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Research Article

INTEGRATING DEEP LEARNING AND CLIMATE MODELLING: PREDICTING REGIONAL BIODIVERSITU LOSS UNDER EXTREME WEATHER SCENARIOS

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Abstract

Accelerating climate change has intensified the frequency and severity of extreme weather events, posing substantial threats to regional biodiversity. Conventional climate-biodiversity models often struggle to capture non-linear interactions between climatic variables and ecological responses, limiting their predictive accuracy under extreme scenarios. This study aims to integrate deep learning techniques with climate modelling to improve the prediction of regional biodiversity loss under extreme weather conditions. We employed a hybrid modelling framework that combines high-resolution regional climate model outputs with deep learning architectures, specifically convolutional and recurrent neural networks. The model was trained using multi-decadal climate data, species distribution records, and ecological indicators across selected regions. Extreme weather scenarios were simulated based on projected temperature anomalies, precipitation extremes, and drought indices. Model performance was evaluated using cross-validation and comparative benchmarks against traditional statistical models. The integrated deep learning–climate model demonstrated significantly higher predictive accuracy and robustness in identifying biodiversity loss hotspots under extreme weather scenarios. Results reveal pronounced spatial heterogeneity, with ecosystems exposed to compound extremes showing disproportionately higher vulnerability. Integrating deep learning with climate modelling offers a powerful approach for anticipating regional biodiversity loss under extreme climate events, providing valuable insights for adaptive conservation planning and climate-resilient biodiversity management.

Keywords: deep learning; climate modelling; biodiversity loss; extreme weather; regional prediction

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INTRODUCTION

Climate change has accelerated the occurrence of extreme weather events, such as heatwaves, floods, and prolonged droughts, which are increasingly threatening global biodiversity. Ecosystems are experiencing shifts in species distribution, altered reproductive cycles, and heightened extinction risks, making biodiversity loss a pressing environmental concern. Understanding how regional ecosystems respond to these climatic extremes is critical for sustainable conservation planning.

The complexity of ecological systems and their interactions with climatic variables presents significant challenges for predictive modelling. Traditional statistical and mechanistic climate-biodiversity models often fail to capture non-linear relationships and multi-scale interactions, limiting their effectiveness in anticipating future biodiversity loss (Feng et al., 2026; Hegde et al., 2026; Isleem & Khishe, 2026; Sabonsolin & Lao, 2026). Accurate predictions require methods capable of integrating large, heterogeneous datasets to detect subtle patterns and emerging threats.

Recent advancements in computational methods, particularly deep learning, offer unprecedented opportunities to analyze complex environmental data. Neural network architectures can learn high-dimensional relationships and temporal patterns that traditional approaches cannot adequately model. Applying these methods to climate and ecological datasets promises improved understanding of regional biodiversity responses under extreme weather scenarios.

Regional biodiversity is experiencing disproportionate impacts from extreme climatic events, yet existing predictive models lack precision and fail to account for spatial heterogeneity. Ecological assessments often rely on coarse-grained data, underestimating vulnerability in localized hotspots. Conservation strategies based on these assessments may therefore be insufficient or misdirected, risking irreversible species loss.

Predictive uncertainty incre ases under compound extreme events where multiple climatic stressors interact simultaneously (Hossen et al., 2026; Khodaverdian et al., 2026; Yadavalli & Ranjan Sahoo, 2026). Many current models assume linear responses and fail to simulate threshold effects, tipping points, or feedback loops within ecosystems. This limitation hinders the ability to identify areas at greatest risk and to implement proactive biodiversity management.

Monitoring and evaluating biodiversity loss in real time is constrained by limited observational data, especially in remote or understudied regions. The absence of integrative tools that combine climate projections, species distributions, and ecological dynamics prevents effective scenario-based planning. Without enhanced predictive capacity, policymakers and conservationists face difficulty in prioritizing interventions (Di Fazio et al., 2026; Fusiripong & Surbakti, 2026; Pavlyuk & Alomar, 2026; Tian et al., 2026).The primary objective of this research is to integrate deep learning techniques with climate modelling to predict regional biodiversity loss under extreme weather scenarios. The study aims to develop a robust computational framework capable of capturing complex interactions between climatic extremes and ecosystem responses.

Secondary objectives include identifying ecological hotspots most vulnerable to extreme events, quantifying species-specific risks, and assessing the spatial distribution of potential biodiversity loss. The research also seeks to evaluate the performance of deep learning models relative to traditional predictive approaches.

The study intends to generate actionable insights for conservation planning, enabling evidence-based decisions to mitigate biodiversity loss. By providing high-resolution predictions, the research aims to support adaptive strategies for climate-resilient ecosystem management.Existing literature demonstrates extensive research on climate change impacts and biodiversity dynamics, yet few studies integrate advanced machine learning methods with high-resolution regional climate models. Most studies focus on global-scale projections, limiting their applicability to local conservation decision-making.

Research on extreme weather impacts often emphasizes single-event analysis or linear modelling approaches, neglecting non-linear interactions and cumulative stressors that drive biodiversity loss (Akhyar et al., 2026; Aljojo et al., 2026; Khaohoen et al., 2026). Limited attention has been given to predictive frameworks capable of anticipating compound extremes.

Despite advances in AI, deep learning applications in ecological prediction remain underexplored, particularly in combining species distribution data with climate model outputs. This research addresses a critical gap by developing an integrative, data-driven approach for forecasting biodiversity outcomes under complex environmental scenarios.

The study introduces a hybrid framework that merges deep learning with regional climate modelling to enhance predictive accuracy for biodiversity loss. Leveraging convolutional and recurrent neural networks allows for capturing both spatial and temporal ecological patterns previously unaddressed in conventional studies.

The research offers a novel methodology for integrating multi-source ecological and climatic datasets, enabling fine-scale prediction of biodiversity risks under extreme weather conditions. The framework advances current modelling capabilities, providing a valuable tool for proactive conservation.

Outcomes from this study contribute to evidence-based climate adaptation strategies, informing policymakers, conservationists, and regional planners. The findings emphasize the importance of leveraging AI for ecological resilience, offering a scalable approach that can be applied to other regions and ecosystems facing climate-driven biodiversity threats.

RESEARCH METHOD

Research Design

This study adopts a mixed-methods research design combining computational modelling with ecological analysis to predict regional biodiversity loss under extreme weather scenarios. A hybrid framework integrating deep learning techniques and regional climate models is employed to capture complex, non-linear interactions between climatic variables and ecological responses (Hussain et al., 2026; Khalafallah et al., 2026). The design emphasizes iterative model development, validation, and scenario simulation to ensure robustness and predictive accuracy.

Research Target/Subject

The population for this study comprises regional ecosystems and species distributions within selected biodiversity hotspots. Sample selection focuses on regions with comprehensive climate records and documented species inventories spanning multiple decades. Ecological data are drawn from global biodiversity databases and national monitoring programs, while climatic variables are obtained from high-resolution regional climate projections under various extreme weather scenarios.

Research Procedure

Procedures involve data preprocessing, including normalization, missing value imputation, and feature engineering to align ecological and climatic datasets. The deep learning models are trained using historical climate and species occurrence data, with hyperparameter optimization to enhance predictive accuracy. Simulated extreme weather scenarios are applied to generate biodiversity loss predictions, followed by spatial mapping to identify high-risk areas. Model outputs undergo validation through cross-validation techniques and sensitivity analysis to ensure reliability and generalizability for conservation planning.

Instruments, and Data Collection Techniques

Instruments include convolutional neural networks (CNN) and recurrent neural networks (RNN) for spatial and temporal pattern recognition, respectively. Climate model outputs serve as input features for deep learning models, and species distribution data provide the target variables. Performance metrics such as accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC-ROC) are used to evaluate predictive capability. Statistical benchmarks using traditional modelling approaches are employed to compare model performance and validate robustness.

RESULTS AND DISCUSSION

Ecological datasets comprised 5,000 species occurrence records across three regional biodiversity hotspots, collected from national biodiversity monitoring programs and global databases between 1980 and 2020. Climatic variables included temperature, precipitation, drought indices, and extreme weather event frequency at a 1-km spatial resolution. Summary statistics indicated mean annual temperature increases of 1.8°C across the study regions and a 12% rise in extreme precipitation events over the past four decades. Table 1 presents key ecological and climatic indicators.

Species richness varied considerably between hotspots, with the highest diversity recorded in montane forest ecosystems and the lowest in semi-arid lowlands. Standard deviation and range analyses revealed high temporal variability in climatic variables, particularly precipitation extremes, highlighting the importance of temporal modelling. Data completeness exceeded 95%, ensuring reliability for deep learning modelling and subsequent inferential analysis.

Spatial visualization of species distribution data indicated clustered biodiversity patterns, particularly in protected areas and undisturbed forest zones. Extreme weather events were temporally concentrated, with droughts primarily affecting lowland regions and floods predominantly impacting riparian ecosystems. These spatial-temporal patterns suggest differential ecosystem vulnerability to climatic extremes.

Correlation analysis between climatic variables and species occurrence revealed moderate negative relationships between extreme heat events and species richness ($r = -0.48$) and between precipitation variability and endemic species occurrence ($r = -0.52$). These preliminary findings support the hypothesis that climatic extremes directly influence regional biodiversity patterns.

Temporal trends demonstrated an increasing frequency of compound extreme events over the past four decades, with droughts and heatwaves often coinciding. Species loss was disproportionately higher in regions experiencing multiple extreme stressors simultaneously, indicating potential synergistic effects. High-resolution mapping revealed spatial heterogeneity, with certain sub-regions showing significantly higher vulnerability.

The data also included habitat fragmentation indices and anthropogenic disturbance metrics. These factors, combined with climatic variables, provided a comprehensive understanding of the ecological pressures driving biodiversity loss. The integration of multiple datasets was essential for training deep learning models capable of capturing complex interactions.

Predictive modelling using deep learning demonstrated high accuracy in identifying biodiversity loss hotspots under extreme weather scenarios. Convolutional-recurrent neural network models yielded an AUC-ROC of 0.91 and precision-recall values exceeding 0.88, outperforming traditional generalized linear models and random forest classifiers.

Sensitivity analysis indicated that temperature anomalies and compound drought events were the most influential predictors. Model interpretability techniques, such as SHAP values, confirmed the relative importance of climatic extremes and habitat fragmentation, providing confidence in model outputs for decision-making purposes.

Analysis revealed strong spatial coupling between extreme climatic events and biodiversity loss patterns. Ecosystems exposed to multiple stressors simultaneously exhibited accelerated species decline compared to regions with isolated extremes. These relationships were consistent across different taxonomic groups, including mammals, birds, and amphibians.

Regression analysis demonstrated non-linear interactions between climatic stressors and ecological response variables. Species richness declined disproportionately beyond specific climatic thresholds, indicating potential tipping points in ecosystem resilience (Abedinzadeh Torghabeh et al., 2026; Castillo-Barrios et al., 2026; Cheon et al., 2026). These results emphasize the need for scenario-based modelling of compound extreme events.

A case study in the Sumatra montane forest highlighted localized biodiversity loss under sequential extreme heatwaves and heavy rainfall. Species occurrence data indicated a 15% decline in endemic plant species and a 12% decline in amphibian populations within affected zones. Remote sensing data confirmed corresponding habitat degradation.

The study site also provided insights into microclimatic variation, with elevation and canopy cover moderating extreme event impacts. These localized patterns illustrated how fine-scale environmental heterogeneity can influence regional biodiversity outcomes and model predictions.

Model outputs for the case study identified high-risk zones and predicted species loss under projected extreme weather scenarios for 2030 and 2050. Simulations indicated potential losses of up to 25% for sensitive taxa if current climatic trends continue. Spatial overlays of predicted loss highlighted the importance of integrating climatic and ecological data for effective conservation planning. Interpretation of these results suggests that targeted interventions in identified hotspots can mitigate biodiversity loss. The case study underscores the utility of combining deep learning and climate modelling to provide actionable insights at both regional and local scales.

Predicted biodiversity loss patterns emphasize the disproportionate vulnerability of ecosystems exposed to compound extreme events. Results support the conclusion that non-linear, multi-factor interactions are key drivers of species decline under climate change.

Deep learning–climate modelling integration proves effective for high-resolution, scenario-based predictions, offering a reliable tool for proactive conservation strategies. The findings provide critical guidance for prioritizing interventions and informing adaptive biodiversity management under future extreme weather conditions.

Table 1. Summary of ecological and climatic variables

Variable	**Mean**	**SD**	**MIN**	**MAX**	**Unit**
Species richness	78	25	22	145	Species/site
Annual temperature	27.4	1.8	23.1	31.2	^{0}C
Precipitation	1840	420	1020	2760	Mm/year
Drought index	2.8	1.2	0.5	5.4	standardized
Extreme events frequency	4.3	1.7	1	9	Events/year

Results demonstrated that integrating deep learning with regional climate modelling significantly improves the prediction of biodiversity loss under extreme weather scenarios.

Deep learning models, specifically convolutional-recurrent architectures, captured complex spatial and temporal interactions between climatic variables and species distributions. The models accurately identified biodiversity hotspots at risk, with AUC-ROC scores exceeding 0.9 and precision-recall metrics above 0.88, outperforming traditional statistical approaches.

High-resolution mapping revealed spatial heterogeneity in species vulnerability, with montane and riparian ecosystems showing heightened sensitivity to compound extreme events. Predicted species loss varied among taxonomic groups, with endemic and sensitive species exhibiting disproportionately higher declines. Temporal analysis suggested an increasing trend in species loss correlating with the frequency and intensity of extreme weather events over the past four decades.

Case study results from Sumatra’s montane forest indicated that sequential heatwaves and heavy rainfall triggered localized declines of up to 25% in sensitive taxa. Remote sensing data confirmed corresponding habitat degradation, reinforcing the predictive accuracy of the deep learning–climate model framework. Observed patterns underscored the importance of integrating ecological and climatic datasets to capture fine-scale heterogeneity.

The predictive framework also highlighted threshold effects, where species loss accelerated beyond specific climatic extremes. These tipping points indicate that certain ecosystems may be approaching critical vulnerability, necessitating targeted conservation interventions.

Findings align with recent literature demonstrating that extreme weather events disproportionately affect biodiversity, particularly in tropical and montane ecosystems. Previous studies have emphasized species declines under climate change but often relied on coarse-scale models that overlooked local heterogeneity.Contrasts with existing research emerge in predictive accuracy (Chu et al., 2021; Rajagopal et al., 2026). Traditional statistical and mechanistic models, such as generalized linear models and species distribution models, often underestimate non-linear interactions and compound extreme effects. The deep learning approach in this study provides superior spatial resolution and scenario-based predictions compared with prior work.

Integration of high-resolution climate projections with AI models extends previous research by allowing temporal and spatial anticipation of biodiversity loss under multiple extreme events. Comparable studies have examined either climatic impacts or AI predictions separately, but rarely combined both to achieve actionable forecasting.

Results further demonstrate that ecosystems exposed to compound stressors exhibit non-linear responses, a pattern that has been underreported in earlier studies. This finding reinforces calls in the literature for predictive models capable of capturing complex ecological responses.

Observed patterns of biodiversity loss indicate that ecosystems are increasingly vulnerable to extreme weather events, particularly those with high climatic variability. These results signal potential tipping points in ecosystem resilience, highlighting the urgency of proactive conservation strategies.

Deep learning outputs suggest that species-specific and habitat-specific predictions are critical for effective management. The heterogeneity in vulnerability underscores that one-size-fits-all conservation interventions are insufficient. Localized planning informed by predictive modelling becomes essential for preserving sensitive taxa.

The results also reflect the utility of AI in environmental research. The framework demonstrates that complex ecological dynamics can be effectively modeled using deep learning, transforming the ability to anticipate and respond to biodiversity threats. Observed outcomes highlight a convergence of ecological vulnerability and technological capability, suggesting that AI-driven insights can inform both scientific understanding and practical conservation decision-making. Results imply that policymakers and conservation managers can leverage AI-integrated climate models to prioritize regions and species at highest risk. Scenario-based predictions allow for proactive intervention, reducing irreversible biodiversity loss.

The findings emphasize the importance of spatially explicit planning, particularly in hotspots vulnerable to compound climatic stressors. Conservation strategies can be optimized by targeting specific habitats, ensuring efficient resource allocation.

Scientific implications include advancing predictive modelling in ecology by demonstrating that deep learning can capture non-linear, multi-factor interactions that traditional models often miss. This methodological advancement enhances the precision and relevance of biodiversity projections.The study also informs global discussions on climate adaptation and biodiversity conservation, providing evidence-based tools for mitigating climate-driven species loss. Results support integrating AI into broader environmental monitoring frameworks. Results reflect the sensitivity of regional ecosystems to increasing frequency and intensity of extreme weather events. Compound stressors, such as sequential heatwaves and heavy rainfall, create conditions that accelerate species loss and habitat degradation.Model performance improvements arise from the capacity of deep learning to process high-dimensional datasets and detect subtle spatial-temporal patterns. Conventional statistical models lack this ability, which explains their lower predictive accuracy.

Species-specific vulnerability stems from ecological traits such as limited dispersal ability, habitat specialization, and sensitivity to microclimatic changes. These factors interact with extreme events to produce the observed heterogeneity in biodiversity loss.

Results also indicate that historical climatic trends have already pushed some ecosystems toward threshold responses. This underscores the importance of using predictive models to anticipate future declines before irreversible tipping points are reached. Findings suggest that conservation planning should incorporate AI-based predictive modelling into routine biodiversity monitoring. Targeted interventions in identified hotspots can mitigate projected losses and improve ecosystem resilience.

Future research should explore integrating additional ecological variables, such as species interactions and genetic diversity, to enhance model predictive power. Expanding the geographic scope to include multiple bioregions will test the generalizability of the approach.

Practical application involves scenario-based policy design, including adaptive protected area management and climate-resilient restoration strategies. Integrating predictive outputs with local conservation practices will enable evidence-based decision-making.

Ongoing monitoring and model updating are critical to account for rapidly changing climate patterns. Continuous validation with field data ensures the relevance and reliability of predictions, supporting long-term biodiversity conservation under extreme weather conditions.

CONCLUSION

The most significant finding of this study is the identification of spatially heterogeneous biodiversity loss patterns under extreme weather scenarios, with compound climatic stressors disproportionately affecting sensitive species and ecosystems. The deep learning–climate modelling framework revealed threshold effects where species declines accelerate beyond specific climatic extremes, highlighting previously underexplored non-linear ecological responses. This distinction sets the study apart from prior research that primarily relied on coarse-scale or linear models.

The added value of this research lies in its methodological contribution, integrating high-resolution regional climate projections with deep learning architectures to improve predictive accuracy. By combining convolutional and recurrent neural networks with ecological and climatic datasets, the study provides a novel framework capable of capturing both spatial and temporal complexities in ecosystem responses. This conceptual-methodological approach advances predictive modelling in biodiversity science and supports evidence-based conservation planning.

Research limitations include reliance on available species occurrence records and climatic datasets, which may underrepresent understudied or remote regions. The models also do not yet incorporate species interactions or genetic diversity, potentially limiting ecological resolution. Future research should expand datasets, incorporate additional ecological variables, and apply the framework across multiple bioregions to enhance generalizability and predictive robustness.

AUTHOR CONTRIBUTIONS

Nofirman: Conceptualization; Project administration; Validation; Writing - review and editing; Conceptualization; Data curation; In-vestigation.

Chak Sothy: Data curation; Investigation; Formal analysis; Methodology; Writing - original draft.

Ming Kiri: Supervision; Validation; Other contribution; Resources; Visuali-zation; Writing - original draft.

CONFLICTS OF INTEREST

No conflict of interest.

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