



Predictive Modeling and Translational Applications for Enhancing Insect and Animal Diversity in Ecologically Sensitive Regions

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Abstract

Ecologically sensitive regions—biodiversity hotspots, montane systems, wetlands, and tropical forests—harbor disproportionate insect and animal diversity yet face accelerating threats from climate change, habitat fragmentation, and land-use shifts. Predictive ecological modeling has emerged as a critical tool for understanding species distributions, anticipating population declines, and designing evidence-based conservation interventions. This article synthesizes current approaches in species distribution modeling, machine learning applications, and GIS-based habitat assessment within the context of insect and animal diversity conservation. We present a conceptual framework linking predictive modeling to translational conservation applications, including protected area optimization, ecological corridor design, and restoration prioritization. Key findings highlight the utility of ensemble modeling approaches, the integration of field validation through emerging technologies (eDNA, acoustic monitoring), and the importance of multi-scale analysis for capturing both fine-scale habitat requirements and landscape-level connectivity. Translational applications demonstrate how model outputs can inform adaptive management, rewilding initiatives, and early-warning systems for population decline. We conclude that the integration of predictive modeling with translational conservation frameworks represents a paradigm shift in biodiversity management, enabling proactive rather than reactive interventions in ecologically sensitive regions.

Keywords: Predictive ecological modeling; insect diversity conservation; species distribution modeling; GIS-based habitat assessment; translational conservation; biodiversity hotspots

1. Introduction

Ecologically sensitive regions—including biodiversity hotspots, montane ecosystems, wetlands, tropical forests, and coastal zones—serve as critical refugia for global insect and animal diversity. These areas, characterized by high endemism and specialized ecological interactions, support disproportionate shares of taxonomic diversity while occupying relatively limited geographic extents^[1, 2]. Insects alone account for more than half of described eukaryotic species, with many thousands confined to single mountain ranges or forest fragments^[3]. The conservation of these regions therefore assumes outsized importance in global biodiversity strategies.

Yet these same regions face unprecedented pressures. Climate change is driving rapid shifts in temperature and precipitation regimes, altering phenological synchrony between insects and their host plants, and forcing upward elevational migrations in montane systems^[4, 5]. Habitat fragmentation severs landscape connectivity, isolating populations and reducing gene flow critical for adaptive capacity^[6]. Invasive species, agricultural expansion, and infrastructure development compound these stressors, creating synergistic effects that accelerate population declines^[7]. For arthropods particularly—the subjects of a growing "insect decline" literature—sensitive ecosystems may represent both the last bastions of diversity and the front lines of extinction risk^[8].

Predictive ecological modeling offers a pathway through these challenges. By relating species occurrences to environmental predictors, models can forecast distributional shifts under climate scenarios, identify critical habitat linkages, and prioritize areas for conservation intervention^[9, 10]. Recent advances in machine learning, remote sensing, and computational capacity have transformed species distribution modeling from a specialized technique into an accessible tool for biodiversity management^[11]. Models now operate at scales from local habitat patches to continental extents, incorporating dynamic predictors and ensemble approaches that quantify uncertainty^[12].

The translational significance of these models lies in their capacity to inform action. Predictive outputs can guide protected area designation, optimize restoration investments, design ecological corridors, and establish early-warning systems for imperiled taxa^[13]. This translational turn—from description to intervention—represents a maturation of computational ecology as an applied discipline. However, realizing this potential requires explicit frameworks linking model outputs to management decisions, validated through field monitoring and adaptive learning^[14].

This manuscript aims to synthesize current approaches in predictive modeling for insect and animal diversity in ecologically sensitive regions, with emphasis on translational applications for conservation and restoration. We examine conceptual frameworks, methodological approaches, field validation strategies, and case studies demonstrating model-informed interventions. Three mandatory tables synthesize major modeling approaches, comparative conservation strategies, and implementation characteristics of integrated frameworks.

2. Conceptual Frameworks and Methodological Approaches

2.1. Ecological and Taxonomic Diversity Frameworks

Understanding insect and animal diversity in sensitive regions requires multi-dimensional approaches to biodiversity measurement. Species richness—the simplest metric—provides baseline information but masks functional and phylogenetic dimensions critical for conservation prioritization^[15]. Functional diversity captures the range of ecological roles within communities, linking species traits to ecosystem processes. In insect communities, traits such as body size, trophic position, dispersal capacity, and phenological timing determine responses to environmental change and contributions to ecosystem functioning^[16].

Phylogenetic diversity adds an evolutionary dimension, recognizing that closely related species may share similar vulnerabilities while evolutionarily distinct lineages represent unique evolutionary history^[17]. In sensitive ecosystems, preserving phylogenetic diversity may safeguard evolutionary potential under rapid environmental change. Community assembly models further reveal how deterministic processes (environmental filtering, biotic interactions) and stochastic processes shape diversity patterns across spatial scales^[18].

Population viability analysis and metapopulation models provide frameworks for understanding persistence in fragmented landscapes. For insects with patchy distributions—many butterflies, beetles, and specialized herbivores—metapopulation dynamics determine regional persistence through colonization-extinction processes^[19].

These models inform minimum patch sizes, connectivity requirements, and corridor design for species conservation.

2.2. Predictive Modeling and Computational Approaches

Species distribution models (SDMs) constitute the core toolkit for predictive biodiversity assessment. Among these, Maximum Entropy modeling (MaxEnt) has emerged as a widely used approach due to its performance with presence-only data and ability to handle complex environmental interactions^[20]. Recent applications demonstrate MaxEnt's utility for predicting distributions of both pest insects and conservation-priority taxa under climate scenarios^[21, 22]. For example, optimized MaxEnt models incorporating R-based tuning have revealed temperature and precipitation as primary drivers of leafhopper distributions, with projected northward shifts under future climates.

Ensemble modeling approaches combine multiple algorithms—MaxEnt, Random Forest, Generalized Additive Models, and others—to reduce algorithm-specific bias and quantify prediction uncertainty^[23]. Ensemble super SDMs, leveraging cloud computing and massive environmental predictor sets (200+ layers), now enable global assessments of species assemblages, identifying hotspots and coldspots for entire taxonomic orders. These approaches prove particularly valuable for data-poor sensitive regions where single-model predictions may be unreliable.

Machine learning advances extend beyond traditional SDMs. Random Forest algorithms effectively model freshwater insect distributions in tropical Andean basins, identifying land use, precipitation, and topography as key predictors for riffle beetle genera. Convolutional neural networks (CNNs) applied to arthropod metabarcoding data reveal seasonal diversity patterns across national scales, capturing ecologically plausible spatial patterns that distinguish habitat types. Transfer learning approaches—such as CORAL (Common to Rare Transfer Learning)—address the "rare species paradox" by borrowing information from common species to model distributions of rare taxa, critical for biodiversity assessment in hyper-diverse insect groups.

Landscape connectivity modeling complements species distribution predictions by identifying movement pathways and barriers. Circuit theory approaches model organisms as moving through resistance surfaces, identifying pinch points and corridors for conservation design^[24]. GIS-based habitat suitability assessment integrates multiple data layers—land cover, topography, hydrology, disturbance regimes—to map conservation priorities at management-relevant scales.

2.3. Field-Based Validation and Monitoring Strategies

Predictive models require empirical validation through field monitoring. Long-term biodiversity surveys provide baseline data for model calibration and temporal validation, capturing population trends across environmental gradients^[25]. For insects, standardized sampling protocols—pitfall traps, Malaise traps, light traps, pan traps—enable quantitative comparisons across sites and time periods.

Camera traps and acoustic monitoring have transformed vertebrate and selected insect monitoring. Autonomous recording units capture vocalizing organisms—birds, primates, frogs, and orthopterans—enabling occupancy modeling across large spatial extents. Camera trap arrays provide data on medium-to-large terrestrial mammals, supporting habitat suitability modeling and population

estimation through capture-recapture frameworks [26]. Environmental DNA (eDNA) and metabarcoding represent revolutionary tools for biodiversity assessment. DNA extracted from water, soil, or bulk arthropod samples reveals species presence without requiring taxonomic expert identification [27]. Metabarcoding of bulk arthropod samples—collected weekly from multiple locations—enables modeling of seasonal diversity dynamics at national scales, generating training data for machine learning models. Integration of eDNA data with predictive models extends coverage to cryptic species and life stages otherwise undetectable through conventional sampling. Integration of empirical data with predictive models occurs through iterative cycles of validation and refinement. Model predictions generate testable hypotheses about species distributions, guiding targeted field surveys. Survey data, in turn, validate model accuracy, identify false presences/absences, and inform model recalibration. This adaptive cycle strengthens both predictive capacity and ecological understanding.

3. Applications and Case Studies

3.1. Predictive Modeling for Biodiversity Risk Assessment

Risk assessment applications identify species and populations most vulnerable to environmental change. Climate vulnerability projections using SDMs reveal species with limited dispersal capacity, narrow climatic niches, or restricted suitable habitat under future scenarios [28]. For insects in montane systems—where upward shifts are constrained by summit geography—models predict disproportionate extinction risk for high-elevation specialists [5].

Early-warning systems for population decline integrate multi-year monitoring data with predictive models to detect incipient declines before they become irreversible. For pest insects threatening sensitive ecosystems or agricultural interfaces, optimized MaxEnt models support "graded response" monitoring frameworks, where management intensity scales with predicted habitat suitability. These systems enable proactive rather than reactive interventions. High-risk taxa identification combines phylogenetic information with distribution modeling. Evolutionarily distinct lineages with restricted ranges and narrow climatic tolerances represent conservation priorities. Modeling frameworks incorporating phylogenetic information—such as HMSC (Hierarchical Modeling of Species Communities)—enable simultaneous modeling of hundreds to thousands of species, identifying community-level vulnerability patterns.

3.2. Translational Applications in Conservation Planning

Protected area optimization represents a mature translational application. Systematic conservation planning algorithms—Marxan, Zonation—integrate species distribution predictions with socioeconomic cost layers to identify efficient reserve networks [29]. In sensitive regions with competing land uses, these tools balance biodiversity outcomes with development

needs. For insect diversity, protected area design must consider both coarse-filter (ecosystem-level) and fine-filter (species-specific) approaches, as many insects require microhabitat conditions not captured in broad-scale assessments.

Ecological corridor design builds on connectivity modeling to maintain or restore landscape linkages. Circuit theory models identify movement pathways through resistance surfaces, guiding corridor placement that maximizes connectivity while minimizing implementation costs [24]. For large mammals—elephants, primates, large carnivores—corridor designs informed by occurrence data and movement studies enable persistence in human-dominated landscapes. For insects, corridor requirements differ: many species require continuous habitat rather than linear connections, and corridor effectiveness depends on habitat quality, not just structural connectivity.

Restoration site prioritization applies predictive models to identify locations where restoration investments yield greatest biodiversity returns. Models predict potential habitat suitability under restored conditions, enabling comparison of alternative restoration scenarios [14]. For freshwater ecosystems in biodiversity hotspots, species distribution models for sensitive taxa (e.g., riffle beetles, hellbenders) identify streams where riparian restoration would most benefit target species.

3.3. Enhancing Insect and Animal Diversity through Model-Informed Interventions

Adaptive management strategies incorporate predictive models into iterative decision cycles. Management actions generate outcomes monitored through field surveys; outcomes compared to model predictions inform subsequent decisions [30]. This approach acknowledges uncertainty while enabling action, particularly valuable in rapidly changing sensitive ecosystems where waiting for complete information risks irreversible losses.

Rewilding and species reintroduction planning increasingly rely on predictive modeling. Habitat suitability models identify potential reintroduction sites meeting species requirements, while population models project long-term persistence under alternative management scenarios. Conservation translocations of greater sage-grouse, informed by integrated population models and before-after-control-impact designs, have demonstrated rapid population recovery following reinforcement, with increased egg hatchability driving positive growth rates.

Monitoring restoration effectiveness using predictive analytics closes the adaptive management loop. Models predict expected biodiversity outcomes following restoration; monitoring data test these predictions, revealing whether restoration achieves intended goals [14]. For insect communities in restored habitats, comparisons of observed versus predicted assemblages identify factors limiting recovery—dispersal limitation, missing resources, continuing stressors—guiding additional interventions.

4. Tables

Table 1: Major Predictive Modeling Approaches Used in Insect and Animal Diversity Research in Ecologically Sensitive Regions

Modeling Approach	Ecological Application	Data Requirements	Spatial Scale	Strengths	Limitations
MaxEnt / Maximum Entropy	Habitat suitability mapping, climate change vulnerability	Presence-only occurrence data, environmental layers	Local to continental	Handles presence-only data, good predictive performance with small samples, user-friendly implementation	Sensitive to sampling bias, assumes equilibrium with environment, limited mechanistic interpretation ^[20]
Ensemble SDMs (Super SDMs)	Biodiversity hotspot identification, community-level assessment	Multi-species occurrence data, extensive environmental predictors (100+ layers)	Regional to global	Reduces algorithm-specific bias, quantifies prediction uncertainty, leverages cloud computing	Computationally intensive, requires substantial occurrence data, complex interpretation ^[23]
Random Forest / Machine Learning	Complex habitat relationships, non-linear responses	Presence/absence or abundance data, multiple predictor types	Local to landscape	Captures non-linear relationships, handles correlated predictors, provides variable importance measures	Black-box interpretation, risk of overfitting, requires larger sample sizes
CORAL Transfer Learning	Rare species distribution modeling, hyper-diverse taxa	Common species data for pre-training, sparse rare species records	Regional to national	Enables modeling of extremely rare species, borrows information across taxa, computationally efficient	Assumes ecological similarity between common and rare species, requires taxonomic/phylogenetic information
Landscape Connectivity / Circuit Theory	Corridor design, fragmentation assessment, metapopulation dynamics	Resistance surfaces, occurrence or genetic data	Landscape to regional	Explicitly models movement and gene flow, identifies pinch points and barriers, management-relevant outputs	Resistance values often subjective, validation requires movement data, computationally intensive for large areas ^[24]

Table 2: Comparative Assessment of Translational Conservation Strategies Informed by Predictive Modeling

Conservation Strategy	Modeling Input Used	Target Taxa	Expected Ecological Outcome	Monitoring Requirements	Implementation Challenges
Protected Area Optimization	Habitat suitability maps, species richness predictions, phylogenetic diversity layers	Multi-taxa (vertebrates, plants, selected insects)	Representative biodiversity protection, persistence of target species	Periodic biodiversity surveys within and outside reserves	Competing land uses, limited resources for acquisition, climate change may shift suitable habitat outside protected boundaries ^[29]
Ecological Corridor Design	Connectivity surfaces, least-cost pathways, pinch point analysis	Wide-ranging vertebrates, dispersal-limited insects, plants	Maintained gene flow, metapopulation connectivity, climate migration pathways	Genetic monitoring, occupancy surveys along corridors, movement studies	Land ownership constraints, corridor width requirements unknown for many species, effectiveness uncertainty ^[24]
Restoration Site Prioritization	Habitat suitability under restored scenarios, species distribution models	Freshwater taxa, habitat specialists, threatened species	Increased suitable habitat, population recovery, ecosystem function improvement	Pre- and post-restoration monitoring, comparison to reference sites	Long timeframes for recovery, multiple interacting stressors, climate change may alter restoration targets ^[14]
Conservation Translocation	Habitat suitability for release sites, population viability models, source population assessment	Imperiled vertebrates, selected invertebrates	Population establishment or reinforcement, genetic rescue, metapopulation persistence	Intensive post-release monitoring, demographic studies, genetic sampling	Source population impacts, disease risk, high costs, low success rates for some taxa
Early-Warning Monitoring Systems	Predictive risk maps, climate vulnerability projections, trend analysis	Pest insects, declining species, climate-sensitive taxa	Proactive management before declines, targeted intervention, reduced economic/ecological impacts	Standardized long-term monitoring, rapid data processing and analysis	Sustained funding requirements, timely data-to-decision pipelines, distinguishing signal from noise ^[25]

Table 3: Advantages, Limitations, and Implementation Characteristics of Integrated Predictive-Translational Biodiversity Frameworks

Methodological Category	Benefits	Technical Constraints	Data Standardization Needs	Resource Requirements	Suitability for Ecologically Sensitive Regions
Species Distribution Modeling	Quantitative, replicable, scenario-testing capacity, spatial explicitness	Model assumptions, transferability limits, scale dependence	Standardized occurrence formats, consistent environmental layers, metadata protocols	Moderate: software, GIS capacity, occurrence data compilation	High: identifies climate refugia, predicts range shifts, guides surveys
Machine Learning / AI	Handles complex data types, captures non-linear relationships, automates pattern detection	Black-box interpretation, training data requirements, overfitting risk	Large training datasets, consistent predictor variables, validation protocols	High: computational infrastructure, specialized expertise, big data management	Moderate to High: processes remote sensing and metabarcoding data, reveals hidden patterns
Field Validation Technologies	Ground-truths models, provides mechanistic understanding, detects unexpected changes	Spatial/temporal limitations, taxonomic expertise requirements, sampling biases	Standardized sampling protocols, metadata standards, open data sharing	Moderate to High: field equipment, personnel, laboratory analysis (eDNA)	Essential: validates predictions in data-poor regions, builds local capacity, adapts models to local conditions [25, 27]
Translational Decision Support	Management-relevant outputs, stakeholder engagement, accountability	Simplification of ecological complexity, value judgments in prioritization	Clear management objectives, transparent decision rules, monitoring-evaluation links	Moderate: decision support software, facilitator expertise, stakeholder process time	High: directly informs conservation action, optimizes limited resources, builds conservation support [13, 29]

5. Challenges and Future Research Directions

Model uncertainty and validation challenges persist across predictive applications. Uncertainty arises from multiple sources: sampling bias in occurrence data, environmental predictor error, algorithm selection, and future scenario projections. Quantifying and communicating uncertainty to decision-makers remains difficult, yet essential for responsible translational applications. Validation against independent data—spatially or temporally—is often lacking, particularly in sensitive regions where data collection is logistically challenging.

Climate change scenario variability introduces additional uncertainty. Projections vary across global circulation models, emission scenarios, and downscaling approaches [28]. For long-lived species with slow population dynamics, the pace of change may exceed adaptive capacity regardless of model predictions. For insects with rapid generation times, evolutionary adaptation may shift climatic niches in ways not captured by equilibrium models.

Data gaps in sensitive ecosystems limit model development. Many biodiversity hotspots remain under-sampled, particularly for insects and other hyper-diverse groups [3]. Remote sensing provides proxy environmental data but cannot substitute for occurrence records. Citizen science initiatives and standardized monitoring programs are expanding coverage, but taxonomic and geographic biases persist [2]. Transfer learning approaches offer partial solutions but require careful validation.

Scaling from local models to regional management presents conceptual and practical challenges. Species distributions emerge from fine-scale processes—microclimate variation, biotic interactions, soil conditions—that regional models may miss. Conversely, management often operates at landscape scales requiring broader predictions. Multi-scale modeling frameworks that nest fine-scale models within

regional assessments address this challenge but increase complexity [18].

Regulatory and policy integration challenges limit translational impact. Predictive models may inform conservation decisions, but legal frameworks often require different evidence standards. Protected area designations, endangered species listings, and environmental impact assessments follow established procedures that may not accommodate model-based predictions. Bridging this gap requires collaboration between modelers, managers, and policy-makers throughout the research-implementation process.

Future research directions include advancing AI integration with remote sensing and bioinformatics. Deep learning applied to satellite imagery can map habitat characteristics at unprecedented resolution, providing dynamic predictor variables for SDMs [8]. Integration with automated biodiversity monitoring—camera traps, acoustic recorders, eDNA samplers—enables near-real-time biodiversity assessment. Predictive conservation engineering—designing landscapes and ecosystems for target biodiversity outcomes using model-optimized interventions—represents an emerging frontier [14].

6. Conclusion

Predictive ecological modeling has transformed capacity to understand and manage insect and animal diversity in ecologically sensitive regions. From species distribution models identifying climate refugia to connectivity analyses guiding corridor design, computational tools enable evidence-based conservation in systems facing unprecedented threats. The translational turn—linking predictions to interventions—represents a maturation of the field, positioning modelers as active participants in conservation practice rather than passive observers.

Key insights from this synthesis include the importance of multi-model ensemble approaches for robust predictions, the value of emerging technologies (eDNA, remote sensing, machine learning) for expanding taxonomic and spatial coverage, and the necessity of field validation for ensuring model relevance. Translational applications demonstrate tangible conservation outcomes: optimized protected area networks, strategically placed corridors, prioritized restoration investments, and successful species reintroductions informed by habitat suitability models. The relevance of this work extends beyond academic ecology to applied biodiversity management. Conservation practitioners in sensitive regions—often operating with limited resources—benefit from tools that identify priority areas, predict intervention outcomes, and adapt strategies based on monitoring data. Computational ecology provides these tools, but only through sustained engagement with managers, policy-makers, and local communities. Future directions point toward increasingly integrated frameworks combining AI, remote sensing, and on-the-ground monitoring into adaptive management systems. Predictive conservation engineering—designing landscapes for biodiversity outcomes—offers hope for reversing declines in sensitive ecosystems. Realizing this potential requires continued methodological advances, sustained investment in biodiversity monitoring, and commitment to translational applications that move from prediction to protection.

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