17(4) 15-31, Winter 2025

Journal of Animal Environment

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

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

Original Research Paper

Machine Learning Assessment of Climate-Driven Shifts in Wildlife Population Dynamics Across Fragmented Landscapes

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Key Words

Climate change, Habitat fragmentation, Wildlife populations, Machine learning, Feature importance, Predictive modelling, Conservation planning.

Abstract

The human factors that have a significant influence on wildlife population dynamics include climate change and habitat fragmentation, which impact the ways species are distributed, abundant, and resilient. The traditional ecological models do not usually exhibit good predictability, usually do not account for the nonlinear interactions of climate variables and landscape structure. In this paper, a machine learning-based model is used to evaluate climate-induced changes in wildlife populations in fragmented natural environments, determine the most important environmental and spatial predictors, and measure the predictive accuracy. Data on wildlife population, climate (change in temperature, variability of precipitation), and fragmentation (patch size, edge density, habitat isolation, and connectivity) were integrated and pre-processed. Models of ensemble machine learning, such as Random Forest, Gradient Boosting, and Neural Networks, were trained and cross-validated with cross-validation. The evaluation of model performance was done using MAE, RMSE, and R2, and these features of importance and partial dependence analysis established prominent drivers of climate and fragmentation. Higher vulnerability when compared to moderately fragmented (0.98 ± 0.14) and low-fragmentation areas (1.12 ± 0.08) was observed with populations in highly fragmented habitats having the lowest mean population index (0.74 ± 0.22). Gradient Boosting was the most predictive (RMSE=0.168, MAE=0.119, R 2=0.81). The importance of features showed that temperature anomaly (0.31) and patch size (0.27) are the most influential factors, and precipitation variability, habitat isolation, and edge density were also significant. Partial dependence plots revealed that there were nonlinear population changes in response to temperature changes, but these were sensitive to extreme weather conditions. Machine learning has the potential to learn complex interactions between climate and fragmentation, and is capable of identifying the major drivers of wildlife populations. The framework gives practical information to conservation planning to assist in restoring habitat connectivity and climate-adaptive management of fragmented landscapes.

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Received: 11 August 2025; Reviewed: 23 September 2025; Revised: 03 November 2025; Accepted: 29 December 2025
(DOI): 10.70102/AEJ.2025.17.4.2

Introduction

Climate change has become one of the biggest agents of ecological transformation, with far-reaching impacts on the dynamics of wildlife populations both in terrestrial and aquatic environments (Shah, 2025). Changes in the temperature regimes, precipitation, and the rate of extreme weather conditions have a direct impact on the survival, reproduction, migration, and distribution of species. These are climate-induced pressures that tend to disturb established ecological relationships, resulting in population reduction, shifts in ranges, and alterations in community structure. The dynamics of wildlife populations under these fluctuating climatic conditions are thus a concern that needs to be understood in order to create proper conservation and management of biodiversity as well as the environment.

The effects of climatic changes are made worse in fragmented habitats with man-made landscape changes like urbanization, agriculture, and infrastructure constructions, which have not only decreased the connectivity of habitats (Bonnot et al., 2017). Fragmentation constrains the movement of species, access to resources, and enhances isolation within populations, hence weakening ecological resilience (Lin et al., 2024). In these landscapes, wildlife populations can be characterized by increased susceptibility to climatic stressors, and it is becoming very challenging to forecast the population changes using traditional ecological methods (Li et al., 2025). The investigation of the population dynamics in the fragmented environment is therefore essential to determine vulnerable species and to come up with adaptive conservation measures (Parengal et al., 2025).

Over the last few years, machine learning has become a popular analytical instrument that can provide a clear and non-linear relationship in extensive and heterogeneous ecological data (Jacobus, 2026). Machine learning algorithms may combine a variety of climatic, spatial, and biological variables in real time, unlike traditional statistical models; this approach provides a better predictive accuracy and more insight into the causes of population change. This study is aimed at using machine learning to evaluate climate-induced changes in wildlife population dynamics in fragmented landscapes to enable the provision of a data-driven framework to improve ecological knowledge and conservation decision-making (McRae et al., 2008).

Key Contributions

- The proposed study creates a machine learning-based framework to simulate and forecast the dynamics of wildlife populations in different climatic conditions on fragmented landscapes.
- It determines and measures how important climate variables and landscape fragmentation measures are in affecting changes in the population of wild animals.
- It compares and contrasts machine learning forecasting with conventional ecological modelling strategies, showing advantages and drawbacks for applying in conservation.

The rest of this paper will be organized in the following way. The literature review provided in

Section II includes the available information on the change in wildlife population and habitat fragmentation induced by climate change and the use of machine learning in ecology. Section III outlines the study region, data sources, and research methodology, such as the machine learning models and metrics of evaluation used. In Section IV, the results of the analysis are provided, and the main drivers of climate and the performance of the models are discussed in relation to population dynamics. Section V is an ecological and conservation implication of the findings, methodological limitations, as well as future research directions. Lastly, the paper ends with a Section VI that sums up the main conclusions and outlines the need to apply machine learning methods to the study of wildlife populations under changing climatic conditions.

Literature Review

Extensive ecological literature has reported a significant effect on wildlife populations by climate change, both by direct physiological stress and indirectly through effects on habitat and food supplies (Jun, 2025). The alterations in breeding phenomenology, survival, recruitment, and migration time used in taxa have been linked to long-term warming patterns and changed rainfall regimes, which frequently made population changes or redistribution to cooler or more favorable microclimates. Climate variability in most systems has been associated with larger demographic instability in which extremes like heatwaves, droughts, and unseasonal storms cause sudden decreases in population size and diminish the ability to recover. These trends suggest that drivers of climate do not act in linear mechanisms and interact with local environmental conditions, which complicate population responses from being generalized across the landscape and the species (Jennings et al., 2020).

Fragmentation of habitat is generally acknowledged to be a significant danger to biodiversity, especially since it decreases habitat size, enhances edge impacts, and breaks connectivity among appropriate patches (Sitotaw et al., 2025). Fragmentation may inhibit dispersal, decrease gene flow, and enhance the extinction probability of small subpopulations through isolating small populations and decreasing access to resources (Cheptou et al., 2017). Numerous studies have revealed that fragmentation changes the behavior of species migration, changes predator-prey relationships, and exposes the species to human disturbance (Benitez et al., 2025). In population dynamics terms, it has been found that fragmented landscapes tend to have lower demographic rescue where residential decreases are not replaced by immigration (Hesselbarth et al., 2024; Schoen et al., 2025). Notably, fragmentation may also enhance climate sensitivity, with isolated patches of species failing to keep pace with changing climate envelopes by dispersing (Das et al., 2022). Such interplay between climate change and fragmentation is becoming a significant theme of concern as a critical process determining the persistence and distribution of people in anthropogenic environments (Lin et al., 2024).

Ecological modelling has seen a rise in the importance of machine learning as it can process high-dimensional data, nonlinear interactions, and combine a wide range of data, including layers of climate data, remote sensing products, and records of species observations. Machine learning has been used in conservation biology in species distribution modelling, habitat suitability mapping, prediction of population abundance, and early detection of biodiversity loss. The tree-based ensemble methods (Random Forest and Gradient Boosting) can often be employed as shown to work with variable complexity ecological predictors and offer variable importance scores (Matyukira & Mhangara, 2023). Deep learning methods have also been of interest, especially in wildlife monitoring with images and acoustics, automated species detection, and ecological indicators of satellite images. Even with these improvements, there are still limitations to model interpretability, data bias, region and time-period transferability, and potential to learn spurious correlations with ecological processes that are not explicitly modeled. As a result, recent studies are placing a growing focus on explainable machine learning and frameworks of rigorous validation so as to have predictive gains that become meaningful ecological inference and decision support.

In general, existing literature gives a good reason to believe that climate change and fragmentation determine the dynamics of wildlife populations, and machine learning can be used to improve the predictability of ecological studies (Wu et al., 2023). Nevertheless, the number of studies that specifically integrate climate variables and fragmentation metrics to determine climate-induced population dynamics over fragmented landscapes with a single machine learning framework that can also be compared to conventional ecological analyses is lower (Fisher et al., 2024). It is this gap that drives the current study, which attempts to establish a combination of climate signals, landscape structure, and population data to create interpretable predictions that are directly applicable in conservation planning (Lapindo & Randhir, 2024).

Methods

Data Collection on Wildlife Populations and Climate Variables

The research combines multi-source information gathered to study the climate-based changes in the dynamics of wildlife populations in fragmented landscapes. The data of the wildlife population was collected using the long-term monitoring records, field surveys, and secondary ecological databases, which contained the abundance of species, density, and the change in population over time. To guarantee uniformity in datasets, it was ensured that records were filtered to come up with observations whose spatial and temporal metadata were reliable and with a high enough sampling frequency. The climate variables were chosen in order to reflect the long-term changes as well as short-term fluctuations that affect the populations of wildlife. Mean, and extreme temperatures, precipitation patterns, seasonal variability, and indicators of climate extremes, drought intensity, and heat stress were some of these variables.

Figure 1 shows the spatial situation and landscape features of the study site on three complementary panels. The figure above (a) shows the geographical location of the study region, defining its territory in the context of the general geography and drawing attention to natural objects that surround the study region to create spatial context. Panel (b) illustrates the land-cover composition and fragmented landscape structure, a representation of the distribution of the patches of forest or natural habitat incorporated between the agricultural and built-up lands. The size, shape, and space isolation of habitat patches are crucial indicators of the landscape reflection, and this panel presents that graphically. The ecological features of connectivity and the sampling framework with possible movement pathways, water bodies, and spatial sampling grids or locations that can be used to analyze wildlife populations are superimposed in panel (c). Collectively, the panels offer a whole space representation of the weaknesses in habitat fragmentation, attributes of connectivity, and data coverage to inform the interpretation of the wildlife population behavior about the landscape structure and environmental heterogeneity.

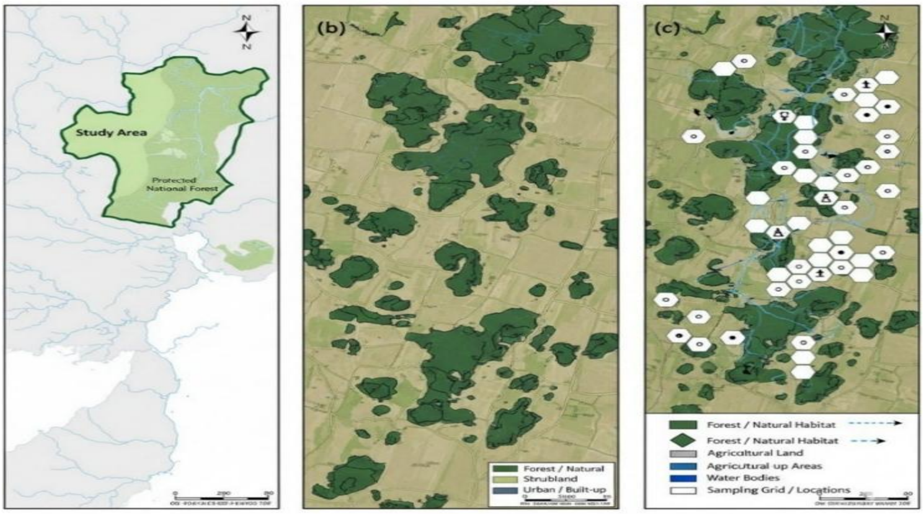

Figure 1: (a) Study Area, (b) Land-Cover Fragmentation and (c) Sampling Framework

A common geographic reference system and time scale were used to match climatic data with records of wildlife populations in space and time. Moreover, the size of patches, the density of edges, and their connectivity were also calculated based on land-cover and remote sensing data to define the structure of the habitat and its level of fragmentation. To enhance the interpretation and numerical stability of the model, all the variables were described, normalized, and checked for multicollinearity before the development of the model.

Predictive Modelling Framework Integrating Climate and Landscape Fragmentation

Figure 2 demonstrates a conceptual framework whereby climate variables and habitat fragmentation measures are combined in a machine learning pipeline in order to measure the dynamics of a wildlife population in fragmented landscapes.

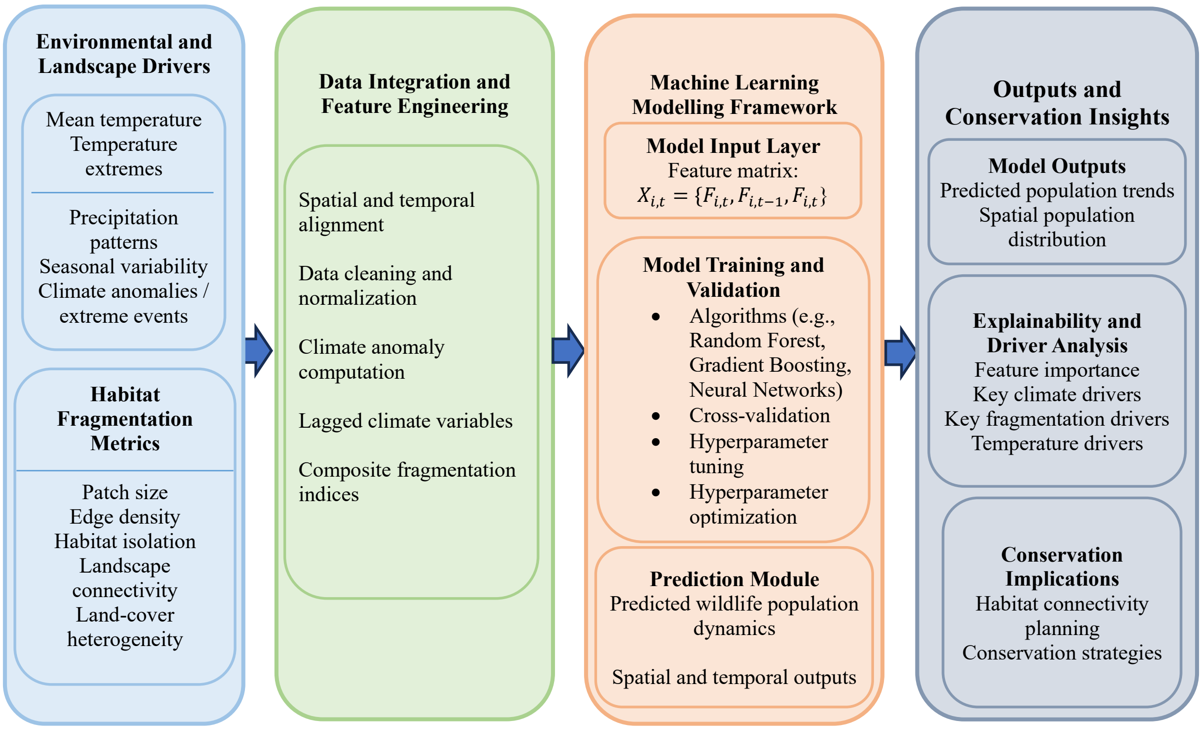

Figure 2: Machine Learning Framework for Climate–Fragmentation–Wildlife Analysis

The data integration and feature engineering process is applied to the environmental and landscape drivers, and then the models are trained, validated, and predicted. The framework generates spatial and temporal population forecasts and discovers significant drivers of climate and fragmentation, which can be used in the interpretation of the results and conservation-focused decision-making.

Different machine learning models were used to view multidimensional nonlinear interactions among climate factors, landscape fragmentation, and population dynamics of wildlife. Ensemble-based models, such as Random Forest and Gradient Boosting, were chosen due to their resistance to noisy ecological data and their ability to capture the interaction between predictors. Besides this, a neural network model was adopted to evaluate the possibility of a deeper architecture to further enhance the predictive ability of trends in populations. The recursive feature elimination method and variable importance rankings were used to select the most influential climatic and landscape drivers, which were the features. The data set was divided into training and testing sets, and the k-fold cross-validation method was used to minimize overfitting to enhance generalization. Grid search procedures were used to optimize hyperparameters of each algorithm, meaning that models were fairly compared.

Evaluation of Model Performance

As a quantitative measure, many quantitative measures were used to determine model performance, suitable for a population prediction task. To evaluate the prediction accuracy, the measures used were root mean square error (RMSE) and mean absolute error (MAE), and to determine the goodness of fit was the coefficient of determination (R2). To make a comparative analysis, machine learning outputs were compared to better traditional ecological models to measure better predictive accuracy and sensitivity to climate drivers. Besides general performance measures, model interpretability was studied with the analysis of feature importance and partial dependence plots, which provided an ecological interpretation of the significant climate and fragmentation variables affecting the population dynamics. Such an evaluation framework guaranteed that the model predictions were not only statistically sound but also ecologically useful, which justified the use of the model predictions in conservation planning and wildlife management.

Mathematical model

Let $Y_{i,t}$denote the wildlife population indicator observed at spatial location $i$and time t. Let $C_{i,t}$ represent a vector of climate variables, $F_{i,t}$ a vector of habitat fragmentation metrics, and $L_{i,t}$additional environmental or land-cover covariates shown in equation (1).

$$X_{i,t} = \left[C_{i,t}, \ F_{i,t}, \ L_{i,t}\right] \qquad (1)$$

The predictive relationship is defined in equation (2):

$$\hat{Y}_{i,t} = f_{\theta}\left(X_{i,t}\right) + \varepsilon_{i,t} \qquad (2)$$

Here, $f_{\theta}(\cdot)$ denotes a machine learning model parameterised by θ, and $\varepsilon_{i,t}$ represents stochastic noise. The formulation captures nonlinear interactions between climate, fragmentation, and population dynamics.

Climate Anomalies

To account for delayed ecological responses, climate anomalies are computed as deviations from recent historical conditions in equation (3):

$$A_{i,t} = C_{i,t} - \overleftharpoonup{C}_{i,(t-k:t-1)} \qquad (3)$$

Results

Population Dynamics in Fragmented Habitats

The analysis showed the existence of obvious spatial and temporal differences in the dynamics of wildlife populations in fragmented landscapes. The populations in highly fragmented regions were more varied and tended to have less stability than those in less fragmented or more connected regions. Specifically, fragmented areas exhibited greater changes in the abundance of the population over time, and more dramatic losses during intervals of climatic stress. These trends suggest that habitat fragmentation decreases the ability of the wildlife populations to cushion against the poor climatic conditions and thus increases vulnerability and decreases resilience. Spatial analysis also revealed that the small and isolated habitat patches were linked to the lower persistence of the population, and a landscape with greater interconnectedness promoted a more persistent population pattern. The collaboration of fragmentation and climate variability proved to be one of the central determinants of population dynamics, in that fragmentation is not only a determinant of base population levels, but it also regulates the population responses to alterations in climatic conditions. Figure 3 shows the time changes of the wildlife population index of low, medium, and high habitat fragmentation landscapes

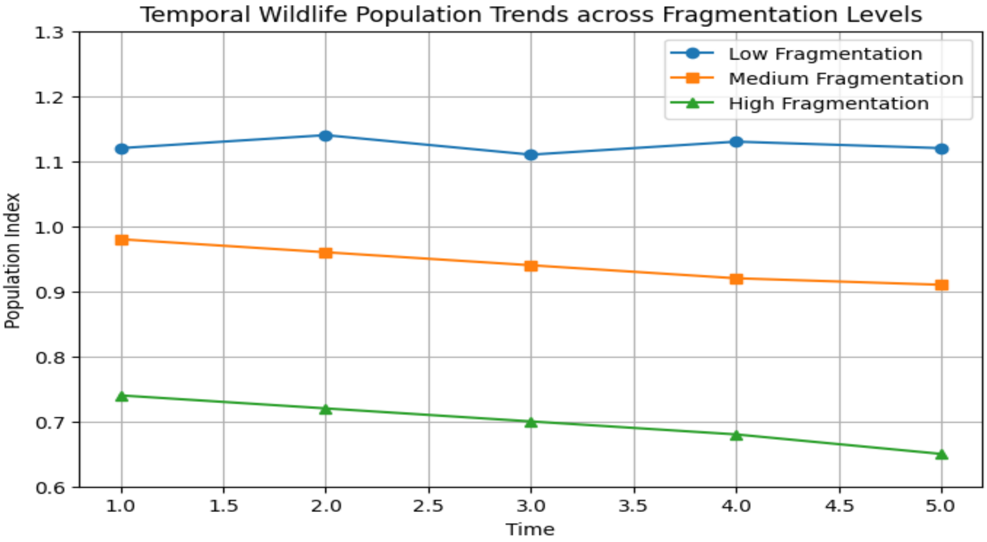

Figure 3: Temporal Wildlife Population Trends across Fragmentation Levels

The populations in low-fragmentation regions do not change as much with time, with a slight upwards movement, but medium-fragmentation landscapes are characterized by a moderate downwards movement. The fragmented habitats are the most vulnerable to changes in population indices due to the steepest decline in the indices. This number proves the existence of a negative correlation between the level of fragmentation and population stability, which indicates the ecological influence of isolation of habitats on the continuity of wildlife and justifies the incorporation of specific conservation actions.

Table 1: Wildlife Population Dynamics across Fragmentation Levels

Fragmentation Level	**Mean Population Index**	**Population Variability (SD)**	**Trend Direction**
Low Fragmentation	1.12	0.08	Stable / Slight Increase
Medium Fragmentation	0.98	0.14	Moderate Decline
High Fragmentation	0.74	0.22	Strong Decline

Table 1 provides a summary of the relationship between wildlife population and a landscape characterized by different levels of habitat fragmentation. The population of low-fragmentation regions had a mean population index with less variance, and this shows that the population conditions were very stable. Intermediate fragments exhibited a significant decrease in the mean population values with a corresponding increase in variability, indicating the building up of population stress. The least mean population index and the highest variability of wildlife population occurred in very fragmented landscapes; this is an indication of high levels of instability and high negative trends. In general, the findings indicate a strong negative dependence between the growing fragmentation of habitat and the stability of the wildlife population, which illustrates the increased susceptibility of the populations to fragmented habitats.

Key Climate Drivers Influencing Wildlife Populations

Temperature-related variables and precipitation patterns were always regarded as the most influential climate drivers by machine learning models, which influenced changes in wildlife population dynamics. Population changes were strongly linked with mean temperature, cold and hot temperatures, and season variation, especially in discontinuous habitats where the adaptive ability of species was low. It was also discovered that precipitation variability and drought indices greatly affected the change in population, especially among species that relied on consistent water supplies and plant cover. The analysis of feature importance identified that with respect to different landscapes, the comparative effect of climate drivers differed, with fragmented environments being more sensitive to extreme weather conditions than more continuous environments. Such outcomes indicate that climatic stressors in combination with landscape structure determine population responses, which is why both climatic and spatial aspects are to be considered within the ecological context.

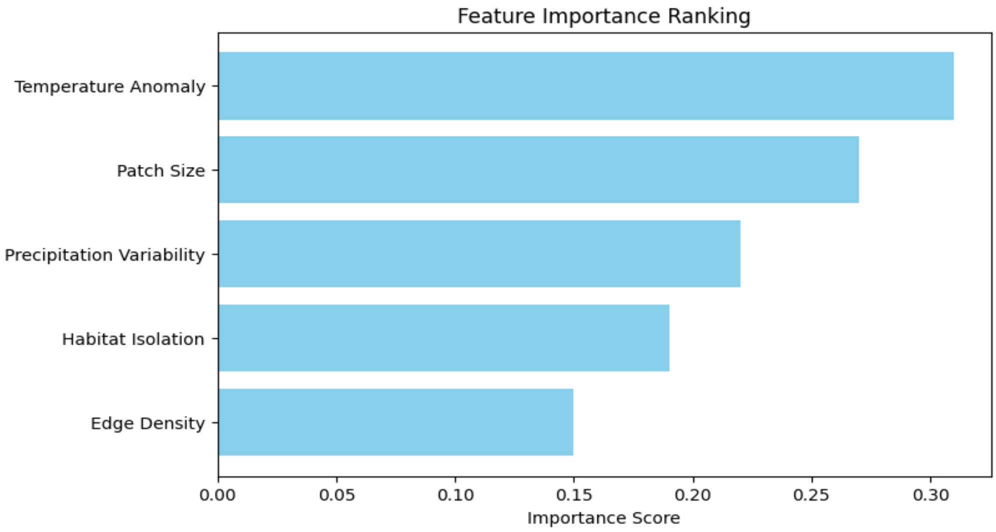

Figure 4: Feature Importance Ranking of Climate and Fragmentation Variables

Figure 4 displays the relative significance of the top five predictors that affect the wildlife population dynamics according to the machine learning model. The most significant climate variable was temperature anomaly, and the patch size was the most important fragmentation variable. The variability of precipitation, isolation of habitats, and edge density also played a significant role, pointing to the integrated impact of climatic and landscape conditions on the trends of populations. The figure enables the interpretation of important drivers, which helps in associating the model predictions with the ecological processes, and this also directs the focus of conservation efforts in fragmented habitats.

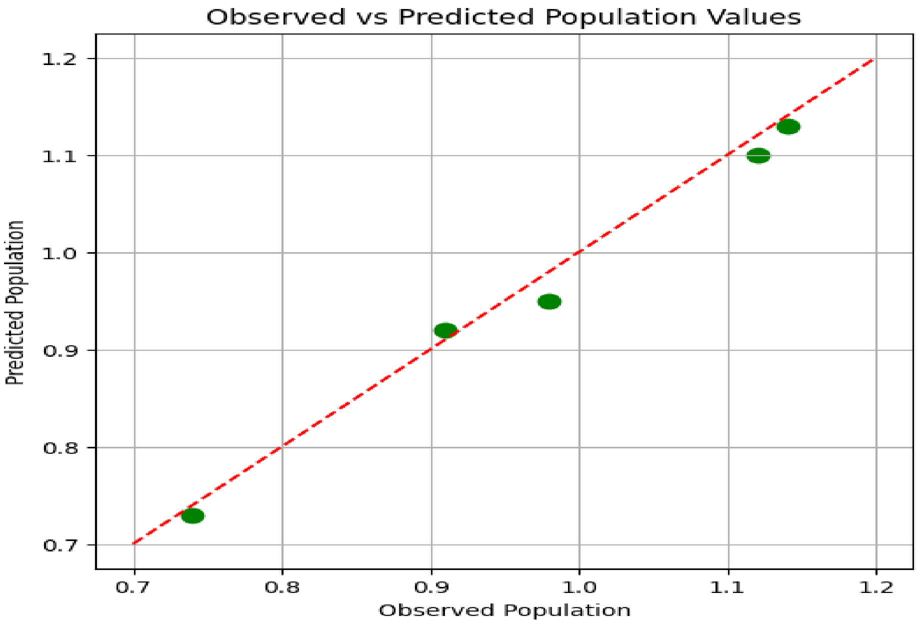

Figure 5: Observed vs Predicted Population Values

Figure 5 presents a scatter plot of actual values of wildlife populations and those of the predictions of the machine learning model with the best performance. The pair of observed and predicted population indices is represented as a point where the diagonal line is meant to be a dashed line, which shows perfect prediction. The near convergence of the points in the diagonal shows that the model has a high predictive power, and it has little bias. This value confirms that the model has been able to measure the many multi-dimensional interactions between climate variables, fragmentation metrics, and wildlife population processes, and this makes the model reliable in drawing ecological inferences and conservation plans.

Table 2: Top Climate and Fragmentation Drivers Identified by the ML Model

Rank	Variable	Category	Importance Score
1	Temperature Anomaly	Climate	0.31
2	Patch Size	Fragmentation	0.27
3	Precipitation Variability	Climate	0.22
4	Habitat Isolation	Fragmentation	0.19
5	Edge Density	Fragmentation	0.15

Table 2 shows a summary of the five most important variables that affect wildlife population dynamics according to the machine learning model. The most significant predictor was the temperature anomaly, which points to the high sensitivity of populations to temporarily deviated climate. Patch size was the second most important metric of fragmentation, which means that bigger habitat patches sustain populations that are more stable. The precipitation variability also played a significant role, and this implied the influence of the water availability on population patterns. Habitat isolation and edge density were also identified as important drivers of fragmentation, with the point that connectivity and patch configuration have a strong influence on wildlife persistence. In general, the table indicates that climate, as well as landscape structure, has a combined influence on population dynamics, which gives clear objectives when it comes to conservation management and restoration of habitats.

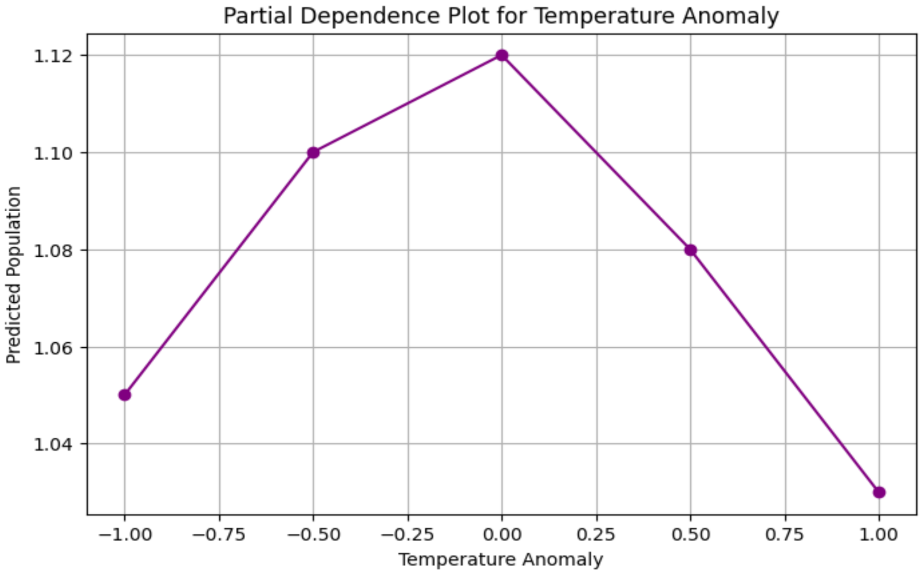

Figure 6: Partial Dependence Plot for Temperature Anomaly

Figure 6 depicts the partial dependence of the predicted wildlife population on the anomaly in temperature, which reveals that the population will respond non-linearly to the deviation of the average climate conditions. The plot shows that there is a slight rise in population indices with moderate negative anomalies, near-zero anomalies, and a decline with positive anomalies, showing that extreme increases or decreases in temperature are sensitive. This index ecologically informs on the effect of temperature changes on population processes, can be used to identify climate-stressing thresholds, and guides climate-adaptive conservation management of fragmented landscapes.

Comparison between Machine Learning and Traditional Ecological Models

Relative assessment showed that machine learning frameworks were more effective than conventional ecological frameworks in forecasting the dynamics of wildlife populations in fragmented environments. Machine learning methods had lower prediction errors and increased values of goodness of fit, suggesting better accuracy in the representation of complex and nonlinear relationships between climate variables, landscape fragmentation, and population responses. On the contrary, the performance of traditional models was lower, especially when climate variability was high and the habitat was fragmented. In addition to predictive accuracy, machine learning models offered additional information in the form of variable importance and interaction effects that were not easily obtained using traditional methods. Though the classical ecological approaches are useful in hypothesis-directed analysis and mechanistic knowledge, the outcomes suggest that machine learning is a complementary and more adaptable framework for massive, data-driven evaluations of climate-driven trends in wildlife population dynamics.

Table 3 shows the comparison of the performance of various predictive models used in forecasting the dynamics of wildlife populations. The lowest accuracy was obtained with the baseline linear regression model, with the highest MAE and RMSE, and the lowest R^2=0.48, which means that the model does not explain a lot. Conversely, machine learning models had a considerable positive impact on prediction.

Table 3: Machine Learning Model Performance Comparison

Model	MAE	RMSE	R^2
Linear Regression (Baseline)	0.214	0.286	0.48
Random Forest	0.126	0.174	0.78
Gradient Boosting	0.119	0.168	0.81
Neural Network	0.123	0.171	0.79

Random Forest was able to reduce its error by far (MAE = 0.126, RMSE = 0.174) and reach the highest R^2 = 0.78, but Gradient Boosting slightly beat all the models in terms of the lowest error and the highest R^2 (0.119 and 0.81, respectively). Neural Network also showed powerful predictions, which are similar to Random Forest, which shows the efficiency of nonlinear and data-driven models, compared to standard linear modelling, to describe the complex interaction between climate and fragmentation and wildlife populations.

Model Evaluation Metrics

The predictive performance of the proposed models is assessed using standard regression-based evaluation metrics.

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{n=1}^{N} | Y_n - \hat{Y}_n | \qquad (4)$$

In equation (4), MAE measures the average absolute difference between observed and predicted wildlife population values. It provides a clear and interpretable estimate of overall prediction error without amplifying extreme deviations.

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n - \hat{Y}_n\right)^2} \qquad (5)$$

In equation (5), RMSE quantifies the magnitude of prediction errors while assigning greater weight to larger deviations. This metric is particularly useful for identifying models that minimize substantial prediction inaccuracies.

Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{n=1}^{N}\left(Y_n - \hat{Y}_n\right)^2}{\sum_{n=1}^{N}\left(Y_n - \check{Y}\right)^2} \qquad (6)$$

In equation (6), the R^2metric indicates the proportion of variance in wildlife population dynamics explained by the model. Higher R^2values reflect stronger explanatory power and improved model performance.

Discussion

Implications of Climate-Driven Shifts for Wildlife Conservation

The results of the current research prove that the effects of climatic changes in the dynamics of the wildlife population depend heavily on the landscape fragmentation, and fragmented habitats are characterized by increased vulnerability to climatic variations and extreme events. Conservation-wise, this means that species that live in secluded and degraded areas have multiplied hazards, in which case it is the scarcity of dispersal and decreased quality of habitats that restrict their capacity to adapt to the altered climatic conditions. The findings highlight that it is important to preserve and recover the connection to habitats since interconnected landscapes were generally linked to higher population stability and low susceptibility to climate pressures. Combining climate forecasts and conservation planning on a landscape level can thus maximize the effectiveness of the strategies that are focused on preserving the wildlife population in the future in the context of environmental change. Priorities in conservation are also actionable insights on the priorities brought out by drawing the key climate drivers. The extremes of temperatures and variations in precipitation were found to be of great significance in changes in population, and therefore, conservation programs ought to consider the growing volatility of the climate in lieu of a long-term average. Offering the possibility of becoming proactive in conservation efforts such as adaptive habitat management and specific species protection, the machine learning system suggested in this paper can be used to find opportunities to implement proactive conservation strategies earlier in cases when population declines are observed as being related to certain climatic stressors.

Limitations and Challenges of Machine Learning in Ecological Applications

Though machine learning models were proven to be predictive, a range of limitations should be taken into consideration. The datasets used in ecological accounts are usually spatially biased, lack values, and are not evenly sampled, and these properties may impact the model reliability and generalization. Algorithms of machine learning can also be subject to learning spurious correlations whenever the algorithms do not have sufficient representations of the underlying processes in the environment, in the input data. In addition, although the ensemble and neural network models are high in predictive accuracy, interpreted complexities may be hindered, which makes it difficult to use them in ecological inferences and communication of policies. The other major issue pertains to the concept of transferability because models that are trained within a particular ecological or climatic environment might not perform equally well when applied to other environments or time scales. The reliance on high-quality and long-term datasets also helps to limit the applicability of machine learning solutions in data-poor conditions. Such restrictions show that it is important to validate the models carefully, report transparently, and incorporate ecological knowledge in the modelling process.

Recommendations for Future Research and Conservation Efforts

Further studies are needed to combine mechanistic ecological models with machine learning methods to strike a compromise between performance and ecological interpretability. The model can also be enhanced by the incorporation of species-specific characteristics, behavioral reactions, and demographic processes, which can strengthen the model and make it ecologically relevant. Increasing the scope of analyses in terms of both time period and taxa would also facilitate the comprehension of long-term climate- fragmentation interactions. Conservation-wise, the findings suggest the implementation of data-based decision-making models based on the integration of climate forecasts, landscape connectivity measures, and population surveillance. It is possible that the translation of the complex outputs of the models into the actions of concrete management can be done with the help of explainable machine learning tools developed specifically to support conservation practitioners. On the whole, it will be crucial to further the development of interdisciplinary methods to bridge ecology, climate science, and machine learning to counter the problem of climate-induced changes in wildlife populations in the landscape that grows significantly more fragmented.

Conclusion

This research proves that climate variability and habitat structure have a significant impact on the existence of wildlife in the fragmented environment. The mean population index was 0.74 ± 0.22 in highly fragmented populations as opposed to 0.98 ± 0.14 in moderately fragmented and 1.12 ± 0.08 in low-fragmentation habitats as a demonstration of how fragmentation reduced and increased variability. These dynamics were well represented using machine learning models, where the Gradient Boosting model had RMSE = 0.168, MAE = 0.119, and R2 = 0.81, which was more effective than a linear regression and showed strong predictive ability. The importance of the analyzed features showed that temperature anomaly (importance = 0.31) and patch size (importance = 0.27) were the most powerful factors of population change, and precipitation variability, isolation of habitats, and edge density played an important role as well.

Such findings highlight the importance of considering how to incorporate machine learning in population monitoring of wildlife species and consequently capture the main environmental and spatial drivers that can be interpreted and offer data-driven information. The framework delivers evidence-based conservation strategies such as re-establishing habitat connectivity and climate-adaptive management by merging predictive accuracy with ecological interpretability. Altogether, the paper provides the dire necessity of proactive measures to alleviate climate-induced changes in fragmented landscapes to secure the stability of the population and the existence of endangered species in the conditions of growing environmental pressures. The future studies should be oriented towards the improvement of the predictive models using the data of real-time monitoring and investigation of the long-term effects of the habitat restoration on the dynamics of populations, especially in the climate-sensitive regions.

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