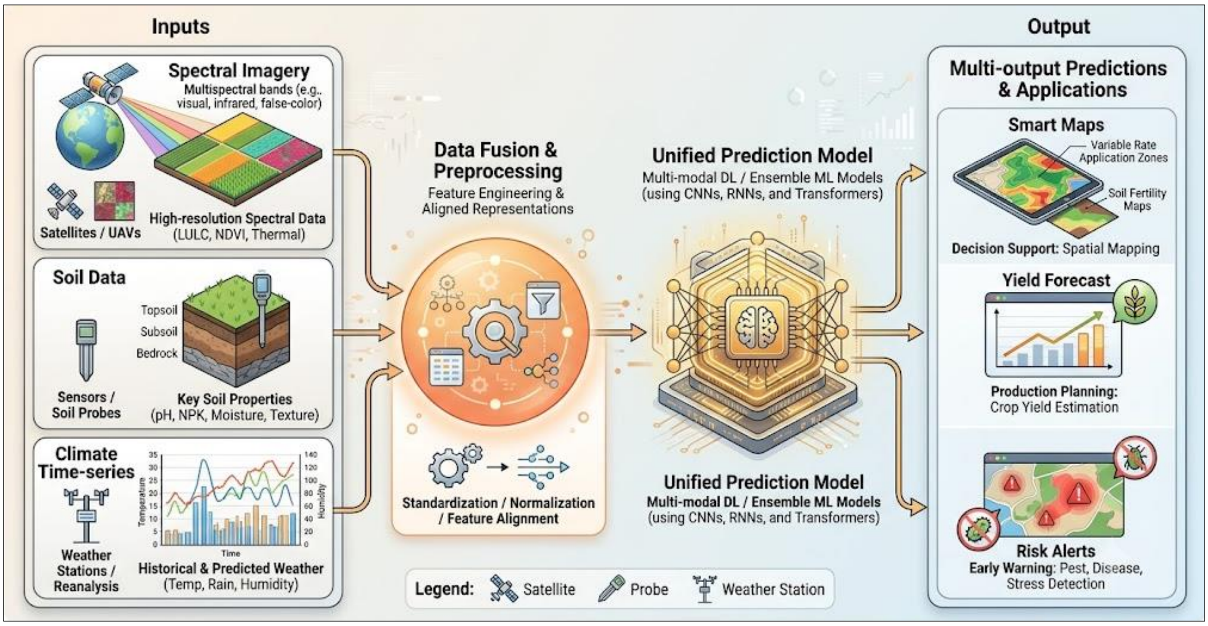

Fig 3: Multi-modal Data Fusion Workflow

4. GIS-Based Spatial Analysis for Land Suitability and Climate Vulnerability

GIS provides the spatial integration and analysis layer through which remote sensing, soil, climate, and topographic data are combined into products directly usable for agroecosystem planning. Land suitability analysis exemplifies this integrative role: recent work combining remote sensing and field-based geospatial data with multiple machine learning classifiers has been used to evaluate agricultural land suitability in urbanizing, semi-arid, food-insecure regions, incorporating slope, rainfall, temperature, soil texture, pH, electrical conductivity, and macronutrient variables within a GIS framework to identify locations most appropriate for continued or expanded agricultural use [20]. Such studies illustrate how GIS-based suitability mapping extends beyond simple overlay analysis toward statistically and machine-learning-informed spatial classification.

GIS integration of remote sensing spectral data with soil sampling has similarly been applied to macronutrient and soil-fertility mapping, for example classifying nitrogen, phosphorus, potassium, and humus content across climatic zones using Sentinel-2 reflectance data combined with geoinformation systems and cartographic visualization, providing a spatially explicit basis for fertility-informed, climate-adapted management zoning [17, 23]. More broadly, reviews of RS–GIS–AI integration for sustainable land management emphasize that the analytical value of any single data stream is substantially enhanced when embedded within a GIS framework capable of reconciling differing spatial resolutions, coordinate systems, and temporal frequencies across data sources [6, 17].

5. Carbon Sequestration and Biodiversity Assessment

Beyond productivity and risk management, AI–RS–GIS integration is increasingly applied to ecosystem-service outcomes relevant to climate mitigation, particularly soil organic carbon (SOC) monitoring and carbon stock assessment. Multiple studies report machine learning models — including random forest, gradient boosting, and generalized additive approaches — trained on satellite-derived spectral indices, radar backscatter, and terrain covariates to estimate SOC content, with reported model performance varying by soil type, land use, and sensor combination but consistently showing that multi-sensor data fusion (for example, combining synthetic aperture radar with multispectral imagery) improves estimation accuracy relative to single-sensor models [21, 22, 26]. Conservation agriculture practices such as no-tillage and mulching have been specifically evaluated for their SOC sequestration effects using such remote sensing–machine learning frameworks, directly linking the technology stack to climate mitigation-relevant management recommendations [21].

Digital soil mapping frameworks have also been developed explicitly to support voluntary carbon market (VCM) programs, using time-series remote sensing features together with climate, weather, and topographic covariates to produce SOC estimates at the spatial and temporal resolution required for carbon-credit verification in row-crop systems [24]. Beyond croplands, machine learning-based remote sensing approaches have been applied to carbon stock assessment in non-agricultural but ecologically linked systems such as mangrove habitats, combining field-based allometric measurement with high-resolution satellite imagery to estimate aboveground biomass and carbon storage, illustrating the transferability of the same core AI–RS methodology across terrestrial and coastal ecosystem types relevant to landscape-scale climate resilience planning [25].

Biodiversity-relevant assessment within this literature remains comparatively less developed than SOC and carbon-stock work, but land-cover and land-use classification studies using remote sensing and machine learning — including neural network-based multilayer perceptron approaches to land-use/land-cover transformation — provide an evidentiary basis for characterizing habitat heterogeneity and land-use change relevant to biodiversity conservation within agricultural landscapes. The convergence of carbon- and biodiversity-relevant spatial layers within a common GIS framework is consistent with the broader argument, recurrent across the reviewed literature, that climate-resilient agroecosystem design benefits from treating productivity, carbon, and biodiversity objectives as jointly mapped rather than separately assessed spatial layers [6, 8, 17].

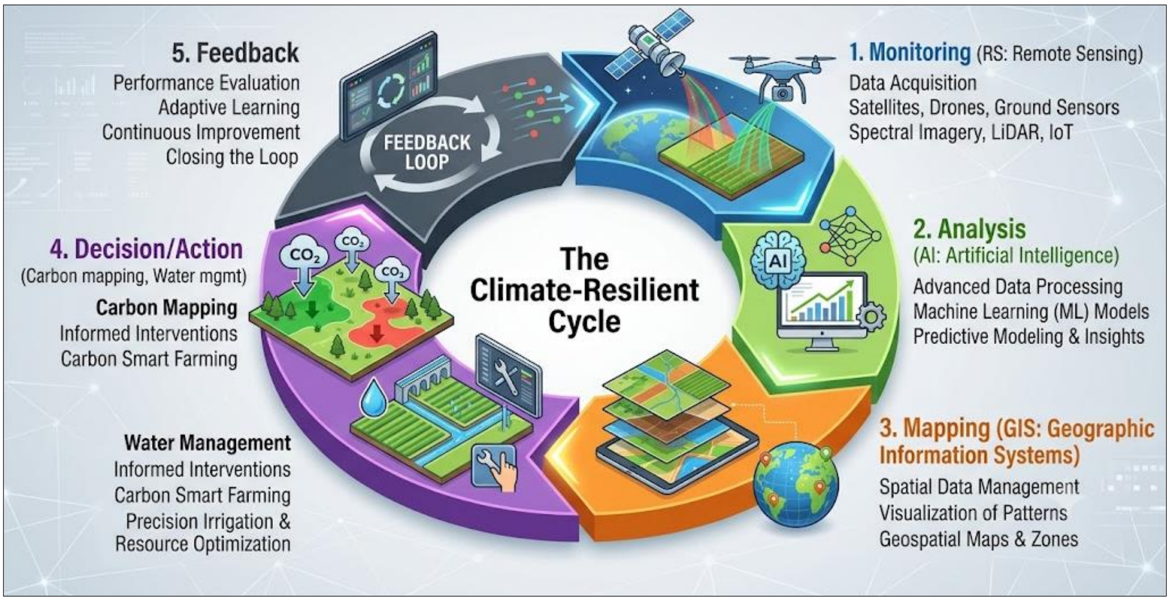

Fig 4: The Climate-Resilient Cycle (Monitoring to Action)

6. Discussion

Across the reviewed literature, three patterns emerge consistently. First, predictive performance for yield, drought impact, and soil carbon estimation improves when multiple data sources — spectral, radar, climate, soil, and terrain — are fused, whether through classical ensemble methods or deep multi-modal architectures, rather than relying on any single sensor or data type [9-15, 21, 22]. Second, GIS functions less as a standalone analytical method and more as the necessary spatial integration layer that reconciles the differing resolutions, extents, and formats of AI outputs and remote sensing products into agronomically and administratively usable maps and zones [6, 17, 20]. Third, the application scope of this integrated technology stack is expanding beyond conventional productivity metrics toward carbon sequestration and, to a lesser extent, biodiversity-relevant land-cover characterization, reflecting the broader reframing of agricultural technology goals around climate mitigation and ecosystem services rather than yield alone [21-26].

Several limitations and implementation challenges recur across this literature. Model transferability across agroecological zones, soil types, and climates is frequently reported as limited, with models trained in one region or cropping system showing degraded performance when applied elsewhere without recalibration [21, 22]. Ground-truth validation — for SOC, biodiversity indicators, or physiological stress — remains labor-intensive and is correspondingly under-represented relative to the volume of published predictive-modeling work, constraining confidence in the absolute accuracy claims reported by many individual studies. Data interoperability between remote sensing archives, climate datasets, and GIS platforms is improving but remains a practical bottleneck, particularly for research and extension groups without access to cloud-based geospatial computing infrastructure. Explainability and interpretability of deep learning-based predictions are increasingly recognized as necessary rather than optional, given that agroecosystem decisions informed by these models carry direct economic and environmental consequences for farmers and policymakers [14, 15].

Economic feasibility and equitable access are comparatively under-addressed in the technical literature reviewed here. Much of the demonstrated capability — high-resolution UAV phenotyping, multi-sensor fusion pipelines, cloud-based deep learning inference — presumes a level of capital, connectivity, and technical capacity that is not universally available, particularly among smallholder farmers in the regions often most exposed to climate risk. Reviews that explicitly foreground climate-smart agriculture in food-insecure and resource-constrained settings note this tension between technological sophistication and practical accessibility, and argue for parallel investment in lower-cost, locally adapted decision-support tools alongside continued advancement of the underlying AI–RS–GIS science [7, 8, 18]. Future research priorities identified across this synthesis include: standardized, cross-regional validation protocols for AI-based yield and carbon prediction models; open, interoperable geospatial data infrastructure to lower the technical barrier to GIS-based integration; expanded biodiversity-specific remote sensing indicators suitable for agricultural landscapes; and explicit economic and equity evaluation of AI–RS–GIS decision-support systems under realistic smallholder and resource-constrained operating conditions.

Table 2: Limitations and Future Research Directions in Integrated Frameworks

Challenge	Impact on Adoption	Research Priority
Model Transferability	Performance drops in new zones	Cross-regional validation protocols
Data Interoperability	Siloed data, format mismatch	Open/Standardized geospatial infra
Ground-Truth Validation	Low confidence in model output	Expanded field-based datasets
Smallholder Access	Tech divide/Exclusion	Low-cost, offline-capable tools

7. Conclusion

According to the peer-reviewed literature, artificial intelligence, remote-sensing technology, and GIS are increasingly utilized as part of an integrated technology stack designed for climate-resilient agroecosystem design. Integrating these technologies allows for improvements in crop and environment monitoring, climate risk and yield forecasting, land suitability and vulnerability mapping, and carbon and biodiversity assessments. Research shows that the use of multi-source data fusion combined with GIS is associated with better mapping and prediction outcomes compared to single-source methods.

Moreover, the application of this integration capability is shifting from productivity-focused applications to addressing explicit climate mitigation and ecosystem service needs. Nevertheless, the major issues hindering the implementation of these technologies for agroecosystem management are not related to technology capabilities but include transferability of models, ability to validate ground truths, data interoperability, the ability to interpret predictions and provide equal access to agroecosystem technologies for farmers operating in different contexts.

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