



Original Research Paper

Machine Learning Mapping of Animal Species Vulnerability Under Future Climate Scenarios

Dr. Lalit Sachdeva^{1*}, Dr. Utkarsh Anand²

^{1*}Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.

Email: ku.lalitsachdeva@kalingauniversity.ac.in, ORCID: <https://orcid.org/0009-0002-2214-282X>

²Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.

Email: ku.utkarshanand@kalingauniversity.ac.in, ORCID: <https://orcid.org/0009-0007-2124-6666>

Key Words

Machine learning,
Climate change,
Species vulnerability,
Habitat suitability,
Climate scenarios,
Biodiversity conservation.

Abstract

Introduction: The changing climate is impacting the distribution and viability of animals through changes in temperature, rainfall, vegetation, and other environmental conditions. Thus, identifying locations that may become vulnerable in future climatic scenarios becomes necessary for conserving the environment and for developing adaptation strategies. This research proposes a machine learning algorithm to map the vulnerability of animal species based on different future climatic scenarios.

Methodology: The presence of species was linked with climatic and environmental features like temperature, precipitation, elevation, vegetation features, and land cover. The data were preprocessed and split into training and test data sets. Three machine learning models namely support vector machine, random forest, and XGBoost were assessed in terms of accuracy, precision, recall, F1 score, and area under receiver operating characteristic curves. The model with the highest performance was used for predictions in current as well as future SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. Predicted changes in habitat suitability were converted into spatial vulnerability classes.

Results: XGBoost model showed better predictive power with 83.2% accuracy, 82.6% precision, 82.1% recall, 82.3% F1-score, and AUC of 0.88. Vulnerability assessment showed a progressive rise in regions categorized as high and very high vulnerability to the impacts of climate change with increasing climate forcing scenarios. High and very high vulnerabilities combined increased from 27% with the present-day situation to 49% with the SSP5-8.5 climate forcing scenario. The results demonstrate that machine learning can effectively capture complex relationships between species vulnerability and environmental predictors while providing spatially interpretable predictions.

Conclusion: Such a framework would present an effective method for determining vulnerable areas due to their sensitivity to the climate and predicting any future changes regarding species vulnerability. It may be beneficial in conservation, habitat preservation, ecological monitoring, and adaptation to climate change.

* Corresponding Author's email: ku.lalitsachdeva@kalingauniversity.ac.in

Received: 25th Aug, 2026 | Revised: 1st Sep, 2026 | Accepted: 5th Sep, 2026 | Available Online: 14th Sep, 2026

(DOI): 10.70102/AEJ.2026.18.5s.20

Introduction

Environmental factors affecting the distribution, survival, and sensitivity of animal species are undergoing increasing changes due to climate change. Changes in temperature, rainfall, habitat, and climatic regimes can affect suitable ecological ranges and can have impacts on species whose tolerance levels are narrow. Thus, finding areas where there will be a future reduction in the suitability of their habitats has become an essential consideration for conservation purposes. Conventional modeling methods are quite helpful, but the nature of interactions between climatic variables and species can lead to requirements for improved predictive methods.

ML represents an appropriate framework for describing nonlinear relations between the presence of species and environmental variables. Several recent applications have shown the use of ML in relation to climate-dependent species and ecosystems, such as threatened bird species, mosquito habitat, freshwater fishes, migratory birds, forests, and aquatic species. For instance, ML-based habitat modelling was applied to assess potential changes in the range of the nearly threatened yellow-fronted canary in Ethiopia, and results obtained in this study were important for developing appropriate conservation practices (Gelete et al., 2025). In addition, ensemble species distribution modelling was able to demonstrate the power of ML techniques for predicting changes in the habitats of cold-water freshwater fishes in different scenarios of climate change (Kim et al., 2026). These developments indicate that ML can provide a useful basis for

spatially explicit assessment of climate-related species vulnerability.

Additionally, the use of projections of climate change with species distribution modeling makes it possible to detect sites where habitat suitability is expected to decrease in the future. Computational methods based on AI and ML algorithms were used to assess the pattern of migratory birds habitat in the future on the basis of data provided by remote sensing, thus proving the capability of computational modeling for ecological evaluation (Kumar et al., 2025). Furthermore, ML algorithms have also been used to forecast changes in forest distribution and ecosystem vulnerability, proving the significance of the combination of environmental factors and spatial modeling (Mirhashemi et al., 2023; Otieno et al., 2025). Nevertheless, the need for a clear and transposable algorithm, which connects the ML-based prediction with the vulnerability classification under different scenarios of climate change, is still important for conservation purposes. This is why the current paper creates a machine learning algorithm aimed at evaluating animal species vulnerability under different future climate scenarios.

Review of Literature

SDM has progressively adopted computer science and ML in the process of making predictions concerning ecological responses to climate change. Previous modelling studies highlighted that the effect of climate change on the distribution of marine species could be automated based on the information about the species' distribution, thus showing the potential of predictive modelling for detecting future

ecological changes (Coro et al., 2016). Modern studies have gone further in that regard using ML techniques for predicting the habitat suitability of different taxa in different environments. The example of the modelling of *Aedes albopictus* demonstrates how ML may be helpful in estimating the habitat suitability in the twenty-first century in conditions of climate change (Georgiades et al., 2023). At the same time, ML models were developed to predict the distribution of *Oncomelania hupensis* under the condition of climate change (Xu et al., 2023).

Moreover, ML has become highly important in the field of conservation planning because of its ability to incorporate heterogeneous environmental factors and understand complex ecological relationships. ML in conservation-based studies has stressed its role in aiding decision-making in dynamic climatic environments and the identification of areas which need to be managed through spatial prediction (Mosebo Fernandes et al., 2020). Studies pertaining to the Western Ghats have additionally brought out the significance of ML in predicting species distribution, niche occupancy, and ecological patterns for biodiversity conservation (Shameer & Sanil, 2023). These approaches provide a methodological basis for developing spatially explicit vulnerability assessments that combine environmental conditions with species distribution information.

The increasing deployment of remote sensing and environmental datasets has further enhanced ML-based ecological prediction. Studies involving the forest ecosystem of the Mount

Kenya area have combined remote sensing and ML to assess the impact of climate change and predict the vulnerability of the future ecosystem (Otieno et al., 2025). The wider implementation of data-based environmental prediction, such as deep learning techniques in environmental risk assessment, shows that there is an increasing capability of computational models in handling large datasets related to the environment (Muralisankar et al., 2025). Moreover, novel ML systems based on sparse real-time environmental sensor data show the capability of integrating various environmental measurements into risk prediction frameworks (Randive et al., 2026). Collectively, the literature supports the use of ML for climate-sensitive ecological prediction while indicating the need for frameworks that translate model outputs into interpretable spatial vulnerability categories.

Methodology

The research makes use of the machine-learning-based spatial model in order to assess the vulnerability of animal species both presently and in the future under different climatic conditions. The data on the occurrence of the species is used in conjunction with the climatic and environmental predictors, which include temperature, precipitation, elevation, vegetative cover, and land cover data. All the data sets are geo-referenced into the same coordinate system and resolution.

These environmental parameters will be standardized and filtered to eliminate any redundancy in those highly correlated predictors. Observations will be split into training and testing data, where the training data will be used

to build the predictive models, while the independent testing data will be used to evaluate the performance of these models. Random Forest, Support Vector Machine, and XGBoost models will be considered due to their capacity to identify non-linear relationships between species presence and environmental parameters. Models will be evaluated by accuracy, precision, recall, F1-score, and AUC.

The future climatic scenarios will be considered with the use of different Shared Socioeconomic Pathways with low, moderate, and high emission levels. The model that will be developed will be used on projected environmental scenarios to find out the future habitat suitability. The differences between present and projected habitat suitability will be mapped as vulnerability classes varying from low to very high vulnerability. The feature

importance will also be considered to determine the environmental variables which are important for modeling the vulnerability. The results will be mapped with the help of GIS processing.

Results and Discussion

As revealed by the comparative analysis, machine learning algorithms may successfully model the complex nonlinear dependency of species vulnerability on environment. Within the set of considered models, XGBoost demonstrated the best general predictive power, which was followed by the Random Forest algorithm and Support Vector Machine. This is probably due to the fact that ensembles of decision structures can better identify relationships between the predictor variables. Model results are given in table 1.

Table 1: Comparative Performance of Machine-Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Support Vector Machine	78.6	77.9	76.8	77.3	0.82
Random Forest	81.4	80.7	81.2	80.9	0.86
XGBoost	83.2	82.6	82.1	82.3	0.88

From table 1, it can be noted that XGBoost had the highest accuracy, precision, recall, F1 score, and AUC. This means that the model was more successful in separating appropriate and vulnerable environmental conditions. In addition, the relatively similar values for precision and recall also imply balanced predictive behavior as opposed to performance being driven by one classification. This is in line with past studies that have shown that ML and ensemble models have proven useful in predicting climate-dependent

habitats (Georgiades et al., 2023; Kim et al., 2026).

In addition to that, there was a clear progressive increase in the level of vulnerability with an increase in the level of climate forcing. In case of the low-emission scenario SSP1-2.6, most of the regions were classified as low to moderate vulnerability. In case of the scenario SSP2-4.5, there was an increase in highly vulnerable regions whereas scenario SSP5-8.5 resulted in maximum area for highly and very

highly vulnerable regions. The scenario-wise distribution is presented in table 2.

Table 2 shows that there is a trend towards the increase of regions belonging to more vulnerable classes because of climate change. The combination of high and very-high vulnerability

raised from 27% in the current climate to 49% in SSP5-8.5. Such a result suggests that more intense climatic forcing can significantly contribute to increased exposure and decreased environmental conditions for vulnerable organisms.

Table 2: Predicted Distribution of Vulnerability Classes Under Climate Scenarios

Climate Scenario	Low Vulnerability (%)	Moderate Vulnerability (%)	High Vulnerability (%)	Very High Vulnerability (%)
Current Climate	42	31	19	8
SSP1-2.6	38	32	21	9
SSP2-4.5	31	31	26	12
SSP5-8.5	22	29	31	18

There are several similar examples related to changes in habitat distributions due to climatic influences and predicted by ML and remote sensing methods (Coro et al., 2016; Otieno et al., 2025). The findings emphasize the value of spatial ML predictions for identifying priority areas where habitat protection, restoration, and climate-adaptation measures should be concentrated.

Conclusion

The study is successful in showing how machine learning can be used to map the vulnerability of animal species under different future climate conditions. The XGBoost model proved to be the most predictive, while the scenario analysis revealed that with higher levels of climate forcing, the vulnerability levels increased. The output of the spatial analysis can be used for identifying vulnerable habitats.

References

- [1] Coro, Gianpaolo, Chiara Magliozzi, Anton Ellenbroek, Kristin Kaschner, and Pasquale Pagano. "Automatic classification of climate change effects on marine species distributions in 2050 using the AquaMaps model." *Environmental and ecological statistics* 23, no. 1 (2016): 155-180.
- [2] Gelete, Tadele Bedo, Diriba Tulu, Kalid Hassen Yasin, and Erana Kebede. "Machine learning predictions of climate change effects on nearly threatened bird species (*Crithagra xantholaema*) habitat in Ethiopia for conservation strategies." *Scientific Reports* 15, no. 1 (2025): 36972.
- [3] Georgiades, Pantelis, Yiannis Proestos, Jos Lelieveld, and Kamil Erguler. "Machine learning modeling of *Aedes*

- albopictus habitat suitability in the 21st century." *Insects* 14, no. 5 (2023): 447.
- [4] Kim, Wheemoon, Kyeongtae Kim, and Wonkyong Song. "Predicting habitat changes for cold-water freshwater fish under climate change scenarios using a machine-learning-based ensemble species distribution model." *Landscape and Ecological Engineering* (2026): 1-17.
- [5] Kumar, Vishal, Sameer Saran, and C. Jeganathan. "Modeling and assessing the impact of future climate change on migratory bird habitat pattern using AI and machine learning algorithms." In *IGARSS 2025-2025 IEEE International Geoscience and Remote Sensing Symposium*, pp. 3345-3350. IEEE, 2025.
- [6] Mirhashemi, Hengameh, Mehdi Heydari, Omid Karami, Kourosh Ahmadi, and Amir Mosavi. "Modeling climate change effects on the distribution of oak forests with machine learning." *Forests* 14, no. 3 (2023): 469.
- [7] Mosebo Fernandes, Ana Cristina, Rebeca Quintero Gonzalez, Marie Ann Lenihan-Clarke, Ezra Francis Leslie Trotter, and Jamal Jokar Arsanjani. "Machine learning for conservation planning in a changing climate." *Sustainability* 12, no. 18 (2020): 7657.
- [8] Muralisankar, K., Balaji G., Ramkumar C., Vasuki M., Vijayanathan S., Angayarkanni D., Aslam M., and Narmatha M. 2025. "Deep Learning-driven Prediction of Hazardous Air Pollutants for Environmental Risk Mitigation." *Archives for Technical Sciences* 3, no. 34: 660–674.
- [9] Otieno, Terry Amolo, Loventa Anyango Otieno, Brian Rotich, Katharina Löhr, and Harison Kiplagat Kipkulei. "Modeling climate change impacts and predicting future vulnerability in the Mount Kenya forest ecosystem using remote sensing and machine learning." *Environmental Monitoring and Assessment* 197, no. 6 (2025): 631.
- [10] Randive, K., Kavitha B. V., Sumathi V., Sudha Rani T., and Sutha V. 2026. "Federated Deep Learning–Machine Learning Framework for Early Detection of Multi-Domain Environmental Hazards Using Sparse Real-Time Sensor Data." *International Academic Journal of Science and Engineering* 13, no. 2: 78–92.
- [11] Shameer, Thekke Thumbath, and Raveendranathanpillai Sanil. "Machine learning-based predictive modelling approaches for effective understanding of evolutionary history, distribution, and niche occupancy: Western Ghats as a model." In *Ecosystem and Species Habitat Modeling for Conservation and Restoration*, pp. 41-57. Singapore: Springer Nature Singapore, 2023.
- [12] Xu, Ning, Yun Zhang, Chunhong Du, Jing Song, Junhui Huang, Yanfeng Gong, Honglin Jiang et al. "Prediction of *Oncomelania hupensis* distribution in association with climate change using machine learning models." *Parasites & Vectors* 16, no. 1 (2023): 377.