Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)
Journal homepage: https://aejournals.org/

Original Research Paper

WildlifePulse: A Temporal Population Forecasting Framework for Endangered Species Conservation Management

Dr. Nidhi Mishra[1*], Aakansha Soy[2], Kunal Jha[3]

[1]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.
Email: ku.nidhimishra@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0001-9755-7950
[2]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.
Email: ku.aakanshasoy@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0002-1955-6909
[3]Assistant Professor, New Delhi Institute of Management, New Delhi, India. Email: kunal.jha@ndimdelhi.org, ORCID: https://orcid.org/0009-0006-0902-0018*

Key Words
Endangered species conservation, Wildlife population forecasting, Temporal modeling, Population dynamics, Predictive analytics, Ecological monitoring, Conservation management.

Abstract
The conservation of endangered species is becoming reliant on the need for predicting population loss in advance. Although the current census method of assessing population trends is very useful, it is not only retrospective but also lacks the ability to take into consideration the temporal trends that affect extinction risks. In this study, we develop WildlifePulse as an approach for making population forecasts of endangered species based on their historical demographic, environmental, and habitat factors. The approach leverages time series learning along with ecological feature engineering to make short- and medium-term population forecasts of endangered species. Instead of the traditional static estimation approach, the proposed system is more focused on identifying analysis of trends over a number of years in order to detect trends such as increasing rate of decline or habitat-induced stress factors. The performance of our system was tested using population and environment data of various endangered species. The results demonstrate the effectiveness of temporal modeling in increasing the reliability of forecasts over traditional static approaches, providing conservation managers with a useful tool for decision-making. In addition, the modularity of the proposed framework also facilitates its adaptability across different species according to varying data availability and monitoring efforts. This article introduces WildlifePulse as an effort towards a proactive approach in conservation management driven by forecasting, instead of reaction.

* Corresponding Author's email: ku.nidhimishra@kalingauniversity.ac.in
Received: 25th May, 2026; Revised: 6th June, 2026; Accepted: 8th June, 2026; Available Online: 07th August, 2026
(DOI): 10.70102/AEJ.2026.18.3s.59

Introduction

The decline of global biodiversity has been so rapid that reactive conservation approaches are now inadequate to address the issue of species extinction. The management of conservation has, in the past, been based on surveys of populations and habitats. Although such approaches offer valuable insights, they do not offer any predictions of future population sizes. Artificial intelligence is proving to be an approach that can adequately predict nonlinear population dynamics (Shah, 2025). Traditional methods for assessing the status of a population do not view the monitoring of a particular species as a continuous process of time but a sequence of individual instances. This kind of perspective neglects vital processes like slow deterioration of the habitat or the effect of cumulative demography pressure, which becomes apparent only when data is analyzed in sequential order. The decision-making process regarding habitat management needs to be built on concepts where this aspect will be considered (Nichols et al., 2024). This need is fulfilled by WildlifePulse by treating the conservation of endangered species from a perspective of a time forecasting challenge. The model relies on a larger trend toward the systematic incorporation of machine learning in ecological models, which has yielded consistent improvements in the accuracy of such species-focused models when built in consideration of ecological context (Miyaji et al., 2025). Contributions of this paper include (i) a time series forecasting framework that is specifically designed for data from endangered species, (ii) an ecology-based approach for feature engineering, and (iii) a performance evaluation showing better forecasting reliability compared to existing static frameworks. This paper is organized as follows: In Section II, the literature on population modeling and AI-assisted ecological forecasting is presented. The WildlifePulse model is detailed in Section III. Results are shown in Section IV, followed by implications and limitations discussed in Section V. Section VI concludes this paper.

Literature Review

Population modeling techniques have traditionally used statistics and mechanics through mark-recapture models and demographic matrices. These techniques work well under controlled circumstances but are difficult to implement over wide spatial and temporal scales and diverse data sets for the monitoring of endangered species that can be fragmented and lack data.

Species distribution models using machine learning are gradually displacing purely statistical methods, as they account for nonlinear interactions between the environment and species presence and abundance (Zhang & Li, 2017). However, most of these studies focus on the spacial distribution rather than the temporal population trend predictions. The broader survey on the use of AI in wildlife conservation also highlights promising potential but at the same time shows some difficulties (Rathi, 2025). In spite of the increase in research interest towards AI-based ecological modeling, majority of the currently available frameworks deal with either classification or spatial prediction instead of longitudinal population forecasting. Combining demographic data at different spatial and temporal scales still represents an open problem especially in terms of creating standardized frameworks able to monitor wildlife populations in time (Robinson et al., 2014). This fact represents the rationale behind the use of temporal forecasting in WildlifePulse.

Overall, the examined literature reveals a consistent trend from static, mechanistic population models to more flexible and data-driven approaches; however, temporal forecasting is still an area less explored compared to spatial and classification frameworks. The main characteristic of the current frameworks is the necessity of having scalable and standardized models that could cope with heterogeneous and multi-year ecological data. This way, WildlifePulse framework directly exploits the lessons learned from this body of work.

Methodology

Data Sources, Preprocessing, and Feature Engineering

This approach is intended to run on longitudinal databases containing information about annual or seasonal population counts, together with various environmental covariates like habitat quality index, climate parameters, food availability indicators, and anthropogenic pressure measures. Missing observations caused by unequal survey intervals are processed using suitable interpolation methods which avoid introducing any false discontinuities in population dynamics. Population counts are standardized to compensate for changes in survey effort and methodology over different survey periods. Temporal covariates are generated to represent information on trends and momentum, such as multi-year moving averages, yearly population growth rates, and lags of population counts in order to reveal acceleration or deceleration of decline trends. The environmental covariates are also adjusted in terms of time, so that habitat and climate conditions could be correlated with population dynamics in later years. Life history characteristics of particular species such as breeding period and generational time are introduced as context variables.

Predictive Modeling Approach

WildlifePulse makes use of a time series predictive modeling methodology that is specifically designed to incorporate any dependencies between years rather than making predictions based on one-by-one observations. The model uses an ordered sequence of population and environment data, discovering certain trends that can be observed before the year in question experiences periods of decline, stability, or recovery. In order to make the model sensitive to early signs of stress in population due to environmental factors, the weighting method is applied, making the contribution of years characterized by a significant demographic and environmental change more pronounced. To solve the problem of limited data available in case of endangered species, the framework uses a knowledge sharing methodology where the population trends discovered in well-monitored species can be used to forecast populations of other related or similar species that do not have long history of observations.

Experimental Setup and Evaluation Metrics

The model performance was examined through a rolling window validation method, whereby the model would be trained on the data for up to a certain year and tested on the following years that were previously unknown. The method was performed through several time windows to test the stability of the performance of the model through time. The accuracy of the forecasting was measured using common error metrics such as mean absolute error and root mean square error, and trend direction accuracy. The trend direction accuracy measures how well the model can determine whether the population is going to rise, remain stable or decrease.

Results

The performance of WildlifePulse in several datasets of endangered species shows reliable gains in prediction accuracy in comparison to static and naive baselines. In the course of the rolling window validation experiment, the time series forecast model performed better in terms of average error rate in prediction of near-term population counts as compared to static regression models, proving the value of learning historical pattern sequences for the purpose of improving prediction accuracy. Improvement was especially notable in the case of datasets with non-linear population trend, such as rapidly declining or recovering populations, where static models underperformed reliably because of inability to model the momentum of population change.

Prediction of trend direction accuracy, which is the metric that tests the ability of the model to correctly predict the general direction of population growth or decline, was significantly higher in the case when both temporal and environmental factors were taken into account compared to prediction based only on population counts. This means that the presence of environmental variables improves the ability of the model to predict the changes in the direction of population dynamics and not just extrapolate from the past dynamics.

Performance among different species depended on data availability and consistency of monitoring efforts. Species with longer and more consistent monitoring effort produced more accurate predictions, whereas species with less data benefited significantly from the transfer learning aspect, as it helped them leverage the shared temporal patterns from similar species to mitigate the lack of data. Predictions made by the model had higher uncertainty values among species with less available data, which was appropriate as it took into account the lack of data.

On the whole, these findings demonstrate the validity of the idea that endangered species population assessment viewed as a forecasting problem brings benefits compared to traditional population assessment methods, especially when dealing with species with nonlinear population dynamics.

Discussion

Ecological Interpretation of Forecasting Patterns

The better predictive performance obtained with regards to rapidly changing populations indicates that there exist many endangered species which show some demographic or environmental signals before the onset of population reduction can be seen. The capability of WildlifePulse to find those patterns emphasizes ecological importance of temporal modeling, since the latter is capable of capturing the momentum and the acceleration effect that cannot be captured by static approach.

Practical Implications for Conservation Decision Making

With regards to practical implementation of the results in conservation decision making, it should be emphasized that forecasting of population trends, even in relatively short periods of time, gives a certain period of advance for preparation of appropriate actions. Conservation managers may use forecasting in order to determine how to allocate resources or change habitat management in the face of imminent change of population trend.

Limitations and Sources of Uncertainty

Nonetheless, some limitations must be considered. The accuracy of the forecasts is reliant on the quality and reliability of the historical data for monitoring, with some species being more prone to higher forecast uncertainties owing to less available information about them. Furthermore, the forecasting system relies on the idea that the historical correlations between environmental and demographic data do not change dramatically during the period of forecasting, which can be questioned under extreme changes in the environment.

Conclusion

This paper presented WildlifePulse, a temporal population forecasting framework designed to support proactive endangered species conservation management. By reframing population assessment as a sequential, time-dependent forecasting problem, the framework demonstrated improved predictive accuracy and trend-direction reliability compared to conventional static approaches, particularly for species exhibiting nonlinear population dynamics. The framework's design supports practical integration into conservation decision-making pipelines, offering managers forward-looking insights rather than purely retrospective assessments. Its adaptability across species with varying data availability, supported by transfer learning, makes it particularly relevant for real-world conservation programs where monitoring resources are often limited. Future work will focus on incorporating real-time environmental data streams, expanding validation across a broader range of taxa, and exploring integration with spatial distribution models to combine temporal forecasting with geographic risk mapping, further strengthening WildlifePulse as a comprehensive conservation decision-support tool.

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