Scientific Research Publishing

American Journal of Plant Sciences, 2026, 17(4), 426-441
https://www.scirp.org/journal/ajps
ISSN Online: 2158-2750
ISSN Print: 2158-2742

Innovative Approaches to Surveying and Monitoring Potentially Invasive Alien Plants in Agro-Ecosystems-Review

Najla Sayari[1]*, Mehdia Fraj[2], Bochra Bejaoui[3,4], Giuseppe Brundu[5], Vanessa Lozano[5], Maryline Abert Vian[6], Naceur M'Hamdi[7], Vincent Lequart[8], Nicolas Joly[8], Patrick Martin[8]*

[1]Department of Plant Protection, High Agronomic Institute of Chott-Mariem, University of Sousse, Sousse, Tunisia
[2]Faculty of Sciences of Tunis, LR18ES06 Laboratory of Diversity, Management and Conservation of Biological Systems, University of Tunis El Manar, Tunis, Tunisia
[3]National Institute of Research and Physico-Chemical Analysis (INRAP), Laboratory of Useful Materials, Technopark of Sidi Thabet, University of Carthage, Carthage, Tunisia
[4]Faculty of Sciences of Bizerte, Department of Chemistry, University of Carthage, Carthage, Tunisia
[5]University of Sassari, Department of Agricultural Sciences, Sassari, Italy
[6]Avignon Université, INRAE, UMR_A 408 SQPOV, Avignon, France
[7]Laboratory of Animal, Genetic and Feed Resources (LRGAA), National Agronomic Institute of Tunisia, University of Carthage, Carthage, Tunisia
[8]Unité Transformations & Agroressources, ULR7519, Université d'Artois, Bethune, France
Email: *sayari.nagla@gmail.com, *patrick.martin@univ-artois.fr

How to cite this paper: Sayari, N., Fraj, M., Bejaoui, B., Brundu, G., Lozano, V., Vian, M.A., M'Hamdi, N., Lequart, V., Joly, N. and Martin, P. (2026) Innovative Approaches to Surveying and Monitoring Potentially Invasive Alien Plants in Agro-Ecosystems-Review. *American Journal of Plant Sciences*, **17**, 426-441.
https://doi.org/10.4236/ajps.2026.174028

Received: January 22, 2026
Accepted: April 24, 2026
Published: April 27, 2026

Abstract

Invasive Alien Plants (IAPs) pose significant threats to biodiversity, crop productivity, and ecosystem services within agroecosystems. Effective surveillance and monitoring are critical for early detection and rapid management. This review synthesizes recent advances and interdisciplinary innovations in IAP monitoring, with a focus on their application in agricultural landscapes. Traditional methods, including field surveys, herbarium records, and farmer reports, provide foundational data but suffer from limitations such as spatial bias, high labor costs, and limited scalability. In response, emerging technologies such as remote sensing, Machine Learning (ML), Deep Learning (DL), citizen science platforms, and smart-chip IoT systems are being integrated into modern monitoring frameworks. Remote sensing coupled with ML enables automated detection across large areas, while citizen science applications expand spatial coverage and public engagement. Smart sensors and AI-driven analytics offer continuous, real-time monitoring and risk assessment. Integrated systems, such as Early Detection and Rapid Response (EDRR) platforms, increasingly combine these tools to support informed decision-making. Despite these advances, challenges remain, including data quality issues, model generalizability, interoperability across platforms, and socio-political barriers. This review highlights key research gaps, including the need for standardized data protocols, federated learning, and ethical frameworks for data use. It concludes with strategic recommendations for future development: fostering interdisciplinary collaboration, advancing scalable technologies, and aligning monitoring systems with governance frameworks. Collectively, these efforts offer a pathway toward more resilient, adaptive, and data-driven approaches to managing IAPs in agroecosystems.

Keywords

Invasive Alien Plants, Management Approaches, Agroecosystems

1. Introduction

Invasive Alien Plants (IAPs) are non-native species that establish, proliferate, and cause ecological, economic, or social harm in their new conquered environments. In agro-ecosystems, IAPs pose serious threats by competing with crops for nutrients, altering habitat quality, and disrupting ecosystem services such as pollination and soil fertility. Effective survey and monitoring frameworks are thus essential to prevent their establishment and mitigate their spread. Traditionally, IAP surveillance has relied on field surveys conducted by experts and farmers, supported by herbarium records and participatory farmer reports. Although these methods provide accurate local identification, they are often sporadic, costly, and geographically constrained. This hampers early detection, especially in complex agro-ecosystems with fragmented landscapes and rapidly shifting land-use patterns. Recent scientific advances seek to address these limitations by integrating innovative technologies into IAP monitoring. Remote sensing combined with Machine Learning (ML) and Deep Learning (DL) has emerged as a potent approach for detecting and mapping invasive plants over large geographic scales with enhanced speed and accuracy. Zaka and Samat [1] conducted a comprehensive review, highlighting that algorithms such as Random Forest (RF) and Support Vector Machine (SVM) consistently deliver high accuracy in distinguishing IAPs from native vegetation [1] [2]. Indeed, RF and SVM handle high-dimensional, heterogeneous, and non-linear remote-sensing data efficiently, which makes them particularly effective for invasive species detection and classification. Moreover, studies employing satellite imagery (e.g., WorldView-3) in tandem with Object-Based Image Analysis (OBIA) and SVM, RF, and XGBoost classifiers have achieved robust mapping outcomes in urban-agricultural interfaces [3].

According to [4], deep learning models applied to action-camera images, such as those used to detect Solidago altissima L., have achieved around 89% accuracy, showcasing high-throughput potential at low operational cost. Additionally, smart-chip and camera systems mounted on vehicles are being trialed along transport corridors to provide rapid roadside IAP surveillance [5].

Citizen science initiatives have rapidly expanded through smartphone applications and web platforms, enabling the public to report sightings of IAPs. Platforms, such as those examined by [6], EASIN [7] and iNaturalist [8], have generated extensive spatial and temporal datasets, often detecting new occurrences earlier than traditional scientific surveys. However, ensuring data quality and expert validation remains a persistent challenge. Despite these advancements, several barriers continue to hinder progress: technical limitations like cloud cover, low spatial or spectral resolution, and species misclassification reduce the effectiveness of remote sensing [9]; machine learning and deep learning can struggle with complex, unstructured data or when generalizing to new, unseen data [10]; and governance issues, such as fragmented legal frameworks, inadequate funding, and weak stakeholder coordination, impede the implementation of cohesive, integrated monitoring systems [11].

This review aims to investigate the state-of-the-art of innovations in IAP surveying and monitoring within agro-ecosystems, evaluate their strengths and weaknesses, and identify gaps ripe for future research. We will specifically assess remote sensing-ML/DL integration, real-time vehicle- and citizen science-based detection, data governance structures, and emerging smart-chip/IoT applications.

2. Overview of Traditional Surveying and Monitoring Methods

2.1 Ground-Based Field Surveys

Field surveys conducted by experts employ systematic sampling techniques, such as quadrats, transects, and plot-based methods, to document the presence, abundance, and spatial distribution of plant species within agroecosystems [12] [13]. These methodologies provide high-resolution data, enabling precise species identification and the collection of detailed trait-based metrics, such as biomass, seed mass, and specific leaf area. A notable example is a recent study in the oasis agroecosystems of Xinjiang (China) where researchers deployed over 600 plots using a combination of 20 × 20 m and 1 m quadrats to catalog 62 alien plant species. The study successfully linked plant functional traits to invasion risk, achieving high predictive performance (AUC = 0.981) [14]. The key advantage of such surveys lies in their accuracy and depth of ecological insight, particularly for rare or morphologically similar species that may evade automated detection methods. However, these surveys are highly labor- and cost-intensive. Comparative analyses, such as those performed for garlic mustard (*Alliaria petiolata* (M. Bieb.) Cavara & Grande), have shown that while random sampling provides comprehensive ecological data, simpler roadside transects can detect similar prevalence levels using only a quarter of the required person-hours [15]. Thus, while expert-led field surveys remain a gold standard for ecological assessments, their scalability and efficiency continue to pose significant operational challenges.

2.2. Herbarium & Floristic Records

Specimens collected, pressed, and stored in herbaria provide historical and taxonomic context for IAP occurrence, allowing frequency and range analyses over time [16]. While invaluable for retrospective studies, they suffer from spatial bias; most collections cluster near accessible areas and do not facilitate real-time monitoring.

2.3. Farmer Reports & Participatory Monitoring

Farmer-based observations and local surveys feed into early detection systems, especially in resource-limited contexts. Integrated methods like mixed surveys, ecological, household, and focus groups form a large part (17%) of IAP studies examining human-plant interactions [17]. These approaches facilitate stakeholder engagement and wider coverage, but may lack taxonomic precision and consistency.

2.4. Traditional Geospatial Techniques

Given major threats represented by biological invasions, both in man-made and natural ecosystems, efforts are made to avoid invasions, eradicate, and/or control established invaders. It has long been recognized that Geographical Information Systems (GIS) could contribute to this through mapping actual invader spread or areas at risk of invasion. GIS could also be used as a synthesizing tool for the undertaken IAP management actions [18]. GIS is primarily a spatial analysis and visualization framework, while modern technologies such as UAVs, hyperspectral sensors, and machine learning provide new data inputs that enhance GIS-based mapping and decision-making. GIS mapping, while powerful, has limitations related to data accuracy, complexity, cost, and expertise required for processing high-resolution imagery. Furthermore, GIS limitations in invasive plant mapping are particularly due to challenges in accurately identifying and differentiating species, especially when they are hidden or mixed within vegetation canopies [19] [20].

2.5. Limitations of Traditional Methods

A US Forest Service review emphasizes that inventory methods must align with explicit land-use goals; misalignment leads to underused or irrelevant data [12]. Further, remote sensing studies note that coarse spatial and spectral resolutions hinder early detection, particularly for understory or low-density invaders [21]. **Table 1** summarizes the advantages and limitations of the commonly used methods to survey and monitor IAP. Despite their limitations, traditional methods (**Table 1**) form the baseline for new approaches: they supply ground-truth data crucial for calibrating remote sensing models and validating citizen science observations.

3. Recent Innovations in Monitoring and Detection

3.1. Remote Sensing Technologies

Remote sensing platforms, satellite, Unmanned Aerial Vehicles (UAVs, mainly drones), aerial, and Light Detection And Ranging (LiDAR), combined with Machine Learning (ML), are transforming IAP monitoring in agro-ecosystems. A comprehensive review by [1] confirmed the effectiveness of supervised classifiers, e.g., Random Forest (RF) or Support Vector Machine (SVM), and weakly supervised methods in detecting invasive plant species from multispectral and hyperspectral data [2]. Satellite sensors (e.g., Sentinel 2) using vegetation indices, e.g., Normalized Difference Vegetation Index (NDVI) or red-edge bands, yielded detection accuracies ranging from 76% - 92% when distinguishing IAP from native vegetation [1]. UAV-based hyperspectral and LiDAR systems enable centimeter-level resolution, which is especially valuable for identifying early-stage infestations across fragmented agricultural landscapes [1]. However, challenges remain, such as cloud cover, spectral similarity among co-occurring species, and the need for extensive labeled training datasets, which limit broader deployment. Advancements like semi-supervised learning, active learning, and automated labeling are being pursued to address these obstacles and reduce dependency on ground truthing.

Table 1. Traditional IAP surveying and monitoring methods.

Method	Advantages	Limitations	Best Use Context	Ref
Field Surveys (Quadrats, Transects)	Accurate species identification; high-resolution trait and abundance data	Time-consuming, labor-intensive, costly, and limited to small spatial areas	Baseline studies; ecological trait analysis; model calibration	[21] [22]
Herbarium & Floristic Records	Historical tracking; taxonomic validation	Spatial and temporal bias; lack of real-time data	Long-term monitoring; species richness and spread analysis	[23] [24]
Participatory Surveys (Farmer reports, Focus Groups)	Inclusive, low-cost, local ecological knowledge integration	Data quality variable; limited species expertise	Early detection in low-resource areas; understanding socio-ecological drivers	[25] [26]
Traditional GIS/Spatial Modeling	Visual mapping; risk zoning; scenario simulations	Input dependent; static; lacks real-time adaptability	National planning; coarse-scale prioritization	[27] [28]
Roadside/Opportunistic Sampling	Cost-effective; scalable; fast	Skewed to linear habitats; under-represents interior landscape zones	Rapid screening; complementary to structured sampling	[29] [30]

3.2. Artificial Intelligence and Machine Learning

Machine learning and Deep Learning (DL) are essential for processing large-scale remote sensing data efficiently. A 2024 review highlighted the use of RF, SVM, Classification And Regression Trees (CART), XGBoost, and Convolutional Neural Networks (CNNs) in classifying IAPs, achieving up to >95% accuracy for some species [2]. Deep learning models, especially CNNs, excel in feature extraction from hyperspectral imagery, further enhancing classification capabilities across complex plant communities. Furthermore, DL-powered approaches have enabled real-time species detection using action-cameras mounted on vehicles or UAVs, with accuracies around 89% for one of Japan's 100 worst invasive species *Solidago altissima L.* These findings suggest that effective identification models can be prepared using inexpensive cameras, and this may open possibilities for citizen science in this field [4].

3.3. Citizen Science and Mobile Applications

Citizen science has emerged as a powerful, low-cost complement to technological monitoring. Platforms such as iNaturalist, European Alien Species Information Network (EASIN), and regional apps have demonstrated success in detecting IAPs through public engagement [31]. For example, European LIFE medCLIFFS volunteers recorded thousands of invasive plant sightings with minimal training [32]. Australia's Atlas of Living Australia developed a Biosecurity Alerts service that delivered 99% of alerts via citizen-submitted observations [33]. Despite challenges in data validation, new quality-control tools, such as expert-curated validation and algorithmic anomaly detection, are enhancing reliability [34].

3.4. Smart-Chip/IoT Systems

Emerging Internet-of-Things (IoT) systems integrate AI-powered smart chips and environmental sensors for continuous, in-situ monitoring. A new 2025 review described IoT-based systems capable of detecting IAP presence, phenology, and physiological stress via environmental variables, allowing real-time alerts and predictive management responses [35]. While still experimental, these systems promise high precision, decreased herbicide use, and less collateral damage, though cost, environmental stability, and policy barriers must be addressed [36].

4. Interdisciplinary and Integrated Monitoring Systems

Innovative monitoring of Potentially Invasive Alien Plants within agro ecosystems is increasingly being approached through interdisciplinary frameworks that combine remote sensing, citizen science, IoT, and ecological expertise, enabling great opportunity for invasion biologists, resource managers and policy makers to develop predictive models for invasion risk analysis as well as early detection strategies [37]. An even more innovative frontier is offered by the use of Unmanned Aerial Vehicles (UAVs) that are capable of low flying and acquiring RGB, multispectral, and hyperspectral images at higher resolution than satellite data [38].

4.1. Fusion of Technologies

Projects like Biodiversa+'s CamAlien exemplify cross-disciplinary integration, mounting cameras on vehicles to collect thousands of roadside images processed using Pl@ntNet's deep learning apps. This approach supports harmonized, large-scale monitoring across Europe; expert review of low-confidence images enhances quality under FAIR data protocols [39]-[41]. Similarly, smart chip IoT platforms embed micro sensors in the field to track environmental conditions (e.g., soil, humidity, phenology), alerting on IAP presence and physiological stress. These systems integrate AI edge-processing for real-time analytics and decision automation.

4.2. Early Warning & Decision Support

Integrated systems now frame Early Detection & Rapid Response (EDRR) workflows: 1) detection via RS + IoT + public reports; 2) validation through expert assessments; 3) rapid management via mobile/AI tools. They align with national regulatory priorities, as documented in U.S. federal EDRR capacity reviews [42]. Advanced AI modules like convolutional neural networks are merging data streams, satellite, UAV, and in-situ sensors to automatically generate risk maps and trigger alerts. Frameworks used in pest detection (e.g., locust, bark beetle) are now being adapted for plant invasions in agroecosystems.

4.3. Stakeholder Engagement & Data Governance

Successful integration requires strong stakeholder networks: scientists, farmers, extension agents, citizens, and policymakers. Platforms such as eBird, iNaturalist, and EASIN exemplify effective data-sharing ecosystems [43]. Governance is aided by standardized data pipelines (image, sensor, report), centralizing datasets in FAIR-aligned archives like Electronic Research Data Archive (ERDA) and Global Biodiversity Information Facility (GBIF). EU projects stress protocol harmonization across borders and long-term institutional collaboration [39] [40].

4.4. Benefits and Challenges

Interdisciplinary and integrated monitoring systems for IAPs offer a transformative approach by combining technologies such as remote sensing, IoT devices, citizen science platforms, and artificial intelligence into cohesive Early Detection and Rapid Response (EDRR) frameworks (**Figure 1**). These systems provide multiple benefits: they enhance comprehensiveness by integrating data from various platforms which provide latency reduction in IAP detection; ensure scalability, as citizen science and IoT tools can function across diverse geographical and ecological contexts; increase resilience which enable swift coordinated responses to new invasions; and offer flexibility, as such systems can often be applied retrospectively, even without prior planning [44]. Furthermore, Proactive risk management involves identifying potential risks before they occur and taking preventive actions to minimize their impact. It is a forward-looking strategy that focuses on preventing risks rather than reacting to them after they have happened [45]. However, several challenges hinder their implementation. Technical interoperability remains a major barrier, as aligning datasets from satellites, sensors, camera networks, and crowd-sourced observations requires robust integration frameworks [46]. Cost and scalability concerns arise from the infrastructure needed for large-scale IoT and camera deployments, which require long-term investment and maintenance. Policy and governance obstacles, including data privacy regulations and coordination across sectors, often delay or constrain system rollout. Moreover, a lack of standardized protocols for data collection, validation, storage, and sharing limits the comparability and usability of monitoring outputs [42] [47] [48]. Several case studies illustrate the potential of these systems in action: the CamAlien project in Europe uses highway-mounted cameras and Pl@ntNet-based processing to detect IAPs in real-time, applying consistent protocols across multiple countries [41]; IoT smart chip arrays in agricultural settings monitor phenological and stress markers to identify early invasion cues [35] [49] and EDRR frameworks modeled after U.S. federal programs integrate detection, verification, and intervention via mobile platforms and AI, setting a precedent for rapid and adaptive IAP management.

Figure 1 illustrates the interconnected components of an integrated monitoring system designed for the detection and management of potentially IAPs in agroecosystems. Each node represents a core method or technology, while dashed lines depict the bidirectional flow of data and insights among components. Remote sensing supplies large-scale imagery that feeds into machine learning algorithms, enabling automated identification of invasive species across broad areas. Field surveys provide critical ground-truth data that validate and refine these models, improving their reliability and ecological accuracy. Citizen science platforms contribute near-real-time, crowd-sourced observations that can enhance species distribution mapping and trigger early alerts. Meanwhile, IoT smart chips capture continuous environmental data, including early plant stress signals, which can be analyzed using AI-driven decision-support systems. The integration of these components creates a synergistic, adaptive, and scalable monitoring network. This framework not only improves early detection and response times but also supports more effective, data-informed strategies for the long-term ecological management of IAPs in dynamic agricultural landscapes.

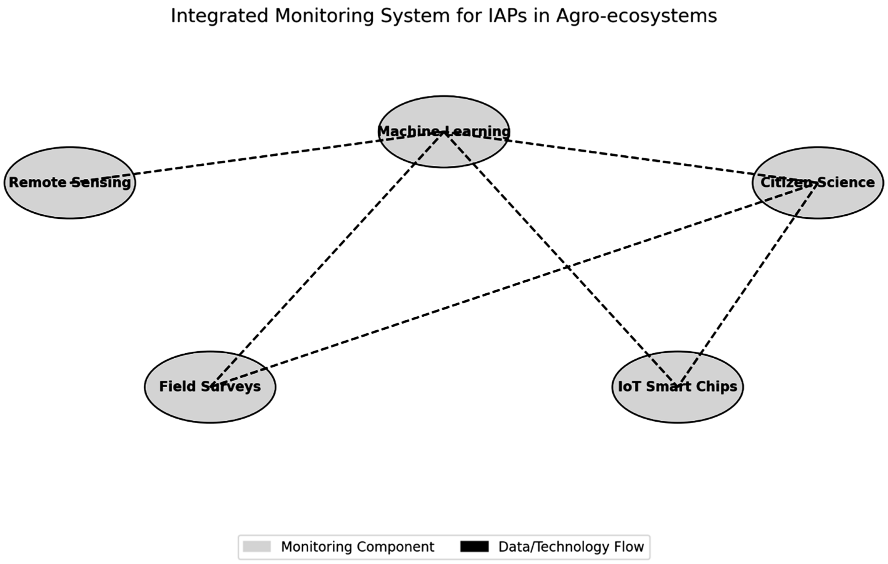

Figure 1. Diagram of integrated monitoring system for potentially invasive alien plants (IAPs) in agro-ecosystems.

5. Challenges and Limitations

Despite rapid technological advancements in monitoring Potentially Invasive Alien Plants (IAPs) in agro-ecosystems, several key challenges continue to limit effective and scalable implementation (Table 2). First, remote sensing technologies such as high-resolution satellite and UAV imagery, while valuable, are costly and often face coverage issues due to cloud interference or inaccessible terrain. Hyperspectral imaging holds promise for species differentiation but remains underused because of its high cost and limited availability [50]. Machine learning applications further depend on large, well-labeled datasets, which are often lacking in diverse agroecosystems. Without extensive ground-truthing, these models struggle to generalize across landscapes and climates, reducing their reliability. Moreover, integrating data from multiple platforms, including satellites, IoT sensors, UAVs, and citizen science tools, is technically challenging due to inconsistent data formats, spatial and temporal resolutions, and a lack of unified metadata standards, all of which hinder interoperability and slow down coordinated response efforts. Data quality is another concern, particularly in citizen science, where species misidentification and uneven reporting lead to spatial bias. Although expert validation helps, it is not always timely or sufficient [51] [52]. Similarly, field and herbarium datasets often overrepresent easily accessible areas, leaving significant detection gaps and skewing policy decisions [53] [54]. Finally, economic and organizational barriers persist. The implementation of IoT networks, drone fleets, and data infrastructure demands substantial initial and ongoing investment, often beyond the reach of low-resource regions. Without sustainable funding and cross-sector collaboration, many promising technologies may remain confined to pilot projects [55].

Table 2. Summary table of key challenges.

Domain	Challenge	Impact
Remote Sensing	High cost, limited coverage, technical barriers to hyperspectral usage [55]	Reduced spatial-temporal resolution; incomplete monitoring
ML/DL	Insufficient labeled data, low generalizability	Model bias, poor detection across contexts
Data Integration	Format inconsistencies and metadata variability	Inefficient workflows, fragmented systems
Citizen Science	Misidentification, uneven reporting	False positives, spatial bias
Economic & Policy	Investment needs, weak coordination	Sustainability issues, lack of coherent response strategies
Ethics & Privacy	Data privacy, IP rights	Public mistrust, legal risks

6. Future Perspectives & Research Gaps

Several promising technologies and methodologies are emerging to enhance the detection and management of IAPs in agroecosystems. Hyperspectral remote sensing, particularly using UAV-mounted sensors, has shown high classification accuracy for species such as Asclepias syriaca L., with machine learning models like Support Vector Machine (SVM) and Artificial Neural Network (ANN) achieving 93% - 99.6% accuracy [56] [57]. However, future work must improve data processing, including real-time dimensionality reduction techniques like Principal Component Analysis (PCA). Smart-chip IoT systems, which embed micro-sensors directly onto plants to monitor stress and phenological changes, offer in-situ monitoring potential when paired with predictive AI [36] [49] [58] [59]. These technologies face challenges such as cost, sustainability, and the need for eco- friendly, biodegradable components. Additionally, blockchain-integrated IoT architectures (BEoT) present a novel yet largely conceptual approach to secure, tamper-proof data sharing, with potential to strengthen citizen science and multi-stakeholder decision systems [60]. On the data side, advances in deep learning for hyperspectral data, including 1D/2D/3D CNNs, Generative Adversarial Networks (GANs), and autoencoders, show promise but still lack models tailored to IAP classification [61] [62]. To address the data labeling bottleneck, semi- and self-supervised learning techniques like weak supervision, transfer learning, and synthetic data generation should be explored. Federated learning offers a way to enhance model robustness across institutions while preserving data privacy, particularly for sensitive land-use information. Integrated systems must evolve toward edge-to-cloud workflows that combine data from remote sensing, UAVs, IoT devices, citizen inputs, and field surveys, enabling near real-time alerts and interventions.

This requires adopting open, FAIR (Findable, Accessible, Interoperable, Reusable) data principles and interoperability standards, e.g., GBIF (Global Biodiversity Information Facility) or EASIN, potentially backed by blockchain for data provenance and trust. Furthermore, addressing governance and stakeholder dimensions is crucial. Participatory, socio-technical co-design with farmers, agencies, and communities ensures more tailored and sustainable solutions. Clear regulatory roadmaps for IoT use, data sharing, and privacy protections will help facilitate technology uptake. Finally, the economic dimension must not be overlooked; scalable deployment of UAVs and IoT systems will depend on cost-benefit analyses, subsidies, and innovative public-private partnerships. Key research gaps include large-scale trials of hyperspectral UAVs, real-time validation of smart-chip sensors, pilot implementations of BEoT systems, development of federated AI models, and the creation of interoperable, blockchain-enhanced monitoring platforms aligned with national EDRR systems.

In practical terms, a BEoT architecture could, for example, maintain an immutable, time-stamped ledger of IAP management actions reported by IoT sprayer units and field teams, including treatment location, herbicide dose, and follow-up monitoring results. Such a tamper-resistant record would simplify regulatory reporting, support audits of eradication programs, and build trust among agencies and landowners that control measures have actually been implemented as agreed, especially when linked to citizen science observations and remote-sensing-based verification layers [60].

7. Conclusion and Recommendations

This review highlights how innovations in technology are transforming IAPs monitoring in agro-ecosystems, providing new possibilities for early detection, rapid response, and informed management. Remote sensing technologies—especially when combined with UAVs and hyperspectral imaging—enable scalable, automated detection of invasive species across diverse landscapes [1]. Citizen science platforms like iNaturalist and EASIN continue to play a crucial role in providing real-time data in under-surveyed areas, though quality control and validation remain essential [51,52]. Smart-chip IoT sensors paired with AI open the door to real-time, in-situ plant health monitoring, but their wider adoption still faces barriers related to cost, infrastructure, and regulatory approval [63]. Interdisciplinary and integrated monitoring systems, such as CamAlien and EDRR frameworks, demonstrate the power of combining multiple data sources (remote sensing, citizen science, IoT, field surveys) to deliver early alerts, risk maps, and decision support tools. Despite these advances, key limitations persist, including fragmented data standards, privacy concerns, funding shortfalls, and limited coordination between stakeholders. To improve future IAP monitoring systems, we recommend promoting edge-cloud technological integration, supporting FAIR-aligned open data infrastructures, and empowering local communities through participatory monitoring and training. Additionally, fostering public-private partnerships will help scale technologies like smart-chip arrays and UAV platforms, while strong policy frameworks are needed to address privacy, interoperability, and cross-border collaboration. Ultimately, the future of IAP surveillance lies not only in technical advancement but also in inclusive design, interdisciplinary collaboration, and practical implementation. Building resilient agro-ecosystems requires bridging science, technology, and society to proactively manage the growing threat of invasive species.

Author Contributions

Conceptualization, N. S., M. F., B. B., M. A. V.; investigation N. S., M. F., G. B., V. L., M. A. V.; resources N. S., M. F., B. B., V. L., N. M.; writing—original draft preparation, N. S., M. F., B. B.; writing—review and editing, N. J., G. B., V. L., V. L.; visualization, N. J., P. M., V. L.; supervision, N. M., P. M.; project administration, M. A. V., N. J., P. M.; funding acquisition, P. M. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Zaka, M.M. and Samat, A. (2024) Advances in Remote Sensing and Machine Learning Methods for Invasive Plants Study: A Comprehensive Review. *Remote Sensing*, **16**, Article 3781. https://doi.org/10.3390/rs16203781

[2] Rakgoale, P.B. and Ngetar, S.N. (2024) Detecting Invasive Alien Plant Species Using Remote Sensing, Machine Learning and Deep Learning. *Journal of Sensors*, **2024**, Article ID: 8854675. https://doi.org/10.1155/2024/8854675

[3] Nininahazwe, F., Théau, J., Marc Antoine, G. and Varin, M. (2023) Mapping Invasive Alien Plant Species with Very High Spatial Resolution and Multi-Date Satellite Imagery Using Object-Based and Machine Learning Techniques: A Comparative Study. *GIScience & Remote Sensing*, **60**, Article ID: 2190203. https://doi.org/10.1080/15481603.2023.2190203

[4] Takaya, K., Sasaki, Y. and Ise, T. (2022) Automatic Detection of Alien Plant Species in Action Camera Images Using the Chopped Picture Method and the Potential of Citizen Science. *Breeding Science*, **72**, 96-106. https://doi.org/10.1270/jsbbs.21062

[5] Espitalier, V., Lombardo, J., Goëau, H., Botella, C., Høye, T.T., Dyrmann, M., *et al.* (2025) Adapting a Global Plant Identification Model to Detect Invasive Alien Plant Species in High-Resolution Road Side Images. *Ecological Informatics*, **89**, Article ID: 103129. https://doi.org/10.1016/j.ecoinf.2025.103129

[6] Howard, L., van Rees, C.B., Dahlquist, Z., Luikart, G. and Hand, B.K. (2022) A Review of Invasive Species Reporting Apps for Citizen Science and Opportunities for Innovation. *NeoBiota*, **71**, 165-188. https://doi.org/10.3897/neobiota.71.79597

[7] Katsanevakis, S., Deriu, I., D'Amico, F., Nunes, A.L., Sanchez Aguado, F., Suominen, T. and Cardoso, A.C. (2015) European Alien Species Information Network (EASIN): Supporting European Policies and Scientific Research. *Management of Biological Invasions*, **6**, 147-157. https://doi.org/10.3391/mbi.2015.6.2.05

[8] (2025) iNaturalist. https://www.inaturalist.org/observations/

[9] Abdelmajeed, A.Y.A. and Juszczak, R. (2024) Challenges and Limitations of Remote Sensing Applications in Northern Peatlands: Present and Future Prospects. *Remote Sensing*, **16**, Article 591. https://doi.org/10.3390/rs16030591

[10] Thompson, N.C., Kristjan, G., Keeheon, L. and Gabriel, F.M. (2020) The Computational Limits of Deep Learning. arXiv: 2007.05558.

[11] Adanma, U.M. and Ogunbiyi, E.O. (2024) Evaluating the Effectiveness of Global Governance Mechanisms in Promoting Environmental Sustainability and International Relations. *Finance & Accounting Research Journal*, **6**, 763-791. https://doi.org/10.51594/farj.v6i5.1151

[12] Rice, P.M. and Halstvedt, M.B. (2001) Field Methods for Monitoring Invasive Plant Species in Western Rangelands. Montana State University Extension Report.

[13] Waheed, A., Shah, M.A. and Hassan, A. (2023) Assessment of Alien Plant Invasions in South Asian Agroecosystems Using Plot-Based Field Surveys. *Agricultural Ecology*, **18**, 104-118.

[14] Dong, S., Qin, T., Xue, Z., Guo, W., Wang, H. and Li, H. (2025) Functional Traits Driving Invasion Risk and Potential Distribution of Alien Plants in Oasis Agroecosystems. *Frontiers in Plant Science*, **16**, Article 1590709. https://doi.org/10.3389/fpls.2025.1590709

[15] Corbin, J.D., Wolford, M., Zimmerman, C.L. and Quirion, B. (2017) Assessing Feasibility in Invasive Plant Management: A Retrospective Analysis of Garlic Mustard (*Alliaria petiolata*) Control. *Restoration Ecology*, **25**, 170-177. https://doi.org/10.1111/rec.12429

[16] Waheed, M., Marifatul Haq, S., Arshad, F., Bussmann, R.W., Ali, H.M. and Siddiqui, M.H. (2023) Phyto-Ecological Distribution Patterns and Identification of Alien Invasive Indicator Species in Relation to Edaphic Factors from Semi-Arid Region. *Eco-*

logical Indicators, **148**, Article ID: 110053. https://doi.org/10.1016/j.ecolind.2023.110053

[17] Tataridas, A., Travlos, I. and Freitas, H. (2023) Agroecology and Invasive Alien Plants: A Winner-Take-All Game. *Frontiers in Plant Science*, **14**, Article 1143814. https://doi.org/10.3389/fpls.2023.1143814

[18] Joshi, C., de Leeuw, J. and van Duren, I.C. (2004) Remote Sensing and GIS Applications for Mapping and Spatial Modelling of Invasive Species. *ISPRS International Journal of Geo-Information* (*IJGI*), **35**, 34-42.

[19] Joshi, C., de Leeuw, J., Skidmore, A.K., Van Andel, J., Lekhak, H.D. and Van Duren, I.C. (2005) Remote Sensing and GIS For Mapping and Management of Invasive Shrub *Chromolaena odorata* in Nepal. https://agile-online.org/Conference_Paper/CDs/agile_2005/papers/93_Chudamani%20Joshi.pdf

[20] Reeves, M., Ibáñez, I., Blumenthal, D., Chen, G., Guo, Q., Jarnevich, C., *et al.* (2021) Tools and Technologies for Quantifying Spread and Impacts of Invasive Species. In: Poland, T.M., Patel-Weynand, T., Finch, D.M., Miniat, C.F., Hayes, D.C. and Lopez, V.M., Eds., *Invasive Species in Forests and Rangelands of the United States*, Springer, 243-265. https://doi.org/10.1007/978-3-030-45367-1_11

[21] Chen, Z., Li, J. and Zhang, M. (2024) Invasion Risk Prediction of Alien Plants in Oasis Agro-Ecosystems Based on Species Traits. *Ecological Indicators*, **158**, Article ID: 113361.

[22] Carter, M.E. and Hall, J.V. (2023) Evaluating Transect versus Random Plot Sampling for IAP Detection. *Biological Invasions*, **25**, 231-247

[23] Wang, Y., Xu, J., Zhang, L., Li, X., Chen, T. and Zhou, Q. (2022) Long-Term Trends in Invasive Species from Chinese Herbaria. *Plant Ecology*, **223**, 741-755.

[24] Heberling, J.M. and Isaac, B.L. (2021) Herbarium Spatial Bias and Invasive Plant Detection. *Biodiversity Data Journal*, **9**, e65241.

[25] Shackleton, R.T., Novoa, A. and Foxcroft, L.C. (2023) Farmer Involvement in Managing Invasive Species in Agroecosystems. *Agricultural Systems*, **211**, Article ID: 103564.

[26] Sharma, S. and Tiwari, P. (2021) Participatory Monitoring of Invasive Weeds in Himalayan Farming Systems. *Mountain Research and Development*, **41**, R1-R9.

[27] Sikka, A., Singh, R., Kumar, P. and Sharma, N. (2022) GIS-Based Risk Zoning for Invasive Species Management in Indian Agro-Ecosystems. *Journal of Environmental Management*, **309**, Article ID: 114661

[28] Liu, X., Zhang, Y., Wang, L., Zhang, Z. and Liu, Z. (2023) Modeling Plant Invasion Risk under Land-Use Change. *Landscape Ecology*, **38**, 721-738.

[29] Nowak, D.J. and Greenfield, E.J. (2023) Roadside IAP Surveys as Early Warning Tools. *Environmental Monitoring and Assessment*, **195**, 346.

[30] Belda, A., Muñoz, A., Sánchez, D. and Medina, S. (2020) Efficiency of Opportunistic Roadside IAP Surveys. *NeoBiota*, **58,** 59-80.

[31] Cock, M.J.W., Day, M.D. and Winston, R.L. (2023) Citizen Science to Monitor the Establishment and Spread of a Biological Control Agent: The Case of *Pareuchaetes pseudoinsulata* (Lepidoptera, Erebidae) for the Control of *Chromolaena odorata* (Asteraceae) in South and South-East Asia. *CABI Agriculture and Bioscience*, **4**, Article 25. https://doi.org/10.1186/s43170-023-00171-5

[32] Santana, C., Bosch-Guiu, A., Gómez-Bellver, C., López-Pujol, J. and Nualart, N. (2024) A Simplified Method to Detect and Monitor Alien Plant Species with Invasive

Potential through Citizen Science: An Application from the European Union-Funded LIFE MedCLIFFS Project Volunteers' Data. *Invasive Plant Science and Management*, **18**, e4. https://doi.org/10.1017/inp.2024.40

[33] Egan, G. (2025) Why Citizen Scientists Are Key in the Fight against Invasive Species. CSIRO (Australia's National Science Agency 2025).

[34] González-Moreno, P., Anđelković, A.A., Adriaens, T., Botella, C., Demetriou, J., Bastos, R., *et al.* (2024) Citizen Science Platforms Can Effectively Support Early Detection of Invasive Alien Species According to Species Traits. *People and Nature*, **7**, 278-294. https://doi.org/10.1002/pan3.10767

[35] Javed, M., Tanveer, A. and Singh, R. (2025) Internet of Things (IoT)-Based Smart Sensors for Early Detection of Plant Stress in Agroecosystems. *Computers and Electronics in Agriculture*, **215**, Article ID: 108052.

[36] Javed, Q., Bouhadi, M., Ban, S.G., Ban, D., Heath, D., Iqbal, B., *et al.* (2025) Smart Chip Technology for the Control and Management of Invasive Plant Species: A Review. *Plants*, **14**, Article 1510. https://doi.org/10.3390/plants14101510

[37] Villalobos Perna, P., Di Febbraro, M., Carranza, M.L., Marzialetti, F. and Innangi, M. (2023) Remote Sensing and Invasive Plants in Coastal Ecosystems: What We Know So Far and Future Prospects. *Land*, **12**, Article 341. https://doi.org/10.3390/land12020341

[38] Große-Stoltenberg, A., Lizarazo, I., Brundu, G., Paiva Gonçalves, V., Prado Osco, L., Masemola, C., *et al.* (2023) Remote Sensing of Invasive Australian *Acacia* Species: State of the Art and Future Perspectives. In: Richardson, D.M., Le Roux, J.J. and Marchante, E., Eds., *Wattles: Australian Acacia Species Around the World*, CABI, 474-495. https://doi.org/10.1079/9781800622197.0029

[39] Høye, T.T., Dalby, L., Mellerup, K., Breschi, J., Šingliarová, B., d'Audeville, A., Albert, A., Costa Prestes, A.L., Pettersson, L.B., Račanský, Z., D'hondt, B., Vi-hervaara, P., *et al.* (2025) Transnational Image-Based Monitoring Schemes for Invasive Alien Species. Biodiversa+.

[40] Høye, T.T., Dalby, L., Mellerup, K., Svenning, A., Pinoy, N., Pettersson, L.B., Arnberg, H., Albert, A., d'Audeville, A., Šingliarová, B., Parelho, C., Blasbichler, H., Tannerfeldt, M. and Vihervaara, P. (2025) Monitoring Invasive Alien Species Using Image-Based Methods: Second-Year Report. Biodiversa+.

[41] Høye, T.T., Penca, C. and Jørgensen, H. (2025) CamAlien: Integrating Automated Roadside Biodiversity Monitoring across European Transport Networks. *Biodiversity and Conservation*, **34**, 457-476.

[42] Martinez, B., Reaser, J.K., Dehgan, A., Zamft, B., Baisch, D., McCormick, C., *et al.* (2019) Technology Innovation: Advancing Capacities for the Early Detection of and Rapid Response to Invasive Species. *Biological Invasions*, **22**, 75-100. https://doi.org/10.1007/s10530-019-02146-y

[43] Lau, C. (2024) Detecting Invasive Species Early through Citizen Science. Planetizen. https://www.planetizen.com

[44] Shafiq A., Aftab, M. and Ali, M.M. (2024) Artificial Intelligence in Invasive Species Management: Transforming Detection and Response. *Trends in Animal and Plant Sciences*, **4**, 82-96.

[45] Smith, P.G. and Merritt, G.M. (2002) Proactive Risk Management in Controlling Uncertainty in Product Development. Productivity Press.

[46] Albouq, S.S., Sen, A.A.A., Almashf, N., Yamin, M., Alshanqiti, A. and Bahbouh, N.M. (2022) A Survey of Interoperability Challenges and Solutions for Dealing with Them

in IoT Environment. *IEEE Access*, **10**, 36416-36428. https://doi.org/10.1109/access.2022.3162219

[47] Liu, J., Zhang, H. and Chen, L. (2024) Standardizing Invasive Species Monitoring: Toward Unified Data Collection and Sharing Protocols. *Environmental Monitoring and Assessment*, **196**, 312.

[48] Liu, J., Zhang, M., Li, J. and Chen, Z. (2024) Can Citizen Science and Social Media Images Support the Detection and Monitoring of Invasive Plant Species? *Ecological Informatics*, **74**, Article ID: 101697.

[49] Javed, M., Tanveer, A. and Singh, R. (2025) Smart-Chip IoT Applications for Plant Stress Monitoring: Emerging Tools for Invasive Species Management. *Agricultural Systems*, **220**, Article ID: 103104.

[50] Zaka, U. and Samat, N. (2024) Barriers to Hyperspectral Remote Sensing for Plant Invasion Monitoring: Costs, Coverage, and Data Accessibility. *Remote Sensing Applications: Society and Environment*, **34**, Article ID: 101001.

[51] Pocock, M.J.O., Adriaens, T., Bertolino, S., Eschen, R., Essl, F., Hulme, P.E., *et al.* (2024) Citizen Science Is a Vital Partnership for Invasive Alien Species Management and Research. *iScience*, **27**, Article ID: 108623. https://doi.org/10.1016/j.isci.2023.108623

[52] Pocock, M.J.O., Roy, H.E., Preston, C.D. and Roy, D.B. (2023) Assessing the Reliability of Citizen Science Data for Ecological Research and Decision-Making. *Biological Conservation*, **283**, Article ID: 110057.

[53] Stephenson, P.J., Londoño-Murcia, M.C., Borges, P.A.V., Claassens, L., Frisch-Nwakanma, H., Ling, N., *et al.* (2022) Measuring the Impact of Conservation: The Growing Importance of Monitoring Fauna, Flora and Funga. *Diversity*, **14**, Article 824. https://doi.org/10.3390/d14100824

[54] Stephenson, P.J., Regan, E.C. and Martin, J.L. (2022) Overcoming Sampling Biases in Bio-Diversity Monitoring: Toward Inclusive and Equitable Data Collection. *Conservation Biology*, **36**, e13926.

[55] Abdelmajeed, A. and Juszczak, R. (2024) Economic and Logistical Barriers to the Deployment of Remote Sensing and IoT Systems in Precision Agriculture. *Journal of Agricultural Informatics*, **15**, 77-91.

[56] Papp, K., Tóth, V.R. and Molnár, V.A. (2021) High-Resolution Hyperspectral UAV Data in the Detection of Invasive Plant Species: A Case Study on *Asclepias syriaca*. *Ecological Informatics*, **63**, Article ID: 101306.

[57] Papp, L., van Leeuwen, B., Szilassi, P., Tobak, Z., Szatmári, J., Árvai, M., *et al.* (2021) Monitoring Invasive Plant Species Using Hyperspectral Remote Sensing Data. *Land*, **10**, Article 29. https://doi.org/10.3390/land10010029

[58] Dash, J.P., Watt, M.S., Paul, T.S.H., Morgenroth, J. and Hartley, R. (2019) Taking a Closer Look at Invasive Alien Plant Research: A Review of the Current State, Opportunities, and Future Directions for UAVs. *Methods in Ecology and Evolution*, **10**, 2020-2033. https://doi.org/10.1111/2041-210x.13296

[59] Dash, R., Moharana, S.C. and Patra, M.R. (2019) A Low-Cost IoT Framework for Early Detection of Crop Disease Using Smart Agriculture Sensors. *Computers and Electronics in Agriculture*, **167**, Article ID: 105036.

[60] Gadekallu, T.R., Alazab, M., Kaluri, R., Maddikunta, P.K.R., Bhattacharya, S. and Srivastava, G. (2022) Blockchain for Edge of Things: Applications, Challenges, and Future Directions. *IEEE Internet of Things Journal*, **9**, 2636-2652.

[61] Guerri, J., Livi, L. and Baraldi, A. (2023) Deep Learning Models for Hyperspectral

Image Analysis in Agriculture: A Systematic Review. *Remote Sensing*, **15**, Article 1234.

[62] Guerri, M.F., Distante, C., Spagnolo, P., Bougourzi, F. and Taleb-Ahmed, A. (2024) Deep Learning Techniques for Hyperspectral Image Analysis in Agriculture: A Review. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, **12**, Article ID: 100062. https://doi.org/10.1016/j.ophoto.2024.100062

[63] Santos, L.M., Chen, Y. and Amini, M. (2025) Smart-Chip IoT Systems for Invasive Plant Monitoring: Potential and Limitations in Agricultural Landscapes. *Precision Agriculture*, **26**, 204-219.