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Predictive Biodiversity Models for Conservation of Insect and Animal Populations under Global Environmental Change

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Abstract

Background: Global environmental change—encompassing climate warming, land-use transformation, invasive species, and pollution—poses existential threats to insect and vertebrate populations worldwide. Biodiversity loss is accelerating at rates unprecedented in human history, necessitating robust predictive frameworks to guide proactive conservation.

Objective: This study aims to develop, validate, and compare predictive biodiversity models integrating multi-source environmental data for forecasting species distribution shifts, habitat suitability changes, and persistence probabilities under projected climate and land-use scenarios.

Methods: We employed a multi-model ensemble approach combining Species Distribution Models (SDMs), Machine Learning classifiers (Random Forest, XGBoost), and Population Viability Analysis (PVA). Data from GBIF, WorldClim 2.1, and remote-sensed land cover layers (2000–2024) were used across 342 focal species in tropical and temperate zones.

Results: Ensemble models achieved mean accuracy of 91.3% (AUC = 0.94). Under RCP 8.5 scenarios, 58% of modelled insect species faced habitat suitability declines exceeding 30% by 2050. Integrated landscape conservation strategies showed the highest species persistence probability (79.3%) compared to single-action interventions.

Conclusion: Predictive biodiversity models are indispensable tools for conservation planning. Ensemble approaches combining ecological and machine learning methods offer superior forecasting accuracy and practical utility for evidence-based decision-making under environmental uncertainty.

Keywords: predictive biodiversity models, species distribution modeling, ecological forecasting, conservation planning, climate change, insect conservation

1. Introduction

Global biodiversity faces compounding threats from anthropogenic environmental change. Temperature anomalies, altered precipitation regimes, land-use intensification, deforestation, and chemical pollution collectively destabilize ecosystems that have co-evolved over millennia [1,2]. Insects, the most species-rich animal group on Earth, have experienced population declines of up to 45% in monitored assemblages over the past four decades [3]. Simultaneously, vertebrate populations face habitat fragmentation and phenological mismatches driven by warming temperatures [4].

Conservation science has historically relied on reactive strategies—responding to population collapses after they occur. This paradigm is increasingly inadequate given the scale and pace of environmental change [5]. Predictive biodiversity modeling offers a proactive alternative, enabling practitioners to forecast where species will be viable in future decades, identify refugia, and prioritize interventions before irreversible losses occur [6].

The emergence of high-resolution environmental data, open biodiversity occurrence databases, and advanced computational modeling has catalyzed the development of sophisticated ecological forecasting tools. Yet, no consensus framework has emerged for integrating these tools into actionable conservation decision systems [7]. This article presents a comparative analysis of predictive modeling approaches, evaluates their conservation utility across taxa, and proposes an integrated framework for biodiversity conservation under global environmental change.

2. Related Work

Early biodiversity modeling efforts relied on bioclimatic envelope models such as BIOCLIM and the Generalized Linear Model (GLM) framework, which matched species occurrences to climatic conditions [8]. These approaches demonstrated that future climate scenarios would produce substantial range contractions and expansions across taxonomic groups [9]. However, their static nature limited ability to capture dispersal dynamics, biotic interactions, and demographic processes.

The introduction of MaxEnt (Maximum Entropy Modeling) marked a significant advance, enabling predictions from presence-only occurrence data and outperforming previous approaches across most evaluation metrics [10]. Concurrently, dynamic global vegetation models began incorporating biodiversity processes, simulating vegetation community shifts under CO_2 enrichment and temperature trajectories [11]. Population Viability Analysis tools such as VORTEX further complemented SDMs by quantifying extinction risk at the population level, integrating demographic stochasticity, genetic diversity loss, and environmental variation [12].

Recent advances have seen machine learning approaches—particularly Random Forest, Gradient Boosting, and Artificial Neural Networks—achieve superior predictive performance for species distributions by capturing complex nonlinear relationships among environmental predictors [13]. Ensemble modeling platforms like BIOMOD2 have gained adoption as gold-standard approaches for reducing model uncertainty [14]. Despite this progress, integration of biodiversity forecasts into conservation planning tools remains limited, especially for insect taxa, which are disproportionately underrepresented in monitoring schemes [15].

3. Predictive Biodiversity Modeling Framework

We propose a hierarchical, multi-scale predictive biodiversity framework comprising three interconnected tiers: (i) environmental driver characterization, (ii) species response modeling, and (iii) conservation decision integration.

The environmental driver layer aggregates climate projections (CMIP6 RCP 4.5 and 8.5 scenarios), land-use change trajectories, pollution indices, and hydrological variables at 1 km² spatial resolution. Species response modeling encompasses both correlative models (SDMs) and mechanistic models (PVA, DVMs) operating at species and community levels. The conservation decision layer translates model outputs—habitat suitability indices, range shift projections, species persistence probabilities—into prioritization maps for protected area design, corridor planning, and adaptive management interventions [16].

Model outputs feed into a Conservation Decision Support System (CDSS) that allows practitioners to simulate intervention scenarios, compare cost-effectiveness of conservation actions, and identify climate refugia for focal species. The framework explicitly incorporates uncertainty quantification through ensemble modeling and Monte Carlo simulations, providing confidence intervals for all conservation-relevant outputs [17].

4. Materials and Methods

4.1. Study Taxa and Occurrence Data

A total of 342 focal species were selected, representing six insect orders (Lepidoptera, Coleoptera, Hymenoptera, Odonata, Orthoptera, Diptera) and four vertebrate classes (amphibians, reptiles, birds, mammals) distributed across 12 biodiversity hotspots. Occurrence records were obtained from the Global Biodiversity Information Facility (GBIF), supplemented by regional museum collections, comprising 1.8 million georeferenced records after spatial thinning (1 grid-cell minimum spacing) to reduce sampling bias [18].

4.2. Environmental Predictors

Nineteen bioclimatic variables from WorldClim 2.1, four land-cover classes derived from ESA Climate Change Initiative (2000–2024), elevation from SRTM 90m, Normalized Difference Vegetation Index (NDVI) from MODIS, and human footprint index were used as predictors. Future climate projections under SSP2-4.5 and SSP5-8.5 scenarios from five CMIP6 general circulation models were ensemble-averaged to reduce inter-model uncertainty [19].

4.3. Modeling Approaches

An ensemble modeling workflow was implemented in R (v4.3) using the BIOMOD2 package, incorporating MaxEnt, Random Forest, Generalized Boosting Machine (GBM), and Generalized Additive Model (GAM) as component models. Model performance was evaluated using 10-fold cross-validation, with metrics including Area Under the ROC Curve (AUC), True Skill Statistic (TSS), and Cohen's Kappa. Population Viability Analysis was conducted for 48 critically endangered species using VORTEX 10.5 with 10,000 simulations per species over a 50-year projection period [20].

5. Results and Comparative Analysis

Ensemble models demonstrated superior and consistent performance across taxa (mean AUC = 0.94, TSS = 0.83), outperforming single-algorithm models by 6–12 percentage points. Machine learning models (Random Forest, GBM) performed best for taxa with complex habitat associations, while MaxEnt remained competitive for rare species with limited occurrence data.

Under the high-emissions scenario (SSP5-8.5), 58% of modelled insect species were projected to experience habitat suitability declines exceeding 30% by 2050, with montane Lepidoptera and specialist pollinators showing the most severe contractions. By contrast, 18% of insect species showed projected range expansions into higher latitudes and elevations, suggesting ongoing community reassembly. Vertebrate species showed more heterogeneous responses:

amphibians exhibited the highest vulnerability (72% projected decline in suitable habitat), while certain generalist bird species showed modest range expansions.

Table 1 presents a comparative evaluation of biodiversity modeling approaches, and Table 2 summarizes conservation performance indicators across strategic interventions.

Table 1: Comparative Evaluation of Biodiversity Modeling Approaches

Model Type	Algorithm/Technique	Input Variables	Accuracy (%)	Key Limitation
Species Distribution Models (SDMs)	MaxEnt, BioClim, GLM	Climate, topography, land use	78–88	Static spatial assumptions
Machine Learning Models	Random Forest, XGBoost, ANN	Multi-source environmental data	85–93	Requires large training datasets
Dynamic Vegetation Models (DVMs)	BIOME4, LPJ-GUESS	CO_2, temperature, precipitation	72–84	High computational demand
Ensemble Modeling	BIOMOD2, stacked SDMs	Combined bioclimatic layers	88–95	Model integration complexity
Population Viability Analysis (PVA)	VORTEX, RAMAS GIS	Demographic, genetic, spatial	74–86	Data-intensive for rare species

Note: Accuracy values represent mean AUC-based performance across taxonomic groups; ANN = Artificial Neural Network; GLM = Generalized Linear Model.

PVA results indicated that without intervention, 34 of 48 critically endangered study species faced extinction probabilities exceeding 50% within 50 years under current trajectories. Climate-adaptive management combined with habitat corridor creation reduced mean extinction probability by 38% for these taxa. The integrated landscape approach—combining protected area expansion, corridor creation, and adaptive management—yielded the highest species persistence probability (79.3%) and habitat suitability index (0.88), underscoring the value of multi-pronged conservation strategies.

Table 2: Conservation Strategy Performance Indicators

Conservation Strategy	Target Taxa	Habitat Suitability Index	Species Persistence Probability (%)	Effectiveness Score
Protected Area Expansion	Lepidoptera, Coleoptera	0.81	72.4	High
Habitat Corridor Creation	Mammals, Birds	0.76	68.9	Moderate–High
Climate-Adaptive Management	Amphibians, Reptiles	0.69	61.5	Moderate
Ex-situ Conservation	Pollinators (bees, wasps)	0.57	54.8	Moderate
Integrated Landscape Approach	Multi-taxa assemblages	0.88	79.3	Very High

Note: Habitat Suitability Index (HSI) ranges from 0 (unsuitable) to 1 (optimal). Effectiveness scores: Very High >75%, High 65–75%, Moderate 50–64%.

6. Discussion

Our findings confirm that ensemble biodiversity models integrating multiple algorithmic approaches provide the most reliable forecasts for conservation planning. The superior performance of ensemble methods (AUC = 0.94) over single-model approaches aligns with growing consensus in the modeling literature and reflects the ecological reality that no single algorithm captures the full complexity of species-environment relationships across diverse taxa and geographies.

The projected habitat suitability losses for 58% of insect species under high-emissions scenarios are deeply concerning and corroborate field-based biomass decline studies. Pollinators are of particular concern: their projected losses threaten ecosystem service provision, including agricultural pollination valued at over $235 billion annually. These findings underscore the urgency of integrating insect conservation explicitly into national and international biodiversity strategies, including the post-2020 Global Biodiversity Framework.

The marked superiority of integrated landscape approaches over single-action interventions highlights a critical lesson for conservation practitioners: no isolated action—whether protected area expansion or corridor creation alone—is sufficient to maintain biodiversity under accelerating environmental change. Rather, spatially coordinated multi-action strategies that address multiple threat vectors simultaneously are needed. The Conservation Decision Support System framework we propose provides a mechanism for operationalizing such coordinated strategies with quantifiable performance targets and uncertainty bounds.

Limitations of our framework include the underrepresentation of biotic interactions (competition, predation, mutualism) in correlative SDMs, which may cause over- or under-estimation of suitable habitat extent. Dispersal constraints and evolutionary adaptation are also not fully captured. Future work should integrate process-based models with machine learning methods and incorporate socio-economic feasibility assessments into the conservation decision layer.

7. Conclusion

Predictive biodiversity models represent an essential frontier for conservation science under global environmental change. This study demonstrates that ensemble modeling approaches, integrating machine learning with traditional SDMs and PVA, deliver high-accuracy forecasts (AUC = 0.94) that can meaningfully inform conservation prioritization. Under high-emissions trajectories, the majority of monitored insect and vertebrate species face significant habitat suitability losses, demanding immediate and integrated conservation responses. The proposed multi-tier modeling framework, linked to a Conservation Decision Support System, provides a scientifically rigorous and practically actionable pathway for evidence-based biodiversity conservation in the coming decades.

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