17(4) 599-611, Winter 2025

Journal of Animal Environment

(E-ISSN 2717-1396, ISSN 2717-1388)

Journal homepage: http://www.aejournal.ir

Original Research Paper

AI-Powered Habitat Suitability Models to Inform Migratory Species Protection and Ecological Restoration Efforts

Hassan Mohamed Mahdi[1], Ola Kamal A. Alkadir[2], Ibrahim Abbas Mohammed[3], Ameer Hassan Idan[4], Roohee Khan[5]*

[1*]*Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University of Al Diwaniyah, Al Diwaniyah, Iraq. Email: iu.tech.hassanaljawahry@gmail.com, ORCID: https://orcid.org/0009-0003-4594-1023*

[2]*Department of Medical Laboratories Technology, Al-Nisour University College, Nisour Seq Karkh, Baghdad, Iraq. Email: ula.k.path@nuc.edu.iq, ORCID: https://orcid.org/0000-0001-6044-8833*

[3]*Department of Medical Laboratories Technology, Mazaya University College, Nasiriyah, Dhi Qar, Iraq. Email: aboroaya2012@gmail.com, ORCID: https://orcid.org/0000-0001-8972-9639*

[4]*Department of Medical Laboratories Technology, Al-Zahrawi University College, Karbala, Iraq. Email: ameer.alzamely@gmail.com, ORCID: https://orcid.org/0000-0001-7276-469X*

[5]*Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India. Email: ku.roohee.khan@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0009-8960-8840*

Key Words

Migratory species, Habitat suitability, Artificial intelligence, Machine learning models, Ecological restoration, Conservation planning, Environmental monitoring.

Abstract

Moving animals also play a critical role in the ecology and the preservation of biodiversity through their interdependence within ecosystems. Nevertheless, patterns of habitat loss, global warming, and human disturbances have disrupted migration pathways and diminished habitat quality, posing severe threats to species survival. This work presents a habitat suitability modeling framework powered by AI, designed to enhance the conservation of migratory species and to aid ecological restoration projects. The given strategy combines data on animal presence with crucial environmental factors, including climatic, land-use, vegetation cover, topographical, and human disturbance indicators. Using machine learning algorithms, intricate associations between species distributions and ecological conditions are captured, enabling more precise, spatially explicit predictions than traditional approaches. The produced suitability maps identify key habitats, including breeding sites, stopover areas, and migration routes, which are essential to the maintenance of migratory populations. The outcomes of model validation indicate strong predictive ability and reliability across a wide range of environmental conditions. The results reveal the practical use of AI in animal and environmental studies, providing important information for conservation planning, ranking habitat restoration priorities, and informing management decision-making. Altogether, the paper reveals the opportunities AI-based applications offer to enhance the security of migratory species and support ecologically sustainable shifts in the evolving environment.

* Corresponding Author's email: iu.tech.hassanaljawahry@gmail.com

Received: 22 September 2025; Reviewed: 28 October 2025; Revised: 03 December 2025; Accepted: 29 December 2025

(DOI): 10.70102/AEJ.2025.17.4.47

Introduction

Migratory species are essential parts of natural ecosystems and play a role in maintaining biodiversity, nutrient cycling, population regulation, and ecological connectivity across geographically separated areas. Migratory terrestrial, freshwater, and marine animals connect ecosystems through seasonal movement, thereby maintaining ecosystem resilience through gene flow. Migration of birds, mammals, fish, and insects can serve as key species or indicators of the condition of the environments they pass through. But the fast-changing environment, habitat fragmentation, climate change, and growing human activities have disrupted traditional migration, and fewer habitats are available. These disruptions have resulted in declining populations and changes in ecosystems, and it is essential to introduce science-based conservation measures to meet spatial and temporal habitat demands (Manjunatha & Raveesha, 2025; Ullah et al., 2025).

Proper conservation planning for migratory species requires comprehensive knowledge of habitat suitability during breeding, stopover, and wintering periods. Conventional methods of habitat assessment, while helpful, are often based on small datasets and fixed assumptions that do not reflect environmental complexity and variability. Habitat suitability models offer a systematic approach to examining species-environment interactions and determining the locations required for survival and movement. These types of models aid decision-making by focusing on conservation areas, informing ecological recovery, and evaluating potential risks from land-use transformation and climate stressors. Recent advances in environmental surveillance and predictive analytics have strengthened the role of habitat suitability modeling in biodiversity conservation by enabling more proactive, focused interventions (Chisom et al., 2024; Lahoti, 2025; Ramakrishnan & Mahadevan, 2025).

Artificial intelligence (AI) has become a disruptive technology in animal and environmental sciences, providing more powerful tools for analyzing extensive, complex ecological datasets. Habitat suitability models based on AI combine a variety of data types, such as satellite images, climate characteristics, land-use trends, species presence histories, and others, to produce fine-grained spatial forecasts. Machine learning algorithms are powerful because they can identify nonlinear relationships that traditional methods miss, thereby enhancing the model's accuracy and ecological relevance. Combining AI with remote sensing technologies has also enhanced habitat surveillance and change detection, providing timely information to support conservation planning (Santhosh, 2025; Yambal et al., 2025; Verma et al., 2025). As noted in recent research, AI-based solutions combine traditional ecological understanding with current computational methods, providing scalable, dynamic solutions to protecting migratory species and promoting a sustainable environment in the long term (Yousef, 2024; Ullah et al., 2025).

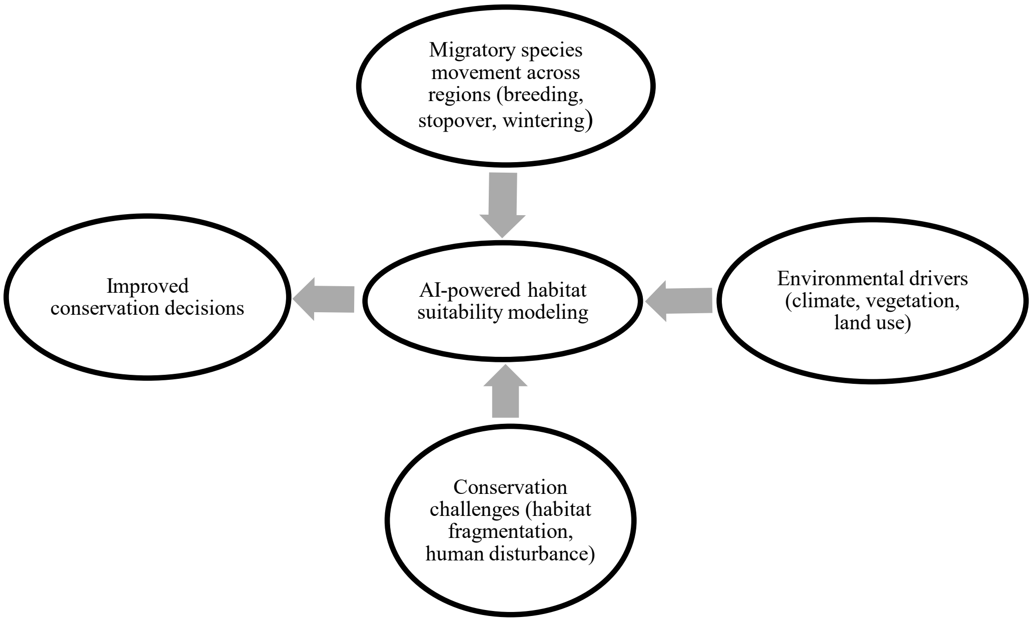

Figure 1: Conceptual Framework of AI-Powered Habitat Suitability Modeling for Migratory Species

This Figure 1 provides a simplified conceptual model describing how environmental determinants (climate, vegetation, and land use) influence when migratory animals move between their breeding, stopover, and wintering areas, and how conservation challenges (habitat fragmentation and human disturbance) limit migratory animals during these movements. Using this integrated approach, in conjunction with habitat suitability modelling that integrates ecological knowledge into AI-supported tools for making informed conservation decisions and for developing better strategies to manage habitats effectively, will provide more accurate assessments of habitat value for migratory species.

The research has several implications for the field of animal and environmental science. To begin with, it shows how AI-assisted habitat suitability models can be used practically to identify key habitats and migratory routes of migratory species, offering higher spatial resolution than conventional methods. Second, the study combines multiple datasets on environmental and species occurrences into a single modeling platform, thereby increasing the validity of habitat analyses across diverse ecological settings. Third, the study provides a systematic assessment of various AI algorithms, evaluating their strengths and weaknesses for conservation planning. Ultimately, the findings can be applied to conservation practice because they demonstrate how AI-based insights can support specific habitat protection, resource prioritization, and decision-making. Collectively, the contributions further the development of artificial intelligence in ecological studies and provide a scalable approach to addressing the complex conservation issues of migratory species and ecosystem restoration (Jaiswal & Pradhan, 2023).

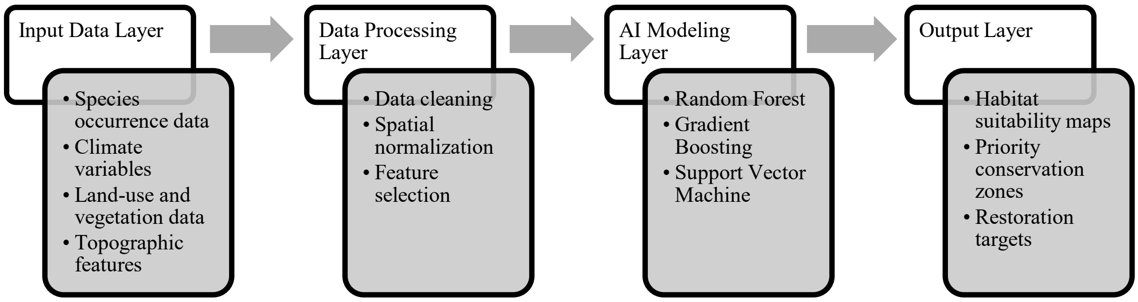

Figure 2: Architecture of the AI-Based Habitat Suitability Modeling Framework

This diagram (Figure 2) presents a complete framework of how the proposed AI system uses habitat suitability modelling to handle all aspects of the system's operation from start to finish; it is built based on species occurrence, climate data, land use, vegetation, and topography, as well as all other variables related to these categories within the environmental context. During processing, the systems will clean each database (removing duplicate values), normalise their geographic position through geographical information systems (GIS), and select features; this ensures consistency in the analysis process among all modelling datasets. Once flushing (cleansing) has occurred, processed datasets are then modelled through the use of Artificial Intelligence (AI) Models (Random Forest, Gradient Boosting and Support Vector Machines), and those modelling results are returned in the form of habitat suitability maps, priority conservation areas and restoration goals being generated through the use of AI Models to aid in evidence-based conservation planning.

The paper presents a methodical analysis of AI-based habitat suitability modeling in the context of migratory species conservation. After the introduction, Section II presents a literature review of existing sources on habitat suitability modeling, including classical methods and the latest developments in artificial intelligence. Section III presents the methodology, including the AI algorithms to be used, data collection and processing methods, and validation tools for evaluating model performance. Part IV presents the results, including species-specific habitat needs, model predictions, and performance evaluation. Section V discusses the implications of the findings by comparing and contrasting the AI-based models with traditional methods and assessing the applicability of the presented models to conservation practice. Lastly, Section VI concludes the study, summarizes the main findings, and highlights suggestions for future research and why technological innovation should be used to combine efforts to conserve the environment.

Literature Review

Habitat modeling has a long tradition of study to understand the spatial distribution of migratory species and to support conservation and land management efforts. The initial methods relied on comparing species occurrence data with environmental factors such as vegetation type, climate, and topography. The models have been used to provide valuable baseline information, especially for determining breeding and wintering habitat. Other contemporary investigations have extended this to include landscape connectivity, seasonal fluctuations, and ecosystem-scale interactions, thereby enhancing its applicability to migratory species that depend on various habitats across extensive geographic areas (Bhakhar et al., 2025; Chauhan & Kumar, 2024). The availability of spatial data, such as satellite-based environmental data, has also helped reinforce habitat modeling by enabling ecological assessment at fine scales. Nevertheless, with advances in methods, numerous studies still focus on stable habitat conditions, limiting their ability to represent dynamic ecological processes important to migratory populations (Wang et al., 2025). Traditional habitat suitability models have several constraints when applied to multifaceted migratory systems. Such methods tend to rely on linear assumptions and simplified ecological relationships, which may not accurately capture species responses to driving environmental interactions. Also, traditional models often do not work with high-dimensional data or with incomplete or biased records of species occurrence. With changing environmental conditions driven by climate change and land-use changes, traditional modeling frameworks may not accurately forecast new habitat patterns. The traditional techniques are also limited by data scarcity, a lack of computational flexibility, and the inability to combine heterogeneous data, especially in large-scale or data-rich ecosystems (Dave et al., 2025; Pimenow et al., 2025). These difficulties highlight the importance of more flexible, resilient modeling that can cope with ecological complexity and uncertainty. Artificial intelligence has also been increasingly recognized as a potent alternative to conventional habitat modeling techniques. Machine learning and deep learning represent AI-based tools and can process large, multidimensional datasets and capture non-linear associations between species distributions and environmental variables. Such methods improve predictive accuracy and enable the model to be continuously updated as new data becomes available. These AI-driven models have been effectively used in forest and wildlife management, demonstrating greater performance in habitat classification, change detection, and scenario analysis (Wang et al., 2025; Whig et al., 2025). Moreover, new AI applications can be used to monitor the ecology in real time and manage ecological forecasting, which could provide useful adaptive conservation planning tools (Fadzly & Yeo, 2025; Yousaf, 2024). By combining multiple data sources and AI-driven analytics, habitat suitability models can be used to scale and flexibly meet the conservation requirements of migratory species in changing environments (Bhakhar et al., 2025; Pimenow et al., 2025).

Methodology

Artificial Intelligence Algorithms of Modeling Habitat Suitability

The framework for habitat suitability modeling was constructed using highly complex artificial intelligence algorithms designed to extract complex interactions between the distributions of migratory species and environmental factors. The machine learning algorithms, such as Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting, were used because they have been shown to handle non-linear interactions and high-dimensional data. Random Forest, in particular, helped rank variable importance, as was Gradient Boosting, which increased predictive accuracy via an iterative error-reduction method. The choice of these algorithms was based on robustness, interpretability, and the ability to handle ecological data with different spatial and temporal resolutions. Model training entailed observing patterns in well-known species occurrence sites and environmental conditions, and using them to generate spatial forecasts of habitat suitability throughout the study area.

Table 1: Artificial Intelligence Methods Used In Habitat Suitability Modeling

Algorithm	Purpose	Key Advantage
Random Forest	Feature importance and classification	Handles non-linearity, reduces overfitting
Support Vector Machine	Boundary optimization	Effective with limited samples
Gradient Boosting	Accuracy enhancement	High predictive performance

Table 1 briefly describes the artificial intelligence algorithms used to develop habitat suitability models and their specific purposes within the models. All the algorithms were chosen for their ability to handle the complexity of ecological data, non-linear associations, and to enhance predictive performance. Random Forest helped to measure the importance of the variables and minimize overfitting, Support Vector Machine helped to classify the best boundaries, and Gradient Boosting helped to improve the accuracy of the model as a whole with the help of the iterative learning. These algorithms combined to provide predictions on the suitability of habitats of migratory species that are robust and reliable.

Data Collection and Process Techniques

The data utilized in this research were summarized using various sources in order to have a full representation of the environment. The species occurrence information has been gathered through long-term records on monitoring and the field observation and the environmental variables have been measured by the climatic factors, land-use features of the areas, vegetation indices, elevation, and distance to anthropogenic characteristics. All the spatial datasets were equated to a shared spatial resolution and coordinate reference frame. Preprocessing of data entailed the deletion of duplicated records, missing values and the minimisation of spatial sampling bias. The environmental variables were normalized to enhance performance of the algorithm and enable comparison of algorithms across datasets. The feature selection methods were used to reduce redundancy and enhance the computational efficiency.

Table 2: Data Types and Sources Used in The Modeling Framework

Data Category	Description	Spatial Format
Species occurrence	Presence records of migratory species	Point data
Climate variables	Temperature and precipitation	Raster layers
Land-use and cover	Vegetation and human activity	Raster layers
Topography	Elevation and slope	Raster layers

Table 2 below presents the various classes of data used in the habitat suitability modeling process and their respective spatial forms. Biological reference points were given by the species occurrence records, and the environmental variables like climate, land use, and topography were also the important habitat drivers. Combining various spatial data enabled the multifacetedness of the characterization of an environment and enhance the realism of the model. Such standardization of these inputs was to provide supremacy among analyses and enable the correct spatial forecasting of suitable habitats.

Methods of Testing the Accuracy of the Models

The validation was done using models to measure the ability to predict as well as generalization. A stratified split was performed to split the dataset into training and testing subsets to keep the spatial representation intact. The cross-validation methods were used to minimize overfitting and evaluate the stability of the model on several runs. The evaluation of performance was based on conventional indicators like Area Under the Receiver Operating Characteristic Curve (AUC), accuracy, sensitivity, and specificity. Such measures gave a fair evaluation of the model in relation to its capability to recognize the appropriate and inappropriate habitats appropriately. Predicted suitability maps were also validated against independent occurrence records in the quest to provide spatial validation and ecological consistency and practical application of the suitability maps in conservation planning.

Results

Account of The Migratory Species and Habitat Demands

The findings are discussed with the help of a long-distance migratory bird species as a representative example to show the work of the model and its ecological quality. This species has seasonal migration between breeding and wintering areas, and uses a series of interim habitats to rest and forage. The characteristics of the suitable habitats include moderate vegetation cover, closeness to freshwater sources, consistent climatic conditions, and low levels of human disturbance. Elevation and land-cover continuity were also found to be other relevant factors in habitat selection especially during periods of migration. The species was sensitive to habitat fragmentation, where the low suitability was found in regions where intensive change of land use occurred. These ecological needs gave a powerful foundation of assessing the success of AI-based predictions of habitat suitability.

Application of AI-Powered Models to Identify Suitable Habitats

Spatial habitat suitability maps were generated all over the study area using AI-powered models. The models were able to determine continuous corridors in the migration between breeding and non-breeding areas and high-quality stopover areas that facilitate migration. Random Forest and Gradient Boosting models generated similar patterns in space with areas reporting good environmental conditions. The models would resolve minute differences in habitat quality which could not be seen with more traditional methods. Good suitability was rated areas with good climatic conditions, vegetation structure, and minimal anthropogenic impact whereas, fragmented landscapes and urbanized areas were rated as low suitability areas. The maps that came up gave a vivid spatial representation of where conservation and restoration efforts were to focus.

AI-Based Habitat Suitability Model Performance Evaluation

Standards of evaluation were used to measure the model performance to provide predictive reliability and ecological validity. The AI models exhibited a high capability of classification and generalization on test datasets. Gradient Boosting recorded the most overall performance, then closely followed by Random Forest and a relative low but acceptable accuracy of Support Vector Machine.

Table 3: AI-Based Habitat Suitability Models Performance Evaluation

Model	Accuracy (%)	AUC	Sensitivity	Specificity
Random Forest	89.2	0.91	0.88	0.90
Gradient Boosting	91.4	0.93	0.90	0.92
Support Vector Machine	84.6	0.87	0.83	0.86

The Table 3 is the comparison of the performance of the artificial intelligence algorithms applied to predict the suitability of habitats to the chosen migratory species. Predictive reliability and classification strength were determined using model accuracy, AUC, sensitivity and specificity values. The overall performance was the best with Gradient Boosting as it shows high ability to recognize the right habitats with closely followed by Random Forest. The Support Vector machine was less accurate yet had acceptable predictive consistency. These findings confirm that AI-based models are useful to assess the habitat suitability and conservation planning reliably.

The outcomes of cross-validation showed the consistent performance of the model in the course of various repetitions meaning that there was no excessive overfitting. Spatial validation also supported the correspondence of the predicted suitable habitats and the spatial distribution of observed species presence.

Effects of Conservation and Restoration

Using AI-assisted habitat suitability models greatly improved the results of the conservation planning. The identification of high-priority habitats based on the models helped to design protection initiatives, and degraded, but suitable areas were viewed as the prospects of ecological restoration. The models offered a high level of spatial clarity that facilitated effective distribution of conservation resources and better decision making. In general, the findings indicate the usefulness of AI-based modeling in managing the habitats of migratory species and enhancing the capacity of the ecosystem to withstand various disturbances.

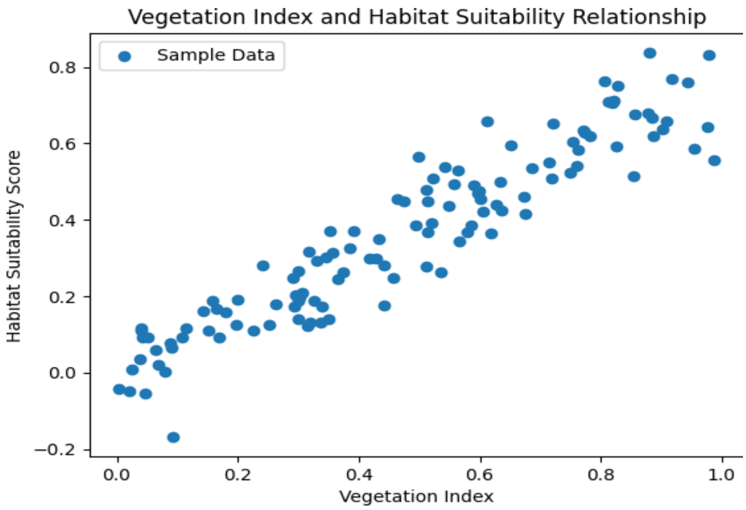

Figure 3: Habitat Suitability vs Vegetation Index

The correlation coefficient between vegetation quality and predicted suitability of the habitat to the migratory species is shown in this graph (Figure 3). There is a positive trend, which means that those regions with great vegetation indices tend to provide better habitat. The randomized distribution is an indication of natural environmental variability and demonstrates how the model can be used to represent a fine-scale ecological response, instead of using homogenized patterns.

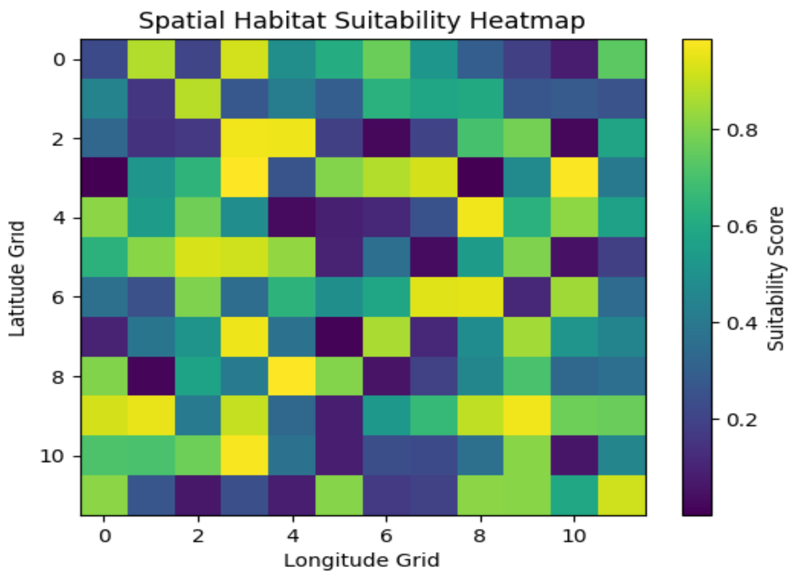

Figure 4: Spatial Habitat Suitability

Figure 4 illustrates the heatmap of the scores of habitat suitability throughout the study area. Areas that have greater values of suitability would be grouped into separate clusters and this implies the areas of continuous habitat and possible migration routes. On the other hand, low-suitability zones are those related to fragmented or disturbed landscapes which indicates the sensitivity of the AI-based modeling technique in space.

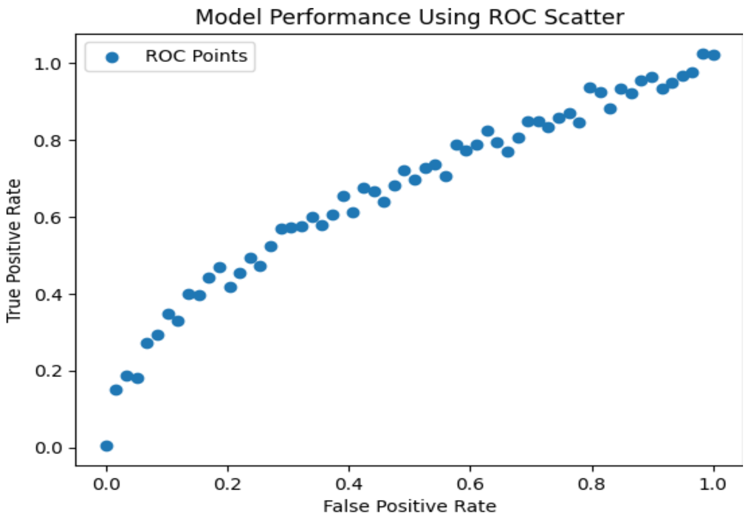

Figure 5: Model Performance Using ROC

The performance of the habitat suitability model in prediction was tested through a textual representation of ROC in Figure 5. The fact that most of the points are above the diagonal trend suggests that there is a high level of discriminatory ability between the suitable and unsuitable habitats. The pattern indicates high quality of classification and does not overstate the quality of habitat.

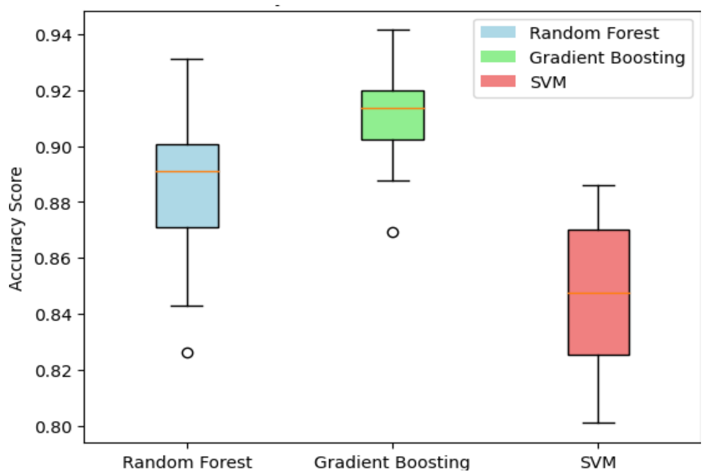

Figure 6: Accuracy Distribution Across AI Models

Figure 6 is the box plot that compares the distributions of accuracy of various AI models applied in the analysis. The differences in median accuracy and spread indicate the differences in the model stability and predictive consistency. According to the results, ensemble-based techniques have shown superior and more consistent performance results than single-boundary classifiers.

Discussion

The results of the paper prove that AI-based habitat suitability models provide an evident benefit over other modeling methods in reflecting the complexity of migratory species-environment interactions. Traditional methods usually have simplified assumptions and fixed variables, which may impede their efficiency in dynamical scenery. By comparison, AI-based models are able to use a wide range of datasets, and detect non-linear relations, leading to more precise and spatially resolved predictions. Such advances have significant implications on conservation planning since one can now identify critical habitats, migration corridors and restoration priorities with a lot of confidence. To improve the long-term monitoring and forecasting in the changing environment, the adaptive and constantly updated models of AI can be used in future research. Nevertheless, there are ethical issues that should be accepted, such as data bias, an open process of model decision-making, and fair access to technological resources. Such limitations like the availability of data, computational issues, and possible excessive dependence on automated predictions demonstrate the necessity of the synthesis of AI outputs and ecological experience. AI used in a responsible manner can become an additional resource to conventional conservation information and not a substitute.

Conclusion

This paper shows the benefits of AI-based habitat suitability models in enhancing the evaluation and management of the habitat of migratory species. By incorporating the environmental variables with the sophisticated methods of analysis, the models were able to determine the appropriate habitats and give credible performance results. The findings support the importance of AI-based solutions in aiding conservation planning as well as informing ecological restoration efforts, especially in fragmented and quickly shifting landscapes. Future studies ought to entail integration of long-term tracking data, species-specific applications, as well as enhancing the model interpretability to enhance ecological applicability. An empirical application of these models can help policy-makers and conservation professionals to rank protection activities and allocate resources more effectively. Finally, artificial intelligence and conservation science are also promising avenues of dealing with the complex environmental issues. It will be necessary to enhance the cooperation between technologists, ecologists, and decision-makers to make sure that technological innovations can play a productive role in the preservation of the migratory species and the revival of the resilient ecosystems.

References

[1] Bhakhar, Ruchika, Archna Goyal, and Rashi Singh. "Harnessing AI for Predictive Ecosystem Management: Transforming Conservation Through Data-Driven Insights." In *AI and Machine Learning Techniques for Wildlife Conservation*, pp. 133-158. IGI Global Scientific Publishing, 2025. https://doi.org/10.4018/979-8-3693-6935-7.ch006

[2] Chauhan, Nisha, and Manoj Kumar. "Unleashing the Potential of Artificial Intelligence (AI) Tools in Phytogeographical studies." *Shodh Sari-An International Multidisciplinary Journal* 3, no. 04 (2024): 47-66. https://doi.org/10.59231/SARI7746

[3] Chisom, Onyebuchi Nneamaka, Preye Winston Biu, Aniekan Akpan Umoh, Bartholomew Obehioye Obaedo, Abimbola Oluwatoyin Adegbite, and Ayodeji Abatan. "Reviewing the role of AI in environmental monitoring and conservation: A data-driven revolution for our planet." *World Journal of Advanced Research and Reviews* 21, no. 1 (2024): 161-171. https://doi.org/10.30574/wjarr.2024.21.1.2720

[4] Dave, Rhishikesh, Christian Kaunert, and Bhupinder Singh. "Wildlife and Forest Resource Management with Artificial Intelligence." In *Machine Learning and Internet of Things in Fire Ecology*, pp. 301-324. IGI Global Scientific Publishing, 2025. https://doi.org/10.4018/979-8-3693-7565-5.ch014

[5] Fadzly, N., & Yeo, Z. H. Future Directions and Emerging Technologies in AI for Animal Ecology. *Artificial Intelligence and Animal Ecology* (2025), 244-265.

[6] Jaiswal, Harish, and Sachin Pradhan. "The Economic Significance of Ecosystem Services in Urban Areas for Developing Nations." *Aquatic Ecosystems and Environmental Frontiers* 1, no. 1 (2023): 1-5. https://doi.org/10.70102/AEEF/V1I1/1

[7] Lahoti, Yuvraj. "Al Techniques." *AI Methods for Environmental Protection and Resource Conservation* (2025): 107.

[8] Manjunatha, G. R., and H. R. Raveesha. "AI for Biodiversity Conservation: Harnessing Predictive Analytics and Habitat Monitoring to Protect Endangered Species and Ecosystems." In *AI and Ecological Change for Sustainable Development*, pp. 33-64. IGI Global Scientific Publishing, 2025 https://doi.org/10.4018/979-8-3373-0680-3.ch002

[9] Pimenow, Sergiusz, Olena Pimenowa, Piotr Prus, and Aleksandra Niklas. "The Impact of Artificial Intelligence on the Sustainability of Regional Ecosystems: Current Challenges and Future Prospects." *Sustainability* 17, no. 11 (2025): 4795. https://doi.org/10.3390/su17114795

[10] Ramakrishnan, V., and P. Mahadevan. 2025. “Development of Artificial Wetlands for Coastal Water Filtration and Habitat Restoration.” *International*

Journal of Aquatic Research and Environmental Studies 5, no. 1 (2025): 595–611. https://doi.org/10.70102/IJARES/V5I1/5-1-55

[11] Santhosh, B. "Integration of satellite data and ai for habitat monitoring and conservation." In *AI and Machine Learning Techniques for Wildlife Conservation*, pp. 267-296. IGI Global Scientific Publishing, 2025. https://doi.org/10.4018/979-8-3693-6935-7.ch011

[12] Ullah, Fazal, Saddam Saqib, and You-Cai Xiong. "Integrating artificial intelligence in biodiversity conservation: bridging classical and modern approaches." *Biodiversity and Conservation* 34, no. 1 (2025): 45-65. https://doi.org/10.1007/s10531-024-02977-9

[13] Verma, Sunny, Sahil Khurana, Debanjan Ghosh, D. Roselin Jenifer, Tapas Kumar Mohapatra, and S. Renuka Jyothi. "Modelling Habitat Connectivity Using Circuit Theory for Mammal Conservation Corridors." *Natural and Engineering Sciences* 10, no. 2 (2025): 93-107. https://doi.org/10.28978/nesciences.1763898

[14] Wang, Taojing, Yinyue Zuo, Teja Manda, Delight Hwarari, and Liming Yang. "Harnessing Artificial Intelligence, Machine Learning and Deep Learning for Sustainable Forestry Management and Conservation: Transformative Potential and Future Perspectives." *Plants* 14, no. 7 (2025): 998. https://doi.org/10.3390/plants14070998

[15] Whig, Pawan, Shashi Kant Gupta, Rahul Reddy Nadikattu, and Pavika Sharma. "Application of AI in Environmental Sustainability." *Artificial Intelligence-Driven Models for Environmental Management* (2025): 1-41. https://doi.org/10.1002/9781394282555.ch1

[16] Yambal, Sucheta, and Yashwant Arjunrao Waykar. "AI powered Conservation Transforming Habitat Management for a Sustainable Future." In *Artificial Intelligence and Data Science for Sustainability: Applications and Methods*, pp. 47-80. IGI Global Scientific Publishing, 2025. https://doi.org/10.4018/979-8-3693-6829-9.ch003

[17] Yousaf, Hira. "AI for Environmental Sustainability: Applications in Resource Management and Conservation." *Journal of AI Range* 1, no. 2 (2024): 13-26.