SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 4, (2026), pp. 11315-11327
Open Access. Online & Print

DOI: 10.5281/zenodo.124261080

ADVANCED SIGNAL AND IMAGE PROCESSING APPROACHES FOR ASSESSMENT OF AGRICULTURAL ECOSYSTEMS AND BIODIVERSITY DYNAMICS

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ABSTRACT

Increasing environmental change and agricultural intensification are changing the way ecosystems operate, and biodiversity is distributed throughout managed landscapes, imposing pressure on the need to monitor systems that are spatially comprehensive, continuous over time and ecologically interpretable. This comprehensive review synthesizes recent advances in sensing, signal processing, image processing, and data integration for assessing agricultural ecosystems and biodiversity dynamics. The evidence base spans satellite multispectral and hyperspectral monitoring, UAV imaging, proximal and in situ sensor networks, bioacoustics, active sensing (radar and LiDAR), and emerging modalities such as thermal, fluorescence, and microwave/SAR observations. Analytical developments in time-frequency decomposition, nonlinear and complexity-aware

characterization, and machine learning enable the extraction of informative patterns from non-stationary environmental signals, while modern computer vision supports correction, feature construction, classification, segmentation, and object detection for crop stress, disease, habitat structure, and biodiversity proxies. Multi-modal fusion and spatiotemporal modeling frameworks are reviewed as mechanisms to reconcile heterogeneous data streams and support real-time inference through edge-cloud deployments. Emphasis is placed on validation, benchmarking, and reproducible reporting as prerequisites for reliable translation to operational decision support, particularly under constraints of labeled data scarcity and regional bias. Collectively, the reviewed approaches provide a pathway toward scalable, uncertainty-aware ecosystem intelligence that can strengthen sustainable agricultural management and biodiversity conservation.

KEYWORDS: Agricultural Remote Sensing, Biodiversity Monitoring, Signal Processing, Computer Vision, Multimodal Data Fusion.

1. Introduction

The structural and functional basis of agricultural ecosystems, biodiversity can affect nutrient cycling, control pests, the fertility of soil, and the resilience of a system. In the contemporary ecological syntheses, biodiversity is recognized as a multidimensional concept, which includes taxonomic, functional and phylogenetic dimensions, which determine stability and productivity of the ecosystem collectively [1]. However, in the agricultural landscapes, intensification processes, such as expansion of monoculture, the use of agrochemicals and mechanical disturbance have significantly changed the ecological communities. The meta-analysis data prove that this intensification results in a serious decrease in soil biodiversity and has a direct effect on ecosystem functionality and sustainability in the long-term [2]. The environmental impact of the agricultural revolution goes beyond the land systems. As a result of nutrient enrichment, hydrological alteration and habitat fragmentation, freshwater ecosystems related to agricultural catchments are becoming more influenced [3]. Such trends are clues to greater variations in biodiversity worldwide, with the anthropogenic stressors reacting to natural ecological interactions to establish species turnover and community structure over time [4]. The nullification of these interacting drivers is important in the understanding of the spatial and temporal variation of agricultural biodiversity.

There are also complex global change processes that entrap agricultural ecosystems. Climate change enhances the loss of biodiversity and combines with land-use pressures, which may make people more susceptible to infectious diseases and unstable ecosystems [5]. In the agricultural environment, ecological imbalance may also increase the problem of pest outbreaks and destabilize trophic relationships. IPM has become a dominant technique of ensuring chemical dependence reduction and ecological stability to allow biodiversity-effective agricultural activities [6]. However, successful IPM and other sustainable methods implementation needs strong, expansive monitoring systems, which can identify minor ecological changes. More broadly, to assess sustainability, new perspectives combine ecosystem services and impacts of the environment in a single assessment model, allowing better overall evaluation of the performance of agricultural systems [7]. These integrative methods require credible environmental information on a spatial and temporal scale. In this regard, the innovative image processing has enabled the ability to make meaningful ecological inferences with the high-resolution imagery to aid in crop health monitoring, land-use classification and biodiversity assessment [8]. Similar progress in AI-powered remote monitoring also aids in constant and extensive biodiversity surveillance, reinforcing conservation and management decision-making [9].

Moreover, with these technological tools, a consistent synthesis of the methods of advanced signal and image processing and the dynamics of biodiversity in agricultural ecosystems has not been established yet. This review fills this knowledge gap by reviewing modern sensing technologies, computational methods and integrative analytical scales that can be used to measure quantitatively and at scale agricultural ecosystems and dynamics of biodiversity.

2. Review Methodology

A comprehensive literature review search was done to compose the developments in signal and image processing to evaluate the dynamics of agricultural ecosystems and biodiversity. Searching was conducted in large academic databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect and Google Scholar. Various combinations of keywords covering remote sensing platforms, proximal and in situ sensing, bioacoustics, radar/LiDAR, thermal/fluorescence/microwave sensing, time–frequency and nonlinear signal analytics, computer vision, multimodal fusion, and validation/benchmarking were used. Peer-reviewed journal articles, high-quality conference proceedings, and authoritative books were included when they presented methodological innovations, evaluation protocols, or demonstrated ecosystem applications. Studies were screened by relevance, methodological clarity, and reproducibility. Evidence was organized thematically by sensing modality, analytical approach, integration strategy, and application domain, with emphasis on cross-scale generalization and validation practices.

3. Data Acquisition Modalities in Agricultural Ecosystems

The foundation of large-scale monitoring of agricultural ecosystems based on satellite remote sensing is the possibility to regularly monitor the agricultural systems in multi-temporal mode and to track the process of cultivating crops. Under Agriculture 5.0 models, the satellite technologies are used to manage precision, sustainability, and resource distribution optimization [10]. Multispectral and hyperspectral data are combined in global satellite-based agricultural surveillance systems to assess the condition of crops, productivity patterns, and climatic stressing factors in various agroecological zones [11]. Proper identification and classification of arable lands using satellite images has continued to be pivotal in mapping and analysis of biodiversity at the landscape level and ecosystem [12]. UAVs increase the level of spatial resolution and flexibility in operations in agricultural surveillance. Topography has been enhanced through the development of various Structure-from-Motion methods, which are more efficient and accurate than the old methods of surveying [13]. High-resolution structural data and field-level measurements can be used complementarily through the complementary integration of airborne and ground-based proximal sensing to enhance precision agriculture [14]. It has also been shown that drone-based sensing is capable of biodiversity monitoring in heterogeneous agroecosystems, performing the fine-scale evaluation of habitat and vegetation structure [15].

Signal-based views are another way of looking at imaging approaches as they seek to explain ecological systems in terms of measurable dynamic patterns upon which the ecological variability of the environment and the biological processes depend [16]. Bioacoustics surveillance systems are automated systems that utilize advanced signal processing and machine learning to identify and categorize insects and would represent scalable tools to monitor pollinators and pest populations in agricultural settings [17]. On-land proximal sensing systems provide in situ measurements of observation, which complement the validation and calibration of remote sensing products. Unified ground and satellite measurements are particularly important to soil moisture measurements, which are one of the key predictors of crop performance and the performance of ecosystems [18]. Trans-scale validation results confirm the idea that soil moisture measurements made through satellites can be properly correlated with in situ measurements under various climatic conditions [19].

Radar and LiDAR are active sensors which can provide the structural and geometrical information regardless of the condition of ambient light. The introduction of the radar and LiDAR signal processing systems has also improved the ability to detect, map the surroundings and characterize structures [20]. Systems based on radar are also reported to be strong in complex environments, yet the issues of signal interference and positioning accuracy are to be considered [21].

The thermal imaging is applied to the non-contact assessment of the physiological response of the plant, identifying the canopy temperature change in terms of transpiration and stress dynamics. It has been discovered in its application in plant and ecosystem ecology, where it can be employed in the monitoring processes of plant stress and energy balance of water [22]. Fluorescence sensing technologies identify biochemical and physiological signs of plant well-being and the environmental condition, allowing for sensitive monitoring of the changes related to stress in agricultural systems [23]. Microwave remote sensing, e.g. Synthetic Aperture Radar (SAR), is capable of all-weather and day-neutral operation with soils and vegetation dielectric properties that can be used to estimate soil moisture, biomass and land-surface characterization in agricultural landscapes [24]. Table 1 sums up the significant sensing modalities applied in the agricultural ecosystem, which comprise their ecological implications, spatial coverage, and operational constraints.

Table 1. Data Acquisition Modalities and Their Ecological Relevance

Sensing Modality	Primary Data Type	Spatial Scale	Ecological Information Captured	Operational Considerations
Satellite remote sensing	Multispectral and hyperspectral reflectance	Regional to global	Vegetation dynamics, habitat distribution, phenology	Atmospheric interference, mixed pixel effects
UAV-based imaging	High-resolution optical and spectral imagery	Field to landscape	Canopy structure, microhabitat variability, species proxies	Limited spatial coverage, calibration requirements
Proximal sensing systems	In situ environmental measurements	Plot to plant level	Soil moisture, canopy traits, microclimate conditions	Spatial sparsity, maintenance demands
LiDAR and radar systems	Structural and backscatter signals	Field to regional	Vegetation structure, biomass estimation, habitat complexity	Signal noise, computational intensity
Thermal, fluorescence, SAR	Physiological and dielectric responses	Plot to regional	Plant stress indicators, biochemical activity, soil moisture	Sensor-specific correction challenges

4. Advanced Signal Processing Techniques for Ecosystem Assessment

4.1 Time-Frequency Analysis

Environmental and ecological signals are naturally non-stationary and multi-scale in nature and they demand analytical structures that have the power to resolve variability of time at various frequencies. Time-frequency analysis offers this by splitting signals into time-frequency space to enable transient and periodic dynamics to be detected [25]. Fourier-based and window-based approaches are classical spectral and time-frequency techniques that still serve as the basis of detecting the existence of dominant oscillatory patterns in environmental data and extracting discriminative features [26]. Wavelets are also well applicable in ecological research due to their ability to retain short-term variations, as well as long-term patterns. Time series of environmental observations converted to time-frequency images generated by the wavelet have facilitated predictive modeling of complicated ecological processes like harmful bloom processes [27]. Likewise, the wavelet analysis of the vegetation indices and meteorological variables can be used to identify the scale-dependent responses between climatic drivers and vegetation responses [28]. The methods play important roles in defining the phenological changes and disruption regimes in agricultural landscapes.

4.2 Nonlinear and Multiscale Dynamics

Regime shifts, abrupt transitions and nonlinear behavior are common in ecological systems which cannot be well represented using linear spectral approaches. Nonlinear and non-stationary patterns in dynamic signals can be easily found with adaptive decomposition methods together with multiscale recurrence analysis, which makes them more sensitive to structural variations [29]. Complexity-based measures can also further the measurement of the ecosystems by measuring the irregularity, and also measuring the entropy and scaling measures of environmental sequences [30]. Such measures provide knowledge of resilience, stability and system organization that aids in the early development of ecological stress or degradation in agroecosystems.

4.3 Machine Learning for Signals

Introduction of machine learning has revolutionized the analysis of environmental signals, allowing the automated pattern recognition and predictive modeling of large amounts of data. Recent developments prove the expansion of the analytical ability of environmental science and engineering practice through the lens of supervised and unsupervised learning methods [31]. The most important part of signal interpretation is featuring extraction. Strong high-dimensional algorithms can be used to improve the representation of salient time and spectral properties, and can be used in classification and anomaly detection [32]. In addition to the monitored frameworks, there are functional unsupervised classification techniques to cluster patterns of spatial-selective biodiversity without pre-established categories to aid in exploratory ecological studies [33]. Biodiversity monitoring has also been developed through deep learning that brings together signal processing and automated pattern recognition. Soundscape analysis and deep neural networks allow tracking the recovery of biodiversity and the changing ecosystem in real-time, which proves the opportunities of signal-based AI-based systems to organize a large-scale ecological assessment [34].

Table 2 also associates significant signal processing methodologies with the ecological patterns and indicators that they facilitate in the agricultural monitoring systems. Figure 1 shows a summary of the ecological indicators by providing the analytical pathway of the raw signals.

Table 2. Signal Processing Approaches and Corresponding Ecological Insights

Signal Processing Approach	Data Input Type	Analytical Objective	Ecological Application	Methodological Limitation
Spectral and time–frequency analysis	Environmental time series	Detection of periodic and transient patterns	Phenological shifts, activity cycles	Sensitivity to window selection
Wavelet-based multiscale analysis	Vegetation and climate series	Separation of short- and long-term variability	Climate–vegetation interactions	Edge effects at scale boundaries
Nonlinear dynamic analysis	Complex ecological signals	Identification of regime shifts	Early warning of instability	Parameter sensitivity
Complexity and entropy metrics	Long-term environmental records	Quantification of system stability	Resilience assessment	Cross-site comparability challenges
Machine learning-based signal modeling	Extracted temporal features	Classification and forecasting	Automated biodiversity detection	Dependence on training data quality

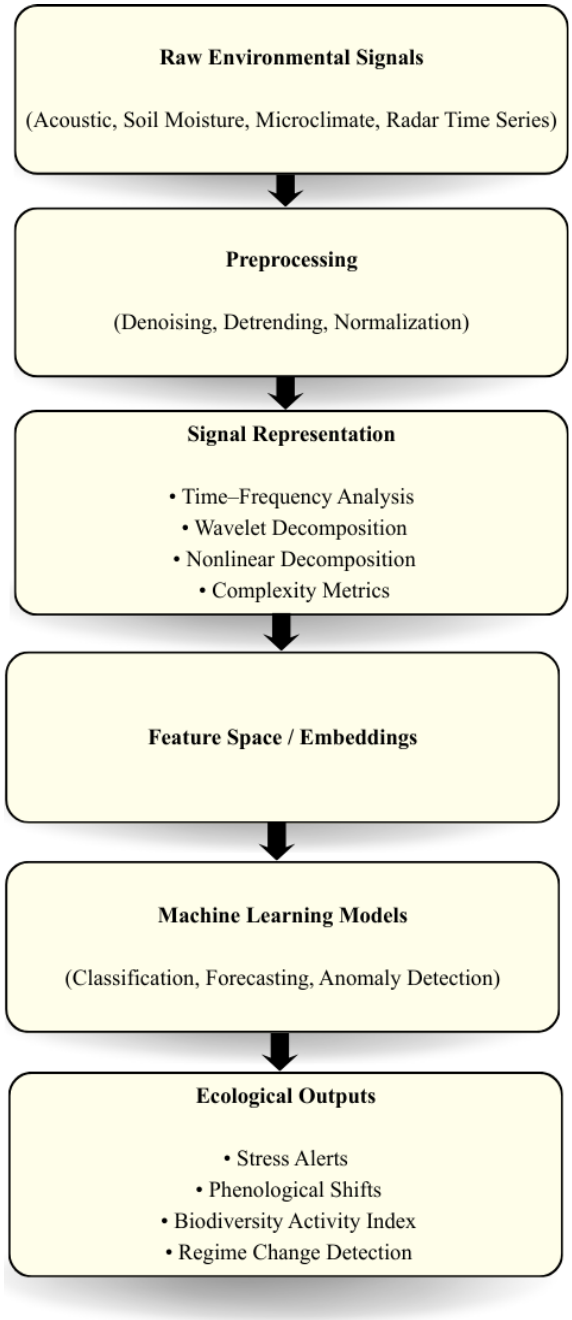

Figure 1. Advanced Signal Processing Workflow for Ecosystem Dynamics

5. Advanced Image Processing and Computer Vision Approaches

5.1 Image Preprocessing Strategies

Well-developed image analysis in agricultural ecosystems commences with a sound preprocessing to diminish noise, correct distortions, and augment discriminative features. Modern computer vision systems combine the latest filtering, normalization, and deep feature learning methods to enhance the robustness of the models in different field conditions [35]. Noise suppression and feature boosting methods have been demonstrated to enhance classification accuracy in image analysis pipelines that are based on deep learning substantially, especially in work with high-dimensional or sensor-degraded imagery [36]. In hyperspectral imaging of the drone, radiometric and geometric corrections are also important in order to achieve spectral fidelity and space congruence. The state-of-the-art techniques improve the consistency of reflections and reduce artifacts due to changes in illumination and instability in the platform, and thus drive ecological inference through downstream techniques [37].

5.2 Spectral and Vegetation Indices

Hyperspectral imaging allows a narrow-band spectral differentiation of vegetation features to be made in a fine way. New hyperspectral vegetation indices enlarge the potential to sense delicate biochemical and structural deficiencies beyond conventional broadband measures to enhance ecological evaluation and tension recognition [38]. High resolution morphological characterization is yet another complement of spectral indices to reflect the terrain structure, the microtopography, and the patterns of land management. Comprehensive morphologic mapping helps to examine conservation activities and landscape heterogeneity, and they are directly connected to the biodiversity genus in agricultural systems [39].

5.3 Deep Learning for Crop Health

Crop health monitoring and disease detection have turned out to be the focus of deep learning. Precision agriculture systems described using machine learning allow the detection of disease symptoms based on imagery of the field using convolutional neural networks and related designs at a progressively more accurate and scalable rate [40]. These strategies facilitate the stressor early identification, decrease the use of manual scouting and aid in timely intervention measures as part of sustainable agricultural management systems.

5.4 Object Detection and Segmentation

The detection algorithms are significant in the detection of crops, weeds, pests and other ecological characteristics in complicated agricultural images. Improved detection structures have enhanced the localization precision, computational efficiency and adaptability in a large variety of field scenarios [41]. Segmentation and detection models based on computer vision have become the cornerstone of automated counting of plants, delineation of the canopy, and identification of a species, enhancing the activities of biodiversity assessment and monitoring the ecosystem.

In developed image processing and computer vision methods, preprocessing, spectral analysis, deep learning classification, and object detection are incorporated into unified analysis pipelines. These technologies make it possible to assess agricultural ecosystems and biodiversity dynamics in large scale and at high resolutions across spatial scales. Table 3 provides an overview of the most important computer vision activities used in the analysis of the agroecosystem and the ecosystem-level outputs they provide. The organized computer vision process used in agricultural ecosystems surveillance is shown in Figure 2.

Table 3. Computer Vision Applications in Agricultural Ecosystem Monitoring

Vision Task	Input Data Type	Analytical Output	Ecosystem Relevance	Implementation Constraint
Radiometric and geometric correction	UAV and satellite imagery	Analysis-ready datasets	Ensures spectral reliability	Requires precise calibration
Vegetation index computation	Hyperspectral imagery	Stress and trait indicators	Physiological condition assessment	Sensor dependency
Image classification	Multispectral and RGB imagery	Crop stress and disease maps	Early intervention support	Risk of overfitting
Object detection and segmentation	High-resolution imagery	Species counts, lesion masks	Biodiversity and pest monitoring	Annotation intensity
Morphological terrain analysis	Digital elevation models	Microtopographic layers	Habitat heterogeneity evaluation	Resolution sensitivity

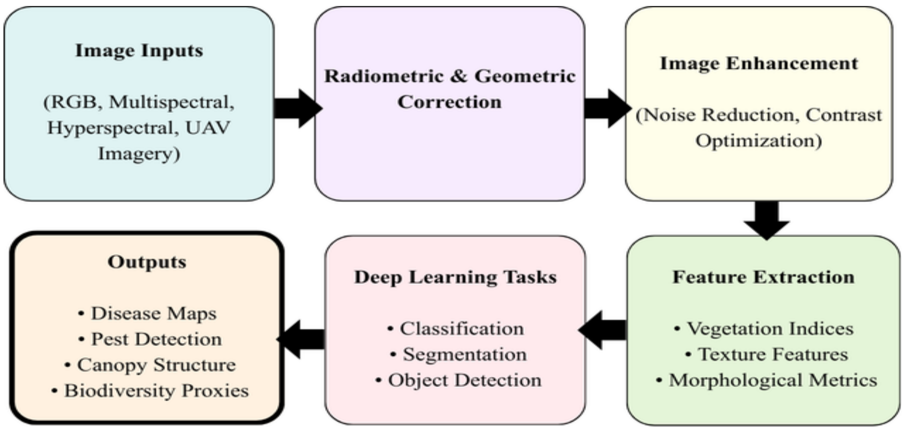

Figure 2. Computer Vision Pipeline for Agricultural Ecosystem Monitoring

6. Integration of Multi-Modal and Multi-Scale Data

6.1 Multimodal Fusion Foundations

Multi-modal Integration Multi-modal integration connects complementary measurements, such as imagery, spectra, acoustics, LiDAR/radar returns and in situ sensor streams, into unified representations that are more representative of ecosystem complexity than any one modality. Fusion via deep learning has now emerged as a leading paradigm of sustainable plant care since it is capable of learning cross-sensor correspondences, managing heterogeneous feature spaces and being more robust to variable field conditions [42].

6.2 Hierarchical and Multilevel Fusion

Smart agriculture has tended to structure fusion as a multilevel pipeline: sensor-level, feature-level, and decision-level. The IoT Multilevel data fusion architectures are developed to address the problems of synchronization, uncertainty and scalable integration of distributed sensing nodes in the IoT environment, which can produce similar inferences by edge devices and cloud analytics [43].

6.3 Spatiotemporal Data Assimilation

The agricultural ecosystems change over the hours (microclimate), seasons (phenology) and years (management and biodiversity turnover), and that needs joint space-time representation to model the agricultural ecosystem. Spatiotemporal deep learning models give structured forecasting of the different environmental variables through learning of temporal interactions and spatial relationships, which are used in the process of predicting and detecting anomalies across the landscapes [44].

6.4 Cross-Scale Harmonization Methods

Successful fusion requires the coordination of modalities in terms of the resolution, sampling frequency, and measurement physics. The fundamental concepts of image and signal processing, which include filtering, normalization, feature extraction and scale-aware representation, are still vital in the pre-processing of environmental data such that a system of integrated models can learn relevant ecological cues as opposed to sensor noises [45].

6.5 Edge–Cloud Integration and Real-Time Autonomous Monitoring

Edge computing is gaining importance in real-time fusion to minimize the latency and bandwidth, but keep the field responsive. AI-enabled edge-cloud solution designs enable pervasive preprocessing and inference with model updates and aggregation on the cloud, with a continuous monitoring application in which both connectivity and energy are major concerns [46]. Multi-modal fusion Mobile and robotic systems combine data on images, environmental sensors, and in some cases, acoustic and depth data, and conduct on-board processing. Robotic systems based on deep-learning have been shown to be able to analyze biodiversity in real-time, a result of the ability to combine sensing and computation to aid in adaptive surveying and specific ecological interventions [47].

7. Applications in Agricultural Ecosystem Monitoring

Many of the smart agriculture functions rely on image processing of fields to transform field images into actionable data on crop status, canopy structure, and management choices [48]. As the maturity of these pipelines increases, more of them incorporate classical enhancement/segmentation with learning-based classification to endorse routine monitoring at the farm scale. The objective of stress detection systems is to detect the initial physiological disturbance before losses on coarse scales are realized. Recent comparative studies indicate that the performance of stress classification can be highly determined by feature representation, selection of sensors and cross-environmental aspects of the stress classification [49]. Deep learning has taken the center stage in stress imaging since it can acquire complex visual and spectral features of drought, nutrient limitation and heat stress when trained on a large collection of images [50].

Digital image processing has been extensively used to identify pests and diseases by localizing symptoms, segmenting lesions and estimating their severity, which is faster to diagnose than manual scouting in most of the places [51]. Surveillance systems based on big data assist in expanding these functions and integrating surveillance of the disease and pest in large areas and seasons with repositories of large images and automated processing [52]. An agricultural imaging method is now being integrated more and more with crop and soil sensing, trying to correlate the status of plants with the edaphic constraint beneath them. Crop imaging Reviews of crop soil imaging underscore the applications of spectral imaging, thermal imaging, and close-range imaging in measuring canopy reaction and soil condition proxy effects on productivity and ecosystem performance [53]. The greenhouse and field microclimates are monitored in great numbers using wireless sensor networks to measure the dynamics of humidity, temperature, and soil moisture, which control the growth of plants and the pressure of pests. Deployments based on microclimate show the value of ongoing measurements in the process of controlling the environment and avoiding stress due to timely feedback [54].

The technologies of biodiversity monitoring are growing at an incredible pace, and the key opportunities include automated sensing and scalable sampling, as well as a combination of various streams of data, and the issues of its validation and long-term comparability [55]. The use of remote sensing has risen to convert spatial dynamics in habitat structure and vegetation features to biodiversity-relevant data, facilitating the control to make inferences about the landscape when sufficiently calibrated in pixels-to-species methods [56]. In addition to land systems, deep learning-based automated monitoring has been used to check aquatic biodiversity to identify species and evaluate ecosystems, and this plot of land can also be applied to freshwater components associated with agricultural catchments [57].

8. Validation, Benchmarking, and Performance Metrics

A sound validation and benchmarking would be a key ingredient in the application of robust image and signal processing systems to agricultural ecosystems to ensure reliability, transferability, and scientific credibility. As the trend of increasing the prevalence of deep learning in processes of remote sensing persists, these concerns have been escalated regarding reproducibility and replicability. Clear data processing, model architecture, hyperparameters, and reporting evaluation procedure are essential to reduce the overstatement of performance and allow an independent verification of researchers [58, 59]. The regularity of the documentation and the possibility of access to the datasets with the help of open access make a significant contribution to the credibility of the outcomes of the ecosystem monitoring through AI-based approaches. Benchmarking is particularly significant in the scenario of the training models based on small or unbalanced datasets, another common weakness of biodiversity research in the agricultural environment. Unless the validation strategies are well designed, small data sets can result in overfitting, unstable generalization and false accuracy estimates [60]. Their cross-validation plans, stratified sampling and independent test sets will therefore be necessary to test the strength of models on spatial, seasonal, and management variation. Performance (precision, recall, F1-score, overall accuracy, and area under the curve) metrics must be considered in the ecological objectives, especially when dealing with the detection of a rare species or the detection of the onset of stress in a crop. Other standards required in remote sensing applications are standard preprocessing processes, coordinated spatial resolution and objective quality measurements. The importance of well-defined sets, preprocessing chains, and measures of fair comparisons between the algorithms is proven by systematic benchmarking systems aimed at solving the problem of creating fusion objects of the high-resolution image [61]. The application to the agricultural ecosystem monitoring is straightforward since the radiometric errors, space resampling and ground-truth acquisition variations can have a significant influence on the model outputs. A systematic benchmarking and validation model of the ecosystem monitoring models is provided in Table 4 in order to permit methodological rigor and operational credibility. Figure 3 is an illustration of the cycle of iteration of validation, deployment and data refinement.

Table 4. Validation and Benchmarking Framework for Ecosystem Monitoring Models

Validation Component	Recommended Practice	Evaluation Focus	Key Metrics	Ecological Significance
Dataset transparency	Document preprocessing and labeling protocols	Data integrity	Not applicable	Prevents hidden bias
Data partitioning strategy	Spatial and temporal separation of test sets	Generalization capacity	Accuracy, F1-score	Avoids site-specific overestimation
Benchmark comparison	Use standardized baselines	Method comparability	AUC, precision, recall	Ensures fair evaluation
Error analysis	Stratified performance reporting	Rare event detection	Class-wise metrics	Critical for biodiversity inference
Deployment monitoring	Periodic model re-evaluation	Stability over time	Calibration measures	Sustains long-term reliability

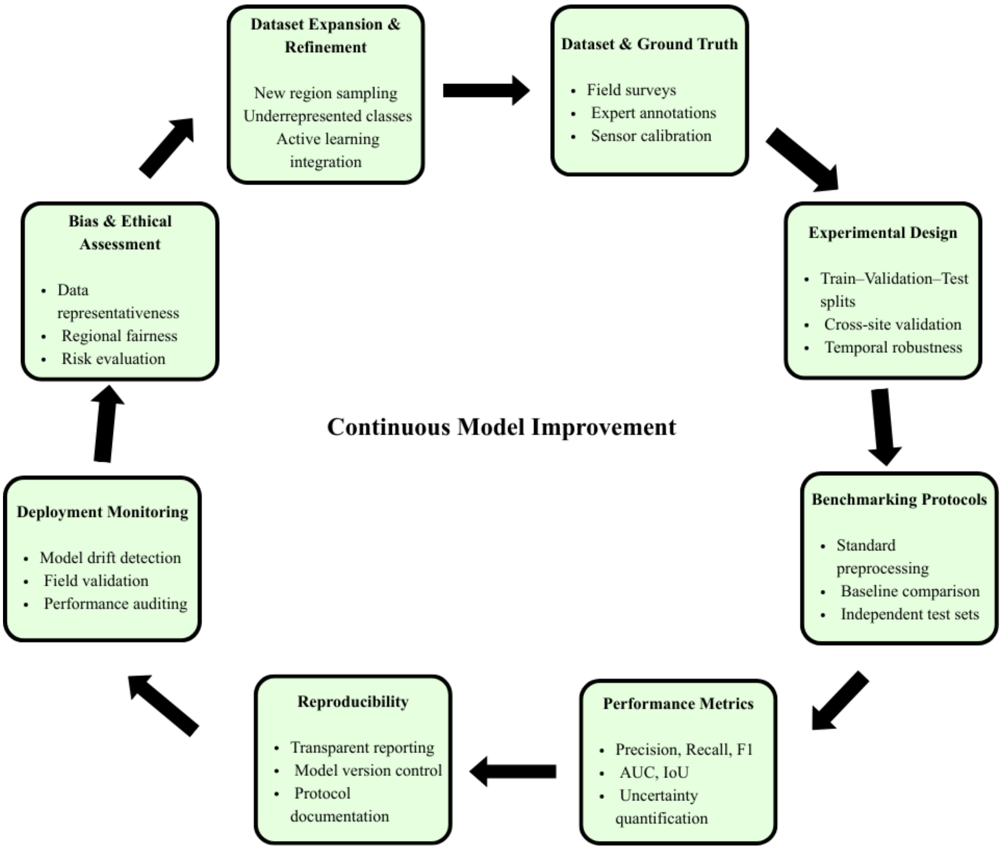

Figure 3. Validation and Trust Framework for AI-Driven Agricultural Ecosystem Monitoring

9. Challenges and Ethical Considerations

One of the main limitations of using high quality of signal and image processing to monitor the agricultural ecosystem is the lack of high-quality labeled information. Ecological data are characterized by their small size, imbalance, and geographic bias, as field-based annotation is expensive and skilled. These constraints decrease the model's generalization to crops, climates, and management systems and make them more susceptible to overfitting. Scarcity of data has been commonly recognized as a bottleneck of deep learning, where transfer learning, data augmentation and semi-supervised methods have been used to enhance performance with limited supervision [62]. Segmentation and detection activities are especially involved since they need dense and precise annotations. Surveys that consider segmentation in the condition of data limitations outline that not only the amount is affected by scarcity, but label quality and spatial accuracy as well, which directly affect the level of trust in the output [63]. This may be changed in a non-agricultural situation to unpredictable crop stress limits or mismatched habitat areas. Besides technical limits, scarcity is also morally dubious. Underrepresented areas can have poor performance on models, which are trained using small datasets and reinforce the disparities in monitoring and decision support. Both algorithmic solutions and open reporting, representative sampling, and critical attention to bias and uncertainty are therefore necessary to the solution of labeled data scarcity [64].

10. Conclusion

The emergence of advanced signal and image processing methods is changing how the agricultural ecosystems and biodiversity dynamics are monitored, comprehended and governed. The combination of satellite, UAV, proximal, and signal-based sensing has enabled the ability to observe crop systems as well as their respective habitats on a continuous basis, and multi-scale, time-frequency, nonlinear, and machine learning technology has increased the ability to detect subtle ecological changes in non-stationary, complex environments. Computer vision systems have become useful to scale up the evaluation of crop stress, disease outbreaks and structural heterogeneity and biodiversity indicators with more and more accuracy. Meanwhile, the accuracy of these technologies is based on stringent validation, open benchmarking, and cautious management of paucity and bias of data. The combination of ecological skills with the computational novelty should be key to making sure that the products of the algorithm sound like biological reality and not the sensor artifacts. The way forward will consist of harmonized data standards, representative sampling, explainable artificial intelligence, as well as adaptive edge-cloud infrastructures, which are capable of real-time analysis. Sustainable technology can be easily applied in the food production sector to enable the application of innovative processing structures that can be viewed as meaningful contributors to the sustainable development of agriculture, resilience, and the conservation of biodiversity in the long-term.

References

1. de Graaff, M.A., Hornslein, N., Throop, H.L., Kardol, P. and van Diepen, L.T., 2019. Effects of agricultural intensification on soil biodiversity and implications for ecosystem functioning: A meta-analysis. *Advances in agronomy*, *155*, pp.1-44.
2. Angon, P.B., Mondal, S., Jahan, I., Datto, M., Antu, U.B., Ayshi, F.J. and Islam, M.S., 2023. Integrated pest management (IPM) in agriculture and its role in maintaining ecological balance and biodiversity. *Advances in Agriculture*, *2023*(1), p.5546373.
3. Díaz, S. and Malhi, Y., 2022. Biodiversity: Concepts, patterns, trends, and perspectives. *Annual Review of Environment and Resources*, *47*(1), pp.31-63.
4. O'Sullivan, J.D., Terry, J.C.D. and Rossberg, A.G., 2021. Intrinsic ecological dynamics drive biodiversity turnover in model metacommunities. *Nature Communications*, *12*(1), p.3627.
5. Gozlan, R.E., Karimov, B.K., Zadereev, E., Kuznetsova, D. and Brucet, S., 2019. Status, trends, and future dynamics of freshwater ecosystems in Europe and Central Asia. *Inland Waters*, *9*(1), pp.78-94.
6. Pfenning-Butterworth, A., Buckley, L.B., Drake, J.M., Farner, J.E., Farrell, M.J., Gehman, A.L.M., Mordecai, E.A., Stephens, P.R., Gittleman, J.L. and Davies, T.J., 2024. Interconnecting global threats: climate change, biodiversity loss, and infectious diseases. *The Lancet Planetary Health*, *8*(4), pp.e270-e283.
7. Farhood, H., Bakhshayeshi, I., Pooshideh, M., Rezvani, N. and Beheshti, A., 2022. Recent advances of image processing techniques in agriculture. *Artificial Intelligence and Data Science in Environmental Sensing*, pp.129-153.
8. Ramani, D.R., Kalaiarasan, K. and Tangade, S., 2025. Remote Monitoring Advancements: A New Approach to Biodiversity Conservation. *Environmental Monitoring Using Artificial Intelligence*, pp.61-69.
9. Soule, E., Charbonnier, R., Schlosser, L., Michonneau, P., Michel, N. and Bockstaller, C., 2023. A new method to assess sustainability of agricultural systems by integrating ecosystem services and environmental impacts. *Journal of Cleaner Production*, *415*, p.137784.
10. Martos, V., Ahmad, A., Cartujo, P. and Ordoñez, J., 2021. Ensuring agricultural sustainability through remote sensing in the era of agriculture 5.0. *Applied Sciences*, *11*(13), p.5911.
11. Nakalembe, C., Becker-Reshef, I., Bonifacio, R., Hu, G., Humber, M.L., Justice, C.J., Keniston, J., Mwangi, K., Rembold, F., Shukla, S. and Urbano, F., 2021. A review of satellite-based global agricultural monitoring systems available for Africa. *Global food security*, *29*, p.100543.
12. Gorokhova, I.N., Chursin, I.N., Khitrov, N.B. and Pankova, Y.I., 2021. Agricultural lands identification on the satellite imagery. *Экосистемы: экология и динамика*, *5*(3), pp.34-59.
13. Ok, E., 2025. Traditional Surveying vs. UAV Drone-Based Structure-from-Motion Advancements in Topographical Mapping Accuracy and Efficiency. *UAV Drone-Based Structure-from-Motion Advancements in Topographical Mapping Accuracy and Efficiency*.
14. Alexopoulos, A., Koutras, K., Ali, S.B., Puccio, S., Carella, A., Ottaviano, R. and Kalogeras, A., 2023. Complementary use of ground-based proximal sensing and airborne/spaceborne remote sensing techniques in precision agriculture: A systematic review. *Agronomy*, *13*(7), p.1942.
15. Afrasiabian, Y., Contiz, F., Van Cleemput, E., Egerer, M. and Yu, K., 2025. Biodiversity monitoring in urban community gardens using proximal sensing and drone remote sensing. *Remote Sensing Applications: Society and Environment*, p.101685.
16. Marshall, S. and Valckenaere, J., 2024. The Signal is the System. *ora. systems*.
17. Kohlberg, A.B., Myers, C.R. and Figueroa, L.L., 2024. From buzzes to bytes: A systematic review of automated bioacoustics models used to detect, classify and monitor insects. *Journal of Applied Ecology*, *61*(6), pp.1199-1211.
18. Babaeian, E., Sadeghi, M., Jones, S.B., Montzka, C., Vereecken, H. and Tuller, M., 2019. Ground, proximal, and satellite remote sensing of soil moisture. *Reviews of Geophysics*, *57*(2), pp.530-616.

19. González-Zamora, Á., Sánchez, N.A.N.U., Pablos, M. and Martínez-Fernández, J., 2019. CCI soil moisture assessment with SMOS soil moisture and in situ data under different environmental conditions and spatial scales in Spain. *Remote Sensing of Environment*, *225*, pp.469-482.
20. Giuffrida, L., Masera, G. and Martina, M., 2023. A survey of automotive radar and lidar signal processing and architectures. *Chips*, *2*(4), pp.243-261.
21. Dawson, E., Mounier, E., Elhabiby, M. and Noureldin, A., 2023. Merits and limitations of automotive radar for land vehicle positioning in challenging environments. *IEEE Sensors Journal*, *23*(21), pp.26691-26700.
22. Still, C., Powell, R., Aubrecht, D., Kim, Y., Helliker, B., Roberts, D., Richardson, A.D. and Goulden, M., 2019. Thermal imaging in plant and ecosystem ecology: applications and challenges. *Ecosphere*, *10*(6), p.e02768.
23. Zacharioudaki, D.E., Fitilis, I. and Kotti, M., 2022. Review of fluorescence spectroscopy in environmental quality applications. *Molecules*, *27*(15), p.4801.
24. Varotsos, C.A. and Krapivin, V.F., 2020. *Microwave remote sensing tools in environmental science* (Vol. 3). New York, NY, USA: Springer International Publishing.
25. Liang, X., Lin, Y., Wu, R., Li, G., Khan, N., Liu, R., Su, H., Wei, S. and Zhang, H., 2023. Time-frequency analysis framework for understanding non-stationary and multi-scale characteristics of sea-level dynamics. *Frontiers in Marine Science*, *9*, p.1070727.
26. Zhang, Z., 2019. Spectral and time-frequency analysis. In *EEG Signal Processing and feature extraction* (pp. 89-116). Singapore: Springer Singapore.
27. Kim, H.G., Cho, K.H. and Recknagel, F., 2023. Time-series modelling of harmful cyanobacteria blooms by convolutional neural networks and wavelet generated time-frequency images of environmental driving variables. *Water Research*, *246*, p.120662.
28. Moreira, A., Fontana, D.C. and Kuplich, T.M., 2019. Wavelet approach applied to EVI/MODIS time series and meteorological data. *ISPRS journal of photogrammetry and remote sensing*, *147*, pp.335-344.
29. Zhang, E., Shan, D. and Li, Q., 2019. Nonlinear and non-stationary detection for measured dynamic signal from bridge structure based on adaptive decomposition and multiscale recurrence analysis. *Applied Sciences*, *9*(7), p.1302.
30. Lange, H. and Hauhs, M., 2025. Complexity analysis of environmental time series. *Entropy*, *27*(4), p.381.
31. Zhong, S., Zhang, K., Bagheri, M., Burken, J.G., Gu, A., Li, B., Ma, X., Marrone, B.L., Ren, Z.J., Schrier, J. and Shi, W., 2021. Machine learning: new ideas and tools in environmental science and engineering. *Environmental science & technology*, *55*(19), pp.12741-12754.
32. Zhang, Y., 2020. Image feature extraction algorithm in big data environment. *Journal of Intelligent & Fuzzy Systems*, *39*(4), pp.5109-5118.
33. Fortuna, F. and Di Battista, T., 2020. Functional unsupervised classification of spatial biodiversity. *Ecological Indicators*, *111*, p.106027.
34. Müller, J., Mitesser, O., Schaefer, H.M., Seibold, S., Busse, A., Kriegel, P., Rabl, D., Gelis, R., Arteaga, A., Freile, J. and Leite, G.A., 2023. Soundscapes and deep learning enable tracking biodiversity recovery in tropical forests. *Nature communications*, *14*(1), p.6191.
35. Davies, E.R. and Turk, M. eds., 2021. *Advanced methods and deep learning in computer vision*. Academic Press.
36. Dalavai, L., Purimetla, N.M., Vellela, S.S., SyamsundaraRao, T., Vuyyuru, L.R. and Kumar, K.K., 2024, December. Improving deep learning-based image classification through noise reduction and feature enhancement. In *2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA)* (pp. 1-7). IEEE.
37. Shin, H.S., Go, S.H. and Park, J.H., 2024. Robust radiometric and geometric correction methods for drone-based hyperspectral imaging in agricultural applications. *Korean Journal of Remote Sensing*, *40*(3), pp.257-268.
38. Sun, G., Jiao, Z., Zhang, A., Li, F., Fu, H. and Li, Z., 2021. Hyperspectral image-based vegetation index (HSVI): A new vegetation index for urban ecological research. *International Journal of Applied Earth Observation and Geoinformation*, *103*, p.102529.
39. Tarolli, P., Cavalli, M. and Masin, R., 2019. High-resolution morphologic characterization of conservation agriculture. *Catena*, *172*, pp.846-856.
40. Majdalawieh, M., Martins, C., Radi, M., Alaraj, M. and Khan, S., 2025. Precision agriculture in the age of AI: A systematic review of machine learning methods for crop disease detection. *Smart Agricultural Technology*, p.101491.
41. Khan, Z., Shen, Y. and Liu, H., 2025. Objectdetection in agriculture: A comprehensive review of methods, applications, challenges, and future directions. *Agriculture*, *15*(13), p.1351.

42. Yang, Z.X., Li, Y., Wang, R.F., Hu, P. and Su, W.H., 2025. Deep learning in multimodal fusion for sustainable plant care: A comprehensive review. *Sustainability*, *17*(12), p.5255.
43. Torres, A.B., Da Rocha, A.R., Da Silva, T.L.C., De Souza, J.N. and Gondim, R.S., 2020. Multilevel data fusion for the internet of things in smart agriculture. *Computers and Electronics in Agriculture*, *171*, p.105309.
44. Amato, F., Guignard, F., Robert, S. and Kanevski, M., 2020. A novel framework for spatio-temporal prediction of environmental data using deep learning. *Scientific reports*, *10*(1), p.22243.
45. Kumar, A., Sihmar, M., Dixit, V. and Pandey, S., 2026. Basics of image and signal processing applied to the processing and analysis of environmental data. In *Perspectives on Artificial Intelligence and Internet of Things for Sustainable Environment* (pp. 55-67). Elsevier.
46. Manduva, V.C., 2020. AI-Powered Edge Computing for Environmental Monitoring: A Cloud-Integrated Approach. *International Journal of Emerging Trends in Science and Technology*, pp.1-21.
47. Panigrahi, S., Maski, P. and Thondiyath, A., 2023. Real-time biodiversity analysis using deep-learning algorithms on mobile robotic platforms. *PeerJ Computer Science*, *9*, p.e1502.
48. Tripathy, A.S. and Sharma, D.K., 2020. Image processing techniques aiding smart agriculture. In *Modern Techniques for Agricultural Disease Management and Crop Yield Prediction* (pp. 23-48). IGI global.
49. Pachpor, K.S. and Rojatkar, D.V., 2024, February. A comprehensive analysis of stress detection and classification models for crop health assessment. In *2024 International Conference on Emerging Systems and Intelligent Computing (ESIC)* (pp. 261-266). IEEE.
50. Gao, Z., Luo, Z., Zhang, W., Lv, Z. and Xu, Y., 2020. Deep learning application in plant stress imaging: a review. *AgriEngineering*, *2*(3), p.29.
51. Gómez-Camperos, J.A., Jaramillo, H.Y. and Guerrero-Gómez, G., 2022. Digital image processing techniques for detection of pests and diseases in crops: a review. *Ingeniería y competitividad*, *24*(1), p.e30110973.
52. Yang, Y., Yang, Y., Shu, H., Zhao, C. and Deng, S., 2024, December. Research on Crop Disease and Pest Surveillance based on Big Data and Image Processing Technologies. In *2024 International Conference on Information Technology, Comunication Ecosystem and Management (ITCEM)* (pp. 243-248). IEEE.
53. Sadiq, M.I., Rahman, S.P., Kayes, S., Sumaita, A.H. and Chisty, N.A., 2021, October. A review on the imaging approaches in agriculture with crop and soil sensing methodologies. In *2021 Fifth International Conference On Intelligent Computing in Data Sciences (ICDS)* (pp. 1-7). IEEE.
54. Kolapkar, M.M. and Sayyad, S.B., 2020, January. Greenhouse microclimate study for humidity, temperature and soil moisture using agricultural wireless sensor network system. In *International Conference on Recent Trends in Image Processing and Pattern Recognition* (pp. 278-289). Singapore: Springer Singapore.
55. Stephenson, P.J., 2020. Technological advances in biodiversity monitoring: applicability, opportunities and challenges. *Current Opinion in Environmental Sustainability*, *45*, pp.36-41.
56. Mallick, M.A.I., 2025. From Pixels to Species: A Review of Remote Sensing for Biodiversity Assessment. *Journal of Sustainability and Environmental Management*, *4*(1), pp.40-61.
57. Salman, I.R., Rasheed, A.A., Hassan, S.A.D.H., Hussein, R.A. and Al-Saady, M., 2025. Automated aquatic biodiversity monitoring using deep learning on the Tigris River: Species identification and ecosystem assessment. *International Journal of Aquatic Biology*, *13*(1), pp.30-40.
58. Pérez-Guaita, D., Quintás, G. and Kuligowski, J., 2020. Discriminant analysis and feature selection in mass spectrometry imaging using constrained repeated random sampling-Cross validation (CORRS-CV). *Analytica Chimica Acta*, *1097*, pp.30-36.
59. Maxwell, A.E., Bester, M.S. and Ramezan, C.A., 2022. Enhancing reproducibility and replicability in remote sensing deep learning research and practice. *Remote Sensing*, *14*(22), p.5760.
60. Brigato, L., Barz, B., Iocchi, L. and Denzler, J., 2022. Image classification with small datasets: Overview and benchmark. *IEEE Access*, *10*, pp.49233-49250.
61. Vivone, G., Dalla Mura, M., Garzelli, A. and Pacifici, F., 2021. A benchmarking protocol for pansharpening: Dataset, preprocessing, and quality assessment. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *14*, pp.6102-6118.
62. Upadhyay, A.K. and Bhandari, A.K., 2024. Advances in deep learning models for resolving medical image segmentation data scarcity problem: a topical review. *Archives of Computational Methods in Engineering*, *31*(3), pp.1701-1719.
63. Khodabandeh, M., 2023. Addressing the labeled data scarcity problem in deep learning.
64. Bansal, M.A., Sharma, D.R. and Kathuria, D.M., 2022. A systematic review on data scarcity problem in deep learning: solution and applications. *ACM Computing Surveys (Csur)*, *54*(10s), pp.1-29.