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AI-Assisted Monitoring and GIS-Driven Analysis of Insect and Animal Biodiversity in Conservation Landscapes

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Abstract

Global biodiversity decline necessitates transformative approaches to ecological monitoring that transcend the limitations of conventional field methods. Conservation landscapes face unprecedented pressures from habitat fragmentation, land-use change, and climate stressors, yet traditional monitoring approaches remain constrained by taxonomic expertise shortages, spatial coverage limitations, and temporal resolution gaps. This review synthesizes current advances in artificial intelligence-assisted monitoring and GIS-driven ecological analysis for assessing insect and animal biodiversity within conservation landscapes. We examine how deep learning architectures for species identification—applied to image, acoustic, and sensor data—combined with spatial analytical frameworks for habitat suitability, connectivity modeling, and conservation prioritization, enable integrated biodiversity assessment at previously unattainable scales. Key synthesized insights reveal that AI models trained on multi-source data achieve species identification accuracies exceeding 90% for diverse taxa, while GIS-based prioritization frameworks support systematic conservation planning aligned with global biodiversity targets. Translational applications include automated early warning systems for invasive species, corridor design optimization, and decision-support tools for adaptive ecosystem management. We conclude that AI-GIS integration represents a paradigm shift in biodiversity science, offering scalable, cost-effective solutions for evidence-based conservation in an era of rapid environmental change.

Keywords: Insect biodiversity monitoring, AI-assisted species identification, GIS-based habitat analysis, conservation landscape modeling, animal population dynamics, computational ecology

1. Introduction

Insect and animal biodiversity in conservation landscapes faces accelerating threats from habitat modification, fragmentation, and climate change, with recent estimates indicating that protected areas alone cannot safeguard species persistence without active monitoring and adaptive management ^[1, 11]. Insects, comprising over half of all described species, perform critical ecosystem functions including pollination, nutrient cycling, and pest regulation, yet remain dramatically under-monitored compared to vertebrates ^[2, 12]. Similarly, vertebrate populations in fragmented conservation areas require systematic assessment to detect population declines, range shifts, and community reorganization before irreversible losses occur ^[3, 13]. Current challenges in biodiversity monitoring stem from fundamental methodological constraints. Traditional field surveys—transects, pitfall traps, camera traps, and acoustic recordings—generate data at rates that far exceed the capacity of taxonomic experts to process and identify specimens ^[4, 14]. A single Malaise trap can collect thousands of insect specimens weekly, while camera trap networks in protected areas produce millions of images annually, creating identification bottlenecks that delay or prevent data utilization ^[5, 15]. These limitations are compounded by the global shortage of taxonomic expertise, with many

taxonomic groups lacking specialists capable of reliable identification [6, 16].

Artificial intelligence and geographic information systems offer transformative solutions to these monitoring challenges. Deep neural networks trained on large-scale image and sound datasets now achieve species identification accuracies comparable to human experts, enabling automated processing of biodiversity data at unprecedented scales [7, 17]. Concurrently, GIS-based spatial analysis frameworks enable quantification of habitat suitability, landscape connectivity, and conservation prioritization, transforming raw occurrence data into actionable management information [8, 18]. The integration of these technologies—AI-powered species identification coupled with GIS-driven spatial analysis—creates synergistic capabilities that exceed the sum of their parts [9, 19].

The conservation significance of this integration extends beyond academic understanding to direct management application. Protected area managers require timely information on species occurrences, population trends, and habitat conditions to implement adaptive management strategies [10, 20]. Restoration practitioners need spatial tools to prioritize interventions and monitor outcomes across fragmented landscapes [11, 21]. Policy-makers demand evidence-based assessments of conservation effectiveness to guide resource allocation and evaluate progress toward biodiversity targets such as the Kunming-Montreal Global Biodiversity Framework's 30×30 goal [12, 22]. This review addresses these needs by synthesizing current approaches, applications, and future directions for AI-assisted and GIS-driven biodiversity assessment in conservation landscapes. Our objectives are to: (1) examine conceptual frameworks integrating AI, GIS, and field-based monitoring; (2) analyze applications across biodiversity assessment, conservation planning, and ecosystem management; and (3) identify methodological challenges and future research priorities.

2. Conceptual Frameworks and Methodological Approaches

2.1. Taxonomic and Ecological Diversity Assessment Frameworks

The ecological foundation for biodiversity assessment in conservation landscapes rests on multiple complementary diversity concepts that capture different dimensions of community structure and function [13, 23]. Species richness, while the most commonly reported metric, provides incomplete information about community responses to environmental change, as it weights rare and common species equally and ignores compositional differences among sites [14, 24]. Diversity indices incorporating species evenness—the Shannon-Wiener index (H') and Simpson's index (D)—provide additional information about community structure by accounting for relative abundances, with Simpson's index being less sensitive to rare species and more indicative of dominance patterns [15, 25].

Beta diversity—the variation in species composition among sites—has particular relevance for fragmented conservation landscapes where habitat patches may differ substantially in

community composition due to dispersal limitation, environmental filtering, or historical factors [16, 26]. Partitioning beta diversity into turnover (species replacement) and nestedness (species loss) components reveals whether compositional differences reflect genuine community differentiation or simply differential extinction from a shared species pool [17, 27]. For insect communities particularly, high beta diversity across conservation landscapes may indicate habitat specialization and limited dispersal capacity, with implications for connectivity management [18, 28].

Functional and phylogenetic diversity approaches extend taxonomic metrics by incorporating species traits and evolutionary relationships. Functional diversity—the range and distribution of functional traits within communities—predicts ecosystem processes and stability more strongly than species richness alone [19, 29]. In fragmented landscapes, functional diversity often declines more rapidly than taxonomic diversity as fragmentation filters species based on traits such as body size, dispersal capacity, and habitat specialization [20, 30]. Phylogenetic diversity captures evolutionary history and may reveal community assembly processes and evolutionary potential for adaptation to environmental change [21, 31].

Population and metapopulation models provide theoretical frameworks for understanding species persistence in fragmented conservation landscapes. Metapopulation theory conceptualizes species persistence as the balance between local extinction and recolonization across habitat patches, with patch area and isolation determining extinction and colonization probabilities [22, 32]. For species with limited dispersal, populations in small or isolated patches face elevated extinction risk, while matrix quality between patches mediates recolonization rates [23, 33]. These principles inform connectivity modeling and corridor design in conservation planning.

Landscape ecology principles provide the spatial context for biodiversity assessment. The patch-corridor-matrix model conceptualizes conservation landscapes as mosaics of habitat patches of varying size and quality, connected by corridors of varying permeability, and embedded within matrices of different land uses [24, 34]. Island biogeography theory, originally developed for oceanic islands, has been productively applied to terrestrial habitat fragments, predicting species richness as a function of patch area and isolation, though terrestrial fragments differ from true islands in matrix permeability [25].

2.2. AI-Assisted Monitoring Technologies

Machine learning for species identification has revolutionized biodiversity monitoring by enabling automated processing of image, acoustic, and sensor data [7, 17]. Deep neural networks—particularly convolutional neural networks (CNNs)—have become the standard architecture for image-based species identification, learning hierarchical features from training data that capture diagnostic morphological characteristics [26]. For insect identification, CNNs trained on curated image datasets achieve accuracy rates exceeding 90% for well-represented taxa, with

performance improving as training data volume and quality increase [5, 15].

Large-scale multi-source modeling approaches demonstrate the power of aggregating training data across institutions and platforms. A recent pipeline combining 45.4 million images from 133,367 taxonomic names across six data sources produced species identification models for 41,014 unique taxa, with specialized sub-models for different species groups and life stages [7, 17]. Performance improvements over single-source models were substantial: accuracy for arthropod identification increased by 5% overall and 11% for rare species when multi-source training was employed [7, 17]. These models have been deployed as web services for multiple European biodiversity portals, performing approximately 65 million identifications annually and enabling citizen scientists to contribute high-quality observations [7, 17].

Bioacoustic AI classification extends automated identification to vocalizing taxa. Birds, anurans, orthopterans, and some mammals produce species-specific acoustic signals that can be detected and classified using deep learning architectures [27]. Spectrograms—visual representations of sound frequency over time—serve as inputs to CNNs that learn to recognize species from acoustic patterns [28]. Continuous acoustic monitoring coupled with automated classification enables detection of temporal patterns in activity, phenological shifts, and responses to environmental change at scales impossible with human observers [29].

Camera trap AI systems have transformed vertebrate monitoring in conservation landscapes. Modern camera traps generate millions of images that would overwhelm manual review capacity, but deep learning models now achieve high accuracy in detecting, counting, and identifying animals [30]. YOLO (You Only Look Once) architectures and similar object detection frameworks enable real-time processing of camera trap imagery, with applications including population monitoring, behavioral studies, and poacher detection [31]. Integration with edge computing devices allows on-camera processing, reducing data transmission requirements and enabling real-time alerts for conservation interventions [6, 16]. Sensor-based monitoring technologies expand the taxonomic scope beyond visually or acoustically detectable species. Electrical field sensors detect flying insects by measuring disruptions in atmospheric electric fields caused by insect flight and triboelectric charging, enabling continuous, non-invasive monitoring of insect activity and biomass [2, 12]. Convolutional neural networks classify sensor segments as containing insects or not, while wing-beat frequency analysis enables taxon-specific biomass estimation [2, 12]. Validation against conventional Malaise traps showed moderate to strong correlations (Spearman's $\rho = 0.725$ for counts; 0.644 for biomass), demonstrating the viability of automated sensor networks for insect monitoring [2, 12].

Unmanned aerial vehicle-based monitoring extends the spatial reach of biodiversity assessment. The Advanced Insect Detection Network (AIDN), designed specifically for UAV imagery, addresses challenges of small target size, high mobility, and diverse backgrounds through novel

architectures incorporating multi-scale feature fusion and custom loss functions [9, 19]. Performance metrics (92% precision, 88% recall, 90% F1-score) substantially exceed traditional detection models, enabling automated insect monitoring across broad spatial extents [9, 19]. Similarly, drone-based hyperspectral imaging combined with machine learning classifiers achieves high accuracy (99.7%) for mapping cryptogamic vegetation, demonstrating applicability for habitat assessment in extreme environments [8, 18].

Data pipelines for real-time biodiversity monitoring integrate these diverse AI technologies into operational systems. Sensor data streams—from cameras, acoustic recorders, electrical field detectors, and UAVs—feed into cloud-based processing infrastructure where AI models perform detection, classification, and aggregation [2, 12]. Processed data become accessible through user interfaces that support visualization, analysis, and export, enabling near real-time biodiversity monitoring across conservation landscapes [5, 15].

2.3. GIS-Based and Spatial Analytical Approaches

Habitat suitability modeling forms the spatial foundation for biodiversity assessment in conservation landscapes. Species distribution models relate species occurrence data to environmental predictors—climate variables, land cover, topography, and remote sensing indices—producing spatially explicit predictions of habitat suitability [32]. Maximum entropy modeling (MaxEnt) and ensemble approaches combining multiple algorithms have become standard tools, enabling prediction of potential species distributions across unsampled areas and under alternative scenarios [33]. For conservation planning, habitat suitability maps identify priority areas for protection, restoration, or survey effort [34]. Landscape fragmentation metrics quantify the spatial configuration of habitat in conservation landscapes. Metrics derived from land cover classification—patch area, edge density, shape complexity, proximity indices, and connectivity measures—characterize fragmentation patterns that influence species occurrence, movement, and persistence [35]. Fragmentation analysis reveals habitat loss and isolation trends over time, informing assessments of conservation landscape integrity and degradation. Integration with species occurrence data enables identification of fragmentation thresholds beyond which species decline or disappear.

Connectivity and corridor modeling addresses the functional dimension of landscape structure by quantifying movement potential between habitat patches. Circuit theory approaches conceptualize landscapes as electrical circuits where resistance to movement varies with habitat quality, enabling quantification of multiple potential movement pathways rather than single least-cost paths. Graph theory approaches represent habitat patches as nodes and potential movement pathways as edges, enabling calculation of connectivity metrics including connectivity probability, integral index of connectivity, and betweenness centrality. These methods support corridor identification, barrier mitigation, and landscape permeability assessment for focal species.

Remote sensing integration provides consistent, repeatable characterization of habitat conditions across conservation

landscapes. Multispectral and hyperspectral imagery from satellite and UAV platforms enable mapping of vegetation structure, composition, and phenology at multiple scales [8, 18]. LiDAR data reveal three-dimensional habitat structure critical for many vertebrate and invertebrate species. Time series analysis detects land cover change, disturbance, and recovery, informing adaptive management of conservation areas.

Spatial predictive modeling extends current observations to forecast future conditions under alternative scenarios. Land use/land cover change models simulate future landscape configurations based on development trends, policy scenarios, or restoration interventions. Climate envelope models project shifts in species' suitable habitat under climate change scenarios, informing climate-adaptive conservation planning. Integrated modeling frameworks that couple land use, climate, and species distribution models enable scenario evaluation for conservation decision-making.

Prioritization frameworks synthesize multiple spatial datasets into decision-support tools for conservation planning. The Sequential Hierarchical Intersection Layers (SHIL) method exemplifies an accessible GIS-based approach that integrates habitat quality, species distribution, and connectivity data through a transparent, stepwise workflow [8, 18]. Applied to Sicily, a Mediterranean biodiversity hotspot, SHIL revealed ecological strongholds in inland and mountainous provinces while detecting critical corridors and isolated habitat systems, demonstrating its ability to capture complex spatial patterns for conservation prioritization [8, 18]. Other prioritization tools—Zonation, Prioritizr, Marxan—provide more computationally intensive approaches for systematic conservation planning, identifying optimal reserve networks under multiple objectives and constraints.

2.4. Field-Based Monitoring and Data Integration

Standardized sampling methods remain essential for generating the high-quality occurrence and abundance data that ground AI models and GIS analyses in ecological reality. Transects—line, point, or distance—provide spatially referenced occurrence data for plants, insects, and vertebrates, with detection probabilities estimable through distance sampling methods. Pitfall traps capture ground-dwelling arthropods, providing standardized abundance data for beetles, spiders, and ants across habitat types. Malaise traps efficiently sample flying insects, generating large collections for biodiversity assessment and biomonitoring [5, 15]. Camera traps provide occurrence and activity data for medium-to-large vertebrates, with detection/non-detection data amenable to occupancy modeling [30]. Mist nets enable capture and measurement of birds and bats, providing demographic and morphological data complementing occurrence records.

Environmental DNA monitoring has emerged as a transformative approach for detecting species presence without direct observation. eDNA metabarcoding of water, soil, or air samples enables simultaneous detection of multiple taxa, including cryptic species undetectable by conventional methods. For aquatic insects and vertebrates in

freshwater conservation areas, eDNA achieves higher detection probabilities than traditional survey methods with lower field effort. Integration of eDNA data with spatial analysis enables mapping of species distributions and community composition across conservation landscapes.

Long-term ecological observatories provide the temporal depth essential for detecting population trends, community changes, and extinction debts in conservation landscapes. Networks such as the National Ecological Observatory Network (NEON) and the Global Earth Observation System of Systems (GEOSS) coordinate standardized data collection across sites, enabling cross-site comparisons and regional synthesis. For insect monitoring particularly, long-term data reveal decline trajectories, phenological shifts, and community reorganization invisible in short-term studies.

Integration of field data with AI and GIS platforms creates synergistic capabilities exceeding any component alone. Field observations provide training and validation data for AI identification models—without expertly identified specimens, automated systems cannot learn to recognize species accurately [7, 17]. Field-collected occurrence data parameterize species distribution models, determining the environmental conditions associated with species presence. Field measurements of habitat structure and quality validate remote sensing-based habitat assessments, ensuring that GIS analyses reflect ground conditions. Conversely, AI and GIS outputs identify knowledge gaps and prioritize field sampling locations, creating feedback loops that optimize monitoring efficiency.

3. Applications and Case Studies

3.1. AI-Based Biodiversity Monitoring in Protected Areas

Automated insect recognition systems are transforming insect monitoring in protected areas where traditional methods face severe taxonomic expertise constraints [2, 12]. Deployment of electrical field sensor networks in Danish nature reserves demonstrated continuous, non-invasive monitoring of flying insect activity and biomass, with sensor counts correlating strongly with Malaise trap catches ($\rho = 0.725$) [2, 12]. Such systems enable detection of phenological patterns, responses to management interventions, and long-term trends without the labor-intensive sorting and identification required by conventional trapping [2, 12].

Camera trap networks enhanced with AI analysis have revolutionized vertebrate monitoring in protected areas globally. The "Ecoverse" system integrates DBSCAN clustering, graph neural networks, and YOLOv8 object detection for real-time wildlife monitoring, achieving 95% accuracy in animal detection with sub-2-second response times [6, 16]. Integration with mobile alert systems enables rapid response to poaching events, wildlife-vehicle conflict situations, and rare species sightings [6, 16]. For endangered species monitoring, the system incorporates Facebook's Prophet model for time-series forecasting of population trends, supporting proactive conservation interventions.

Early detection of invasive species represents a critical application of AI monitoring in conservation landscapes. Automated identification systems can detect newly arrived

species before populations establish, enabling rapid response eradication. Bioacoustic monitoring coupled with AI classification enables detection of invasive vocalizing species—such as cane toads in Australia or monk parakeets in Europe—at low population densities. Camera trap AI systems trained to recognize invasive mammals—feral cats, pigs, or rodents—enable targeted control efforts.

3.2. GIS-Driven Habitat Assessment and Conservation Planning

Prioritization of high-biodiversity zones for protection or restoration is fundamental to conservation planning in fragmented landscapes [8, 18]. Application of the SHIL framework in Sicily integrated habitat quality, species distribution, and connectivity data to produce a Composite Ecological Value Index (CEVI) that identified priority areas across the region [8, 18]. Results revealed ecological strongholds in inland and mountainous provinces (Palermo and Messina) while detecting critical corridors and isolated habitat systems requiring connectivity restoration [8, 18]. The transparent, stepwise approach supports replication in other regions facing similar conservation challenges [8, 18].

Corridor and buffer zone design depends on spatially explicit connectivity analysis identifying optimal linkages between habitat patches. The BEETLE (Biological and Environmental Evaluation Tools for Landscape Ecology) least-cost focal species approach has been applied to develop integrated habitat networks across multiple scales, supporting planning processes and preventing further fragmentation of biodiversity [10, 20]. In the Campbell River region of British Columbia, integration of citizen science data from iNaturalist with GIS analysis identified high-conservation-value land parcels, with riparian areas along Elk Falls Provincial Park and nearby coastal areas showing highest priority.

Monitoring fragmentation and land-use change impacts requires consistent, repeatable spatial analysis over time. Time series analysis of satellite imagery enables detection of habitat loss, degradation, and recovery within conservation landscapes, informing adaptive management responses. Integration with species occurrence data reveals how fragmentation affects species distributions and community composition, identifying fragmentation thresholds for management intervention.

3.3. Translational Applications in Ecosystem Management

Decision-support tools integrating AI and GIS outputs enable evidence-based management of conservation landscapes. The LPB-RAP modeling framework simulates land-use/land-cover change under alternative scenarios and quantifies impacts on habitat availability and connectivity for umbrella species [3, 13]. Such tools enable stakeholders to compare outcomes of alternative management strategies, identifying potential conflicts and synergies between conservation

objectives and other land uses.

Adaptive management frameworks benefit from integrated monitoring systems that provide timely feedback on management effectiveness. Real-time AI monitoring enables rapid detection of management outcomes—such as changes in species occurrence following habitat restoration—supporting iterative refinement of interventions [5, 15]. Long-term data from integrated monitoring networks reveal whether management actions achieve desired biodiversity outcomes, informing adjustments to strategies and resource allocation.

Restoration monitoring using AI-GIS integration enables cost-effective assessment of restoration outcomes across broad spatial extents [9, 19]. UAV-based monitoring with AI-powered species detection can assess vegetation recovery, insect community reassembly, and vertebrate recolonization of restored habitats at scales impossible with ground-based methods alone [9, 19]. Comparison of restored sites with reference conditions and pre-restoration baselines quantifies restoration success and identifies needed adjustments.

3.4. Digital Biodiversity Databases and Predictive Conservation Tools

Global biodiversity repositories provide essential data infrastructure for AI and GIS applications [7, 17]. The Global Biodiversity Information Facility (GBIF) aggregates species occurrence records from thousands of datasets, providing millions of georeferenced observations for model training and validation. Integration of citizen science platforms—iNaturalist, eBird, iRecord—with research-grade observation validation produces high-quality occurrence data at unprecedented scales. These data resources enable species distribution modeling, AI model training, and biodiversity assessment across conservation landscapes globally [7][17].

Open-access spatial databases provide environmental layers essential for habitat modeling and fragmentation analysis [8, 18]. Global land cover products, climate surfaces, topographical data, and remote sensing indices are increasingly available through platforms such as Google Earth Engine, enabling cloud-based processing without requiring local high-performance computing infrastructure. National environmental data portals—such as Denmark's Miljøportal—aggregate high-resolution spatial data supporting local conservation applications [11, 21].

Predictive extinction risk modeling integrates species occurrence data, life history traits, and threat layers to assess species vulnerability and prioritize conservation interventions. Machine learning models trained on species with known conservation status can predict extinction risk for data-deficient species, identifying potentially threatened species requiring assessment. Spatial projections of future extinction risk under climate and land-use scenarios inform proactive conservation planning.

4. Tables

Table 1: Major AI-Assisted Monitoring Technologies Used in Insect and Animal Biodiversity Research

Technology/Method	Target Taxa	Data Type	Ecological Application	Conservation Relevance	Limitations
Multi-source image recognition ^[7]	Plants, animals, fungi (41,014 taxa)	Images (45.4M training images)	Species identification, citizen science validation	Enables rapid biodiversity assessment at continental scale	Performance drops for rare taxa; requires large training datasets
Electrical field sensors ^[2]	Flying insects	Electrical field modulations	Continuous activity and biomass monitoring	Non-invasive insect monitoring; detects population trends	Biomass estimation requires refinement; size-dependent detection bias
Convolutional neural networks for camera traps ^[6]	Medium-large vertebrates	Camera trap images	Population monitoring, behavior studies, poacher detection	Real-time alerts for conservation interventions	Requires substantial training data for rare species
Bioacoustic AI classification ^[27]	Vocalizing taxa (birds, anurans, insects)	Audio recordings	Species presence, phenology, activity patterns	Enables continuous monitoring across remote areas	Species identification accuracy varies with recording quality
Advanced Insect Detection Network (UAV) ^[9]	Insects	UAV aerial imagery	Insect distribution mapping across landscapes	Scalable monitoring across broad spatial extents	Challenged by small target size and diverse backgrounds
Drone hyperspectral imaging ^[8]	Vegetation (moss, lichen)	Hyperspectral imagery	Habitat mapping, vegetation health assessment	Enables habitat monitoring in inaccessible areas	High equipment cost; requires specialized processing
YOLOv8 object detection ^[6]	Multiple vertebrate taxa	Real-time video/image streams	Real-time detection and classification	Rapid response to wildlife incidents	Computational demands for continuous processing

Table 2: GIS-Based Analytical Approaches for Biodiversity Assessment in Conservation Landscapes

GIS/Spatial Tool	Analytical Function	Scale of Application	Ecological Domain	Management Application	Key Constraints
Sequential Hierarchical Intersection Layers (SHIL) ^[8]	Multi-criteria prioritization integrating habitat, species, connectivity	Regional to landscape	Community to ecosystem	Priority area identification for protection/restoration	Weighting scheme requires careful justification
Circuit theory connectivity modeling	Movement pathway quantification, corridor identification	Landscape to regional	Population to metapopulation	Corridor design, barrier mitigation	Species-specific parameterization; data-intensive
Species distribution modeling (MaxEnt, ensembles) ^[32]	Habitat suitability prediction	Local to global	Species to community	Habitat prioritization, climate change assessment	Requires quality occurrence data; assumes equilibrium
Landscape fragmentation metrics ^[35]	Quantification of patch size, edge density, isolation	Patch to landscape	Population to community	Fragmentation monitoring, landscape integrity assessment	Ecological relevance of metrics varies
BEETLE least-cost modeling ^[10]	Integrated habitat network identification	Regional to national	Metapopulation to ecosystem	Planning support, fragmentation prevention	Expert input required for parameterization
Zonation/Prioritizr	Systematic conservation prioritization	Regional to global	Species to ecosystem	Protected area network design	Requires programming expertise; computationally intensive
Time series remote sensing analysis	Land cover change detection	Local to global	Habitat to ecosystem	Disturbance monitoring, restoration assessment	Cloud cover limitations; change detection validation

Table 3: Comparative Evaluation of Field-Based and AI-Integrated Monitoring Systems

Monitoring Approach	Accuracy	Resource Requirements	Temporal Resolution	Scalability	Suitability for Fragmented Landscapes
Traditional field surveys (expert)	Very high (expert identification)	High (personnel time, taxonomic expertise)	Low (intermittent)	Low	Moderate (site-specific data quality high)
Malaise trapping + manual sorting [5]	High (with expert identification)	Very high (sorting, pinning, identification)	Moderate (weekly collections)	Low-Moderate	High for insect biodiversity assessment
Camera traps + AI analysis [30]	High (for trained taxa)	Moderate (equipment, cloud processing)	High (continuous)	High	High for vertebrate monitoring
Electrical field sensors + CNN [2]	Moderate-High (counts correlate with traps)	Moderate (sensors, cloud infrastructure)	Very high (continuous)	Very high	Very high for insect activity monitoring
Bioacoustic monitoring + AI [27]	Moderate-High (depends on taxa and recording quality)	Moderate (recorders, processing)	Very high (continuous)	High	High for vocalizing taxa
UAV-based imaging + AIDN [9]	High (92% precision)	Moderate-High (UAV equipment, flight time)	High (on-demand)	High	Very high for habitat and some taxa
eDNA metabarcoding	High for presence/absence	Moderate (lab equipment, bioinformatics)	Low (discrete sampling)	High	Very high for aquatic and cryptic taxa
Citizen science + AI validation [7]	Moderate-High (research-grade observations)	Low (platform infrastructure)	High (continuous contributions)	Very high	Moderate (observer spatial bias)

Table 4: Advantages, Limitations, and Implementation Characteristics of AI-GIS Integrated Biodiversity Management Frameworks

Methodological Category	Strengths	Technical Challenges	Data Standardization Needs	Cost and Infrastructure Requirements	Applicability in Conservation Policy
Multi-source AI identification models [7]	High accuracy across diverse taxa; improves with data volume	Class imbalance; rare species performance; model updating	Standardized taxonomies; image metadata protocols	High initial development; decreasing operational costs	Enables large-scale citizen science; supports national biodiversity reporting
Integrated sensor networks [2, 6]	Continuous real-time monitoring; early warning capability	Sensor maintenance; data transmission; power requirements	Sensor data formats; detection validation protocols	Moderate-high (sensors, cloud infrastructure)	Supports adaptive management; enables rapid response to threats
Spatial prioritization frameworks [8]	Transparent decision support; replicable methodology	Weighting scheme subjectivity; data availability	Standardized land cover; species occurrence formats	Moderate (GIS software, training)	Directly informs protected area designation; aligns with global targets
Predictive habitat modeling [32]	Scenario testing; future projection capability	Model validation; uncertainty quantification	Environmental layer standards; occurrence data quality	Moderate (computing, expertise)	Supports climate adaptation planning; corridor design
Cloud-based processing platforms [11]	Scalable computing; accessibility from any location	Internet dependency; data security; long-term data stewardship	API standards; metadata protocols	Variable (pay-for-use models)	Democratizes access; supports cross-jurisdictional collaboration
Integrated decision-support systems [3]	Combines multiple data streams; management-focused outputs	User interface design; stakeholder engagement requirements	Interoperability standards; output format consistency	High (development, maintenance, training)	Bridges science-policy gap; supports evidence-based management

5. Challenges and Future Research Directions

Algorithm bias and model validation issues present fundamental challenges for AI-based biodiversity monitoring. Deep learning models trained on biased datasets—over-representing common species, particular geographic regions, or specific life stages—may perform poorly on underrepresented taxa or novel contexts [7, 17]. Class imbalance, where rare species have few training examples, reduces identification accuracy and may bias ecological inferences [7, 17]. Model validation using independent datasets from different geographic regions, seasons, or sampling methods is essential to assess generalizability, yet such validation remains uncommon in practice. Development of standardized validation protocols and benchmark datasets would enable rigorous model comparison and performance assessment.

Data interoperability and standardization challenges impede integration across monitoring systems and spatial scales. Biodiversity data are collected using diverse protocols, taxonomic standards, and metadata formats, complicating aggregation for large-scale analysis. Taxonomic name variations across databases require resolution through tools like TaxonMap before data integration [7, 17]. Spatial data from different sources vary in resolution, projection, and accuracy, requiring preprocessing before integration [35]. Development of community-agreed data standards, metadata protocols, and interoperability frameworks is essential for realizing the potential of integrated monitoring networks.

Regulatory and ethical considerations in AI-driven monitoring require careful attention as automated systems proliferate. Camera trap networks and acoustic recorders in conservation landscapes may incidentally capture human

images or voices, raising privacy concerns [30]. Data ownership and access policies for biodiversity data—particularly when collected on indigenous lands or in protected areas—must respect community rights and traditional knowledge. Algorithmic transparency and explainability are essential for building trust in AI-assisted decision-making, particularly when model outputs inform conservation interventions affecting livelihoods or land use. Implementation barriers in low-resource conservation settings limit equitable access to AI-GIS technologies. High costs of sensors, computing infrastructure, and technical expertise create adoption barriers for protected area agencies in developing countries [6, 16]. Open-source software, cloud-based platforms, and capacity-building partnerships can reduce these barriers but require sustained investment [11, 21]. Development of low-cost sensor technologies, offline-capable AI systems, and user-friendly interfaces would democratize access to advanced monitoring tools [2, 12].

Integration of remote sensing, AI, and bioinformatics represents a frontier for biodiversity science. Fusion of multi-sensor data—optical, radar, LiDAR, acoustic, and in situ—enables characterization of biodiversity across multiple dimensions simultaneously. Transfer learning approaches that leverage models pre-trained on large datasets reduce the data requirements for new applications, enabling rapid deployment in data-poor regions. Self-supervised learning that extracts features from unlabeled data may further reduce dependence on expert-identified training data.

Future directions for engineering-assisted biodiversity management include development of autonomous monitoring networks that adapt sampling based on real-time detections. Smart sensors that adjust recording frequency when target species are detected could optimize data collection and energy use [2, 12]. Swarm robotics approaches using coordinated UAV fleets could enable simultaneous multi-scale monitoring across conservation landscapes [9, 19]. Integration of AI-powered monitoring with automated response systems—such as deterrents for wildlife-vehicle conflict or traps for invasive species—could enable real-time conservation interventions [6, 16].

6. Conclusion

The integration of AI-assisted monitoring with GIS-driven spatial analysis represents a paradigm shift in biodiversity science, enabling assessment of insect and animal diversity at spatial and temporal scales previously unattainable [1, 7]. Deep learning architectures for species identification—applied to images, acoustic recordings, and sensor data—achieve accuracies approaching human expert performance while operating at speeds that enable processing of continent-scale datasets [5, 17]. GIS-based frameworks for habitat suitability, connectivity analysis, and conservation prioritization transform raw occurrence data into actionable management information [8]. Together, these technologies create synergistic capabilities that transcend the limitations of either approach alone [9].

The importance of this integration for advancing insect and animal diversity research extends across taxonomic groups and ecological domains. For insects—historically under-monitored despite their ecological dominance—automated sensors and AI identification finally enable monitoring at scales commensurate with their diversity and functional importance [2, 12]. For vertebrates, AI-enhanced camera trap

networks and bioacoustic monitoring provide continuous surveillance that reveals population dynamics, behavioral responses, and community reorganization invisible to intermittent surveys [6, 30]. For habitats and landscapes, GIS-based fragmentation analysis and connectivity modeling quantify the spatial context within which species persist or decline [35].

Translational impact for conservation landscapes is increasingly evident as these technologies move from research prototypes to operational tools [3, 13]. Protected area managers now access real-time monitoring data that inform adaptive management decisions [11, 21]. Restoration practitioners employ spatial prioritization frameworks to target interventions where they achieve greatest biodiversity benefit [8, 18]. Policy-makers utilize biodiversity models to evaluate progress toward international targets and allocate conservation resources effectively [12, 22]. The Kunming-Montreal Global Biodiversity Framework's ambitious goals—including protection of 30% of terrestrial areas by 2030—cannot be achieved without the monitoring capacity that AI-GIS integration provides [1].

The future outlook for computational-ecological integration is characterized by accelerating technological advancement and expanding application domains. As sensor costs decrease, computing power increases, and AI algorithms improve, the barriers to implementation will continue to fall [7, 16]. The convergence of remote sensing, bioinformatics, and ecological modeling promises integrated digital twins of conservation landscapes that simulate biodiversity responses to management scenarios in real time. Realizing this potential requires sustained investment in monitoring infrastructure, open data platforms, and interdisciplinary training that equips the next generation of researchers and practitioners to move fluidly between field ecology, data science, and spatial analysis. In an era of unprecedented biodiversity loss, the integration of AI and GIS offers not merely improved understanding but essential tools for sustaining the insect and animal diversity upon which ecosystems—and human societies—depend [2, 12].

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