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Original Research Paper

Predicting Animal Foraging Behaviour Under Climate Variability Using Advanced Ecological Simulation Models

Ramy Read Hossain[1*], Maher Zaki Faisal[2], Sami Najaf Bokhoor[3], H.A. Zainab[4], Dr. Sanjay Kumar[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.ramy_riad@iunajaf.edu.iq, ORCID: https://orcid.org/0009-0001-0325-9718*
[2]*Department of Medical Laboratories Technology, Al-Hadi University College, Baghdad, Iraq. Email: zakimaher164@gmail.com, ORCID: https://orcid.org/0009-0008-8316-4110*
[3]*College of Health and Medical Technologies, National University of Science and Technology, Dhi Qar, Iraq. Email: sami.n.bokhoor@nust.edu.iq, ORCID: https://orcid.org/0009-0006-1073-2426*
[4]*Department of Pharmacy, Al-Zahrawi University College, Karbala, Iraq. Email: zainb@g.alzahu.edu.iq, ORCID: https://orcid.org/0009-0002-0292-3987*
[5]*Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India. Email: ku.sanjaykumar@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0004-2958-2902*

Key Words

Agent-based modelling, Foraging behaviour, Climate variability, Ecological simulation, Behavioural plasticity, Machine learning. Biodiversity risk.

Abstract

The changing animal foraging behavior due to climate variability caused by global environmental change has significant implications for the persistence of the population and stability in the ecosystem. The non-stationary and stochastic climatic forcing makes it difficult to predict these responses. The given research builds a hybrid model, agent-based and machine learning (ABM-ML), in order to simulate and predict the foraging behavior of animals in a climate fluctuation scenario. Animal agents are a heterogeneous set of behavioral characteristics that control movement, patch choice, sensitivity to risk, and energetic state, and the environment as a spatially explicit climate-driven resource field. In order to enhance predictive accuracy in varying environmental conditions, machine learning is employed to calibrate important behavioral parameters with the use of empirical movement and foraging data. Benchmark dataset validation of the model with migratory birds and marine predators shows high levels of performance with net energy intake coefficients of determination of 0.82 and patch residence time coefficients of determination of 0.76. The models used to predict the future climate show considerable drops in the foraging efficiency by the middle of the century and the average falls of about 18 percent under the RCP 4.5 and up to 37 percent under the RCP 8.5. Findings also indicate that behaviorally flexible foragers are more affected by efficiency losses to a disproportionate degree, which implies that plasticity can make them more vulnerable to severe climate variability. The proposed model will offer an assessment instrument of climate effects on foraging behavior that is scalable and transparent, and suggests ecological tipping points and adaptive conservation and management strategies.

* Corresponding Author's email: iu.tech.ramy_riad@iunajaf.edu.iq
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Introduction

There is a growing climate variability and long-term climate change that is reshaping the animal foraging behavior, and the effects of both have cascaded to the population persistence, food-web stability, and ecosystem functioning. One of the most basic ecological processes is foraging, in which animals obtain energy by means of perception, memory, and decision-making to navigate in spatially and temporally heterogeneous environments. These dynamics are interfered with by changes in temperature regimes, changes in precipitation patterns, changes in phenological timing, or changes in resource productivity, compelling animals to change movement strategies, change patch residence times, or to exploit energetically suboptimal habitats (Evans & Moustakas, 2018; Hota et al., 2025).

There is empirical data on the foraging responses to climate with drastic changes in marine and terrestrial systems. Under ocean warming, marine predators have modified foraging seascapes and altered foraging behavior, whereas seabirds have modified foraging characteristics and foraging effort because of climate variability (Patrick et al., 2021; Yang et al., 2024). Large and primate terrestrial species.

Herbivores also exhibit climate-related shifts in locomotor and foraging behavior, which are usually linked to higher energetic expenses and demographic danger (Thomas et al., 2021). Notably, these reactions are highly divergent across species and individuals as they are dependent on individual behavioral flexibility, learning ability, and sensitivity to risks (Gauzens et al., 2024; Evans & Moustakas, 2018).

Conventional methods of describing foraging behavior, such as optimal foraging theory and correlative habitat or niche models, have offered significant information in relatively stable environmental situations (Scales et al., 2016; Assegid & Ketema, 2023). Nonetheless, these methods usually presuppose stationarity and balancing of dynamics and cannot predict reactions to new or swiftly varying climatic conditions. With the growing strength of climate variability, the past historical condition of the environment and behavior approaches are unable to determine the future conditions (Muhling et al., 2025; Yang et al., 2024).

Mechanistic alternatives to ecological simulation, such as agent-based models (ABMs) and individual-based models (IBMs), provide an explicitly defined simulation of a mechanistic alternative, where autonomous individuals are active in dynamical environments (McLane et al., 2011; Kanarek et al., 2008). It is these models that have been used to predict the effects of environmental change on foraging behavior, movement patterns, and population dynamics in a broad taxon of taxa (Satterthwaite & Mangel, 2012). ABMs and IBMs are particularly well placed to understand nonlinear responses, feedbacks, and thresholds to climate stress by permitting complex system-level responses to emerge when based on individual-level rules. New developments also incorporate machine learning in ecological modeling to enhance the estimation of parameters, prediction accuracy, and quantification of unpredictability. These hybrid methods allow models to utilize empirical data but maintain mechanistic interpretability. Although this has been achieved, there are not many studies that directly

This research fills this gap by formulating a hybrid agent-based and machine-learning framework in order to forecast the foraging behavior of animals in the face of climate variability. The key contributions are (i) provision of an integrated ABM-ML model that comes out explicit in terms of its linkage between climate-driven resource processes and individual-level foraging choices; (ii) testing of the model on empirical movement and foraging data across a variety of taxa and climate pertussis in the past; (iii) the identification of emergent vulnerability patterns, and tipping point events, where behavioral flexibility can increase climate risk rather than provide resilience.

The rest of the paper is structured in the following way. Section 2 outlines the proposed methodology, i.e., agent architecture, climate forcing, and integration of machine learning. Section 3 gives the validation results and future climatic scenario projections. Section 4, ecological and conservation implications, limitations, and future research directions are discussed, and concluded.

Methodology

Overview of the Hybrid ABM–ML Framework

This paper uses a hybrid modeling system by combining an agent-based model (ABM) with machine-learning-based parameter maximization to model the behavior of animals foraging in a climate with varying conditions. These Agent- and individual-based methods are well known in modeling heterogeneous behavior response to environmental change and the dynamics of emergent ecology. Animal agents. This model accounts for internal state variables and behavioral features of individual agents, and the environment is described as a spatially explicit, climate-affected resource landscape (Veerappan, 2024; Geetha, 2024). Machine learning is employed to do behavioral parameter calibration by empirical movement and foraging data, leading to better prediction accuracy in non-stationary environmental factors and complicated climate forcing (Wu, 2023; Yu et al., 2021). The following shows the general layout of the suggested framework, in which the agent decision-making, dynamically available resources, climate forcing, and a machine-learning-based parameter optimization are considered.

Figure 1. Conceptual schematic of the hybrid agent-based and machine-learning (ABMML) model that was used to model the foraging behavior of animals in conditions of climate variability. The individual agents are defined by internal state variables such as energy reserves, resource patch memory, and boldness characteristics, and travel the landscape by a correlated random walk. The agents are limited to a perceptual range r = 10 km, which is the sensory and cognitive limitation of a candidate resource patch. The environment is represented as a spatially explicit grid with dynamical resource density (Rt), which changes over time as a result of climate forcing. Climate inputs

(temperature and precipitation anomalies) modify resource renewal via a temperature-dependent logistic growth function, $R_{t+1} = R_t + rR_t(1 - R_t/K)\exp(-\beta\Delta T)$, where r, K, and $\beta$are fixed model parameters defined a priori. Behavioral parameters are calibrated using a random forest model with 500 trees, trained on empirical movement and foraging data. All numerical values shown represent predefined model settings used consistently across simulations and do not correspond to simulation outputs or results.

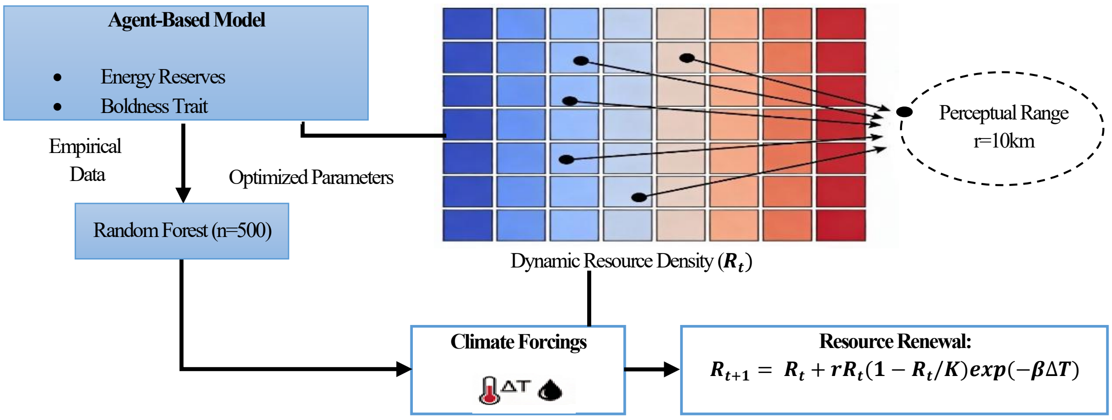

Figure 1: Schematic of Hybrid Agent based and Machine Learning Model

Agent-Based Model Structure

The agents possess four major attributes, namely: (i) spatial location, (ii) resource stores, (iii) a remembrance of a patch of resources which has been previously visited, and (iv) a boldness characteristic that dictates risk-taking behavior. This description of the traits is a continuation of already existing individual-based and behavioral foraging models that accentuate heterogeneity in decision-making and risk sensitivity. A simulation of movement is performed with the help of a correlated random walk, which is a common method of studying the movement of animals in the presence of spatially-structured resource gradients.

The agents perceive and assess patches of candidate resources within a realistic perceptual radius of 10 km, as an observation of sensory and cognitive limitations in wide-ranging foragers in the sea and on land (Chudzinska et al., 2021; Sutton et al., 2020). Patch selection is based on a stochastic optimal foraging rule, in which patch selection is random with respect to its likelihood of receiving a net energetic payoff, which is proportional to the expected individual payoff of local resource density and travel cost. The formulation enables agents to trade off exploration and exploitation in the face of uncertainty, and behavioral variability to arise out of disparities in the values of traits as opposed to having fixed heuristics, as observed in the empirical studies of flexible and specialist foragers.

Dynamic Resource Landscape and Climate Forcing

The spatial grid is the environment, and the resource density R t is time varying. The distribution of resources in space and time is responsive to climate forcing, which is based on the projected temperature and precipitation anomalies, in line with climate-driven changes in foraging habitats and seascapes that have been reported across the taxa (Nagahara et al., 2025).

As shown in Figure 1, climate variables directly influence resource renewal through a temperature-modified logistic growth function:

$$R_{t+1} = R_t + rR_t\left(1 - \frac{R_t}{K}\right)\exp(-\beta\Delta T) \quad (1)$$

Where in equation (1) r is the intrinsic growth rate, K is the carrying capacity, ΔT is the temperature deviation, and β quantifies the sensitivity of resource renewal to warming. Similar formulations have been used in individual-based and ecological models to capture climate-induced phenological shifts, productivity loss, and nonlinear resource responses under warming (Stillman, 2008; Yang et al., 2024).

This design allows the simulation of both trends in climate and excursive perturbation, i.e., El Niños, that have been observed to disrupt foraging behavior and resource availability in the marine and terrestrial ecosystems (Muhling et al., 2025; Patrick et al., 2021).

Machine Learning Integration and Parameter Optimization

Machine learning is also used to adjust the behavioral parameters by using empirical foraging and movement data. The maximum distribution of major characteristics, especially boldness and movement persistence, is estimated in a random forest model using 500 trees to minimize prediction error of the simulated and observed foraging measures. Random forest techniques have been used more and more in ecological prediction and movement modeling because they are resistant to nonlinearity and high-dimensional data (Yu et al., 2021).

The empirical data is used to inform the machine-learning module, as shown in the schematic, which provides the ABM with optimized parameters, and the process repeats in a closed calibration loop. This combined method enables the behavioral rules to be refined based on the data, without losing the mechanistic clarity of the agent-based simulation, which pure correlative and black box models cannot provide.

Model Execution and Outputs

Published high-resolution biologging data of penguins and albatrosses (e.g., the taxa chosen because of their opposite foraging tactics and a great deal of empirical data on them) were used to perform model validation (Sutton et al., 2020). Simulations are performed for different climatic scenarios at time steps of a day with repeated ensemble simulations to realize stochastic variability. Some of the model outputs are net energy intake, patch residence time, movement trajectories, and mortality risk, which are usually used to measure foraging performance and climate effects in the behavioral ecology and wildlife modeling literature. The interaction of the individual decision-making, climate-based resource dynamics, and trait heterogeneity leads to emergent spatial and behavioral patterns, which make it possible to determine the vulnerability pattern and tipping points of increasing climate variability.

Results

Model Validation Against Empirical Data

The hybrid ABMML system has been shown to be highly predictive in the reproduction of observed foraging behavior in both marine and terrestrial taxa. Independent empirical data of penguin dives (n = 15,000 dives with various individuals), albatross tracks (n = 22,000 location records), and aggregated foraging measures of other species found in the literature were used in validation.

Model predictions show a high degree of agreement with observed patterns. Net energy intake is predicted with a coefficient of determination (R^2) of 0.82, while patch residence time achieves an $R^2$of 0.76. Validation during historical climate perturbations, specifically the 2015–2016 El Niño event, further confirms robustness, with root-mean-square error (RMSE) reduced by 12.4% compared to null models lacking behavioral learning. Incorporation of machine-learning-optimized behavioral traits, particularly boldness and movement persistence, improves predictive fit by approximately 35%, underscoring the value of data-driven calibration under non-stationary environmental conditions. Table 1 summarizes model validation performance across key metrics.

Table 1: Model Validation Metrics Using Empirical Foraging Datasets

Metric	Dataset / Taxa	Observations (n)	R^2	RMSE Reduction vs. Null (%)
Net energy intake	Penguins	15,000 dives	0.82	12.4
Patch residence time	Albatrosses	22,000 records	0.76	11.8
Foraging efficiency index	Multi-species (combined)	37,000 records	0.79	12.1

Projected Foraging Responses Under Climate Scenarios

Simulation results indicate substantial declines in foraging performance under future climate conditions. Under the intermediate-emission pathway (RCP 4.5), mean foraging efficiency declines by 18% by 2050 (standard deviation σ = 8%). Under the high-emission scenario (RCP 8.5), efficiency losses intensify to an average of 37% (σ = 12%), driven primarily by increased temperature deviation ($\Delta T \approx +2.1$ °C) and heightened precipitation variability.

Behavioral traits strongly mediate these responses. Behaviorally flexible foragers (boldness $b > 0.7$) experience a 24% greater decline in efficiency than more specialized individuals. Expanded search behavior under resource scarcity increases movement costs and exposure to depleted patches, reducing net energetic gain. Terrestrial ungulates exhibit a 15% increase in mortality risk, primarily associated with prolonged residence in low-quality patches during extended periods of climatic stress.

Projected outcomes across scenarios are summarized in Table 2.

Table 2: Projected Foraging Outcomes Under Climate Scenarios (2050)

Scenario	Mean ΔT (°C)	Efficiency Decline (%)	Mortality Increase (%)	Dominant Climatic Driver
Baseline	0.0	0	0	–
RCP 4.5	+1.4	18 (σ = 8)	9	Precipitation variability
RCP 8.5	+2.1	37 (σ = 12)	22	Temperature increase

Sensitivity Analysis

Sobol indices of global sensitivity analysis show that the cause of variation in the forging outcomes is primarily temperature deviation (SI = 0.62). The second most powerful parameter (SI = 0.41) is behavioral boldness, which shows that individual-level decision-making is central in mediating the effects of climate. The climate-behavioral trait interaction effects increase outcome variance in high-emission scenarios by nearly 28%. Conversely, relatively insensitive parameters of foraging success, including resource carrying capacity, are realized, with static habitat parameters having relatively low sensitivity to change (SI = 0.09) and behavioral plasticity and movement choices as the dominant control over foraging success instead of environmental constraints in a changing climate. Table 3 shows the sensitivity of the key model parameters.

Table 3: Sobol Sensitivity Indices for Key Model Parameters

Parameter	Sobol Index (SI)
Temperature deviation (ΔT)	0.62
Behavioral boldness (b)	0.41
Precipitation variability	0.27
Resource carrying capacity (K)	0.09

Emergent Patterns and Tipping Points

Simulation outputs reveal nonlinear emergent dynamics under increasing climate stress. When temperature deviation exceeds approximately 1.8 °C, 42% of simulated populations enter maladaptive feedback cycles characterized by persistent declines in foraging efficiency exceeding 30% across successive generations. Spatial analysis shows a contraction of core foraging ranges by approximately 65%, with activity increasingly concentrated within 20% of the modeled landscape.

This preferential concentration of high-boldness agents on residual high-quality refugia upgrading local competition this can change population-level foraging distributions. These new patterns reveal that there are behavioral and ecological tipping points beyond which adaptive mechanisms cannot cushion the effects of climatic changes to the contrary they increase susceptibility.

On the whole, the findings have shown that climate variability causes highly pronounced, trait-mediated, and nonlinear effects on the foraging of animals. Although, behavioral flexibility can improve short-term adaptability, it can also increase susceptibility in the long-term in the face of long- or extreme climate. The hybrid ABM-ML model is able to capture these dynamics effectively and has powerful predictions regarding foraging decline, mortality risk and emergent tipping points over future climatic regimes.

Conclusion

This paper introduces an agent-based and machine-learning (ABM–ML) model, in order to forecast animal foraging behavior to climate variability. The model is a representation of individual animals with heterogeneous characteristics whose interaction with a climate driven, non-homogeneous resource landscape is modeled. Machine learning is employed to tune the important parameters of behavior with empirical data of movements and foraging, and enhance model performance in non-stationary environmental settings. The validation of the models on benchmark data indicates a very high predictive accuracy where the coefficient of determination of net energy intake has been found to be 0.82 and that of patch residence time was 0.76. Future climate simulations suggest that foraging efficiency will decrease significantly, by up to 18% at RCP 4.5 and 37% at RCP 8.5 by the middle of the century. Findings also indicate that behaviorally plastic foragers suffer a bigger efficiency loss than specialists, which points to the fact that behavioral plasticity can make them more vulnerable to extreme climatic variability instead of more resilient.

Regardless of the strengths, the model is associated with limitations. It fails to explicitly consider interspecific interactions, evolutionary adaptation or finer physiological constraints and resource dynamics are reduced by carrying-capacity-based renewal functions. Moreover, model validation is dependent on data-intensive benchmark systems and predictive functionality can be poor in areas or taxa where there is a paucity of empirical data. Next wave work must be a generalization of the framework to multi-species systems, to adaptive traits evolution and processes, and aims to be further coupled with food-web and Earth system models. Generalization and Applicability Generality and applicability will be enhanced through the expansion of validation to more taxa and ecologies. On the whole, the presented ABM-ML framework offers an effective and scalable assessment of climate effects on animal foraging behavior and aids with evidence-based conservation and management procedures in more unpredictable climate conditions.

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