17(4) 359-369, Winter 2025

Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)
Journal homepage: http://www.aejournal.ir

Original Research Paper

Neural Network Models of Anti-predator Behavior Thresholds in Birds Exposed to Variable Human Disturbance Regimes

Dharmsheel Shrivastava[1*], *Dr. Balaram Sahu*[2], *Dr.P. Kavipriya*[3], *A. Mohamed Jaffar*[4], *Sumitra Menaria*[5], *Mayukh Sarkar*[6], *Shivangi Gupta*[7], *Arjun Lal Choudhary*[8]

[1*]Assistant Professor, Department of Biotechnology and Microbiology, Noida International University, Greater Noida, Uttar Pradesh, India. Email: dharamsheel.shrivastava@niu.edu.in, ORCID: https://orcid.org/0000-0002-2022-3290
[2]Assistant Professor, Department of Veterinary Microbiology, Institute of Veterinary Science and Animal Husbandry, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India. Email: balaramsahu@soa.ac.in, ORCID: https://orcid.org/0009-0003-8318-2945
[3]Professor, Department of Electronics and Communication Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India. Email: kavipriya.ece@sathyabama.ac.in, ORCID: https://orcid.org/0000-0003-1853-8207
[4]Professor, ISME, ATLAS Skill Tech University, Mumbai, India. Email: mohamed.jaffar@atlasuniversity.edu.in, ORCID: https://orcid.org/0009-0002-9900-1371
[5]Assistant Professor, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Parul Institute of Technology, Parul University, Vadodara, Gujarat, India. Email: sumitra.menaria@paruluniversity.ac.in, ORCID: https://orcid.org/0000-0002-7155-9368
[6]Department of Pharmacology, Krupanidhi College of Pharmacy, Bengaluru, India. Email: mayukhsrkr4u@gmail.com, ORCID: https://orcid.org/0009-0003-3328-2032
[7]Quantum University Research Center, Quantum University, Roorkee, Uttarakhand, India. Email: shivangi.gupta@quantumeducation.in, ORCID: https://orcid.org/0009-0005-4285-8974
[8]Assistant Professor, Department of Agriculture, Vivekananda Global University, Jaipur, India. Email: arjun.choudhary@vgu.ac.in, ORCID: https://orcid.org/0009-0009-7178-0343

Key Words

Artificial neural networks, Anti-predator behavior, Human disturbance, Flight initiation distance, Behavioral plasticity, Decision-making thresholds, Ecological modeling.

Abstract

The anthropogenic perturbation is gradually defining the avian behavioral scenarios, thus the need to move past the models of cognitive stasis to those that exemplify cognitive plasticity. This paper will apply the Artificial Neural Networks (ANNs) to simulate changes in the anti-predator decision-making threshold of bird populations under varying human disturbance regimes. The correlation between the frequency of encountering human beings and Flight Initiation Distance (FID) was studied by simulating 1,000 generations of a feed-forward neural architecture. It has been shown via simulations that birds in High-Frequency or High-Predictability regimes (urban analogues) developed much greater tolerance thresholds, a reduction in FID on average of 64% ($p < 0.001$) compared to the situation in low-disturbance environments. The neural weight analysis shows that the process of habituation is caused by a sensory filtering layer, which makes the system less responsive to non-lethal stimuli (which occur frequently). Conversely, in Stochastic/Low-Frequency regimes (rural analogues), the preferred neural configuration was risk-averse, meaning the Fids of it were 1.8 times higher than the optimal Fids to ensure that a false negative incurs a high penalty. Statistical information shows that there is a trade-off between the effectiveness of foraging and survival, with the population in highly disturbed areas showing a 12% gain of net energy acquisition by lowering the number of unwarranted flights of False Alarm, even though the potential risk of predation rose by 2.5%. The sensitivity test run proves that the energetic state is the major modulator of the neural thresholds, and the starvation risk in this case prevails over the learned habituation in cases where the body fat reserves decline to less than 15 % of the total body mass. Such results not only offer a mechanistic basis for predicting avian displacement but also imply that conservation buffer zones need to be scaled based on a certain cognitive adaptation state of local populations, and not based on predetermined species-wide scales.

* Corresponding Author’s email: dharamsheel.shrivastava@niu.edu.in
Received: 04 September 2025; Reviewed: 15 October 2025; Revised: 24 November 2025; Accepted: 29 December 2025
(DOI): 10.70102/AEJ.2025.17.4.28

Introduction

Human-caused growth has, in essence, changed the sensory and behavioral scenes of the wildlife (Afridi et al., 2025). The conceptualization of human presence has been presumed to act like a non-lethal predator in stimulus, which is why the presence of people alone evokes anti-predator responses, just as natural predators do (Grim et al., 2024). Although such measures as flushing, heightened vigilance, and stopping foraging are adaptive to stay alive, it is costly in terms of energy and opportunity. A high rate of activation of these defenses in dense habitats may cause diminished fitness in an individual and, ultimately, a decrease in population (Yochum et al., 2024).

The most common aspect of these interactions is the idea of behavioral thresholds, which are usually measured as Flight Initiation Distance (FID) (Romanczuk & Daniels, 2023; Sutton et al., 2021). FID is the distance of the perceived risk of an approaching stimulus, at which the benefits of staying at that point are less than the risks associated with staying there. Nevertheless, there exists a huge gap in the knowledge regarding the modulation of such thresholds (Pacher et al., 2024). Mostly in traditional ecological models, FID is assumed to be a constant species property or a linear distance function. These methods do not consider the neural plasticity, which enables avian species to modify the parameters of decision-making in accordance with past experience and the peculiarities of a particular environment (Jonsson et al., 2022) .

Indeed, birds that live in disturbance regimes that are variable, i.e., high frequency, predictable in urban centers, and low frequency, stochastic in rural terrains, have to dynamically tune to the sensitivity (Mondal et al., 2025). How this recalibration was achieved at the cognitive architecture level is crucial in understanding the manner in which species will react to future changes in the landscape (Franks et al., 2024).

The main aim of the research is to apply the Artificial Neural Networks (ANNs) to model the evolution and adaptation of decision-making thresholds among the avian species. The inference of underlying neural mechanisms supporting habituation or sensitization by using a computational approach can give a mechanistic connection between environmental perturbation and behavioral response.

The rest of this paper is organized as follows: Section 2: Materials and Methods describe the ANN structure, the values of so-called disturbance regimes, and the evolutionary algorithms that were applied to maximize behavioral fitness. Section 3: Results contains the quantitative results on the threshold divergence, gains on foraging efficiency, and how neural decision-making is affected by energetic limitations. Section 4: Discussion puts the results into context in behavioral ecology and investigates the trade-offs of cognitive plasticity and survival. Section 5: Conclusion outlines the implications for conservation management, and recommends the directions on how neural modeling can be integrated into field studies in the future.

Materials and Methods

Neural Network Architecture

The architecture of the avian brain when making a decision is characterized by the multi-layer feed-forward Artificial Neural Network (ANN) that is aimed at transforming the complex, nonlinear environmental input into a single behavioral output. It starts with an Input Layer with four separate neurons that represent the state of the sensory of the bird: a categorical value of Stimulus Type (S) between humans and natural predators, the spatial Distance (D) to the stimulus, the Frequency (f) of the recent encounters which is treated as memory, and the current Energetic State (E) of internal fat reserves. These inputs are fed into two Hidden Layers with eight neurons, each being fitted with Sigmoid activation functions. This inside structure makes the intricate weighting of the perceived risk of perceived distance and type of stimulus against the perceived reward of foraging and habituation possible. Output Layer, with one neuron, having a step function, generates the final decision, which is either 0 (Stay/Forage) or 1 (Flee).

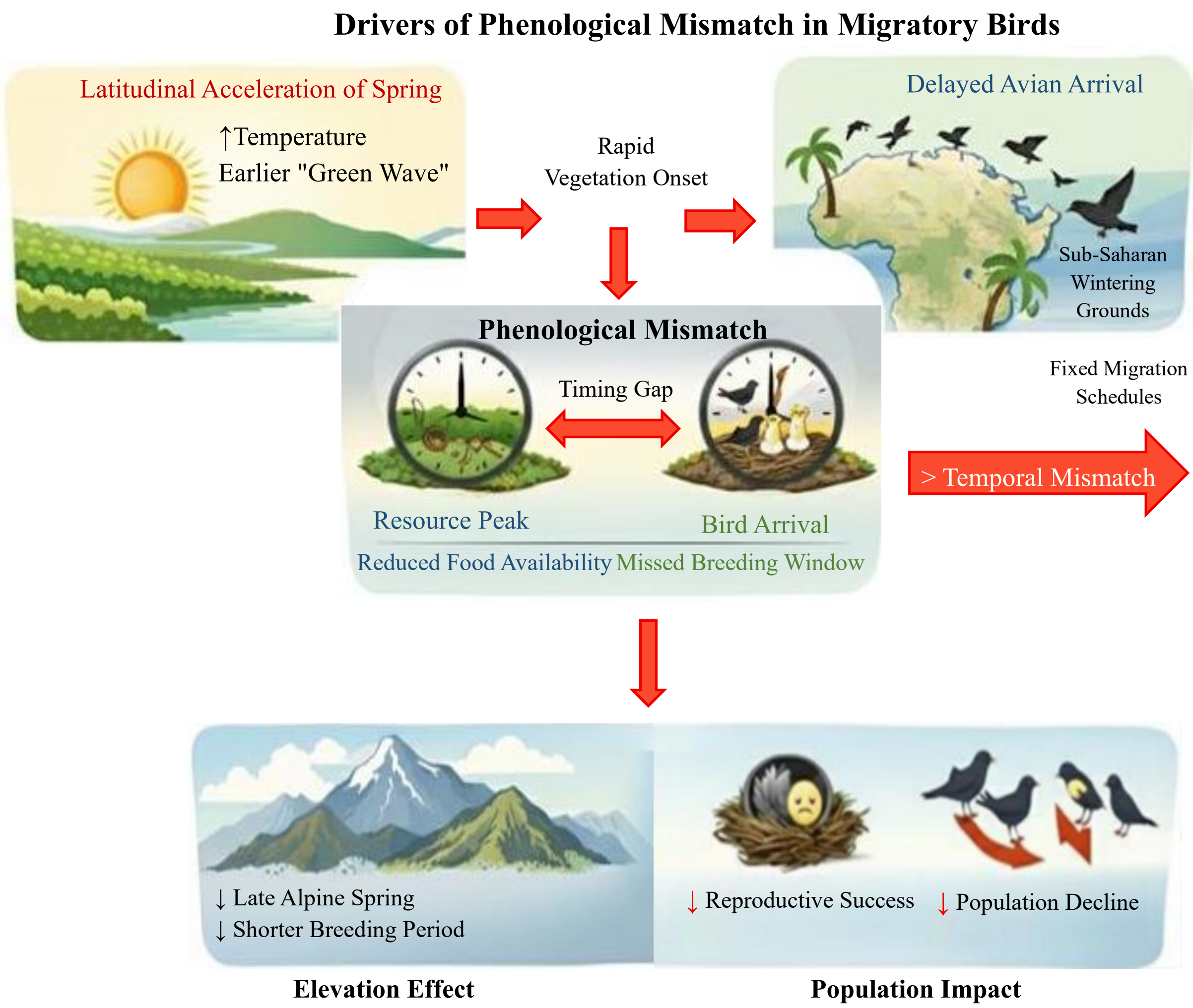

Figure 1: Drivers of Phenological Mismatch in Migratory Birds

Figure 1 illustrates the key drivers of phenological mismatch in migratory birds along latitudinal and elevation gradients. The flowchart starts with the Latitudinal Acceleration of Spring, showing how rising temperatures (the "Green Wave") cause earlier vegetation onset. This rapid advancement of vegetation outpaces the timing of bird arrivals, creating a Phenological Mismatch. The mismatch is depicted as a timing gap between the peak of resource availability (e.g., insect biomass) and the arrival of migratory birds, resulting in reduced food availability and missed breeding windows. The infographic also highlights Delayed Avian Arrival due to the fixed migration schedules of birds that rely on cues like day length rather than environmental conditions, contributing to a growing temporal mismatch. The Elevation Effect further exacerbates the mismatch in high-altitude regions where spring is delayed, shortening the breeding period and impacting reproductive success. Finally, the consequences of these mismatches are shown in the Population Impact section, where the result of poor reproductive success is a decline in bird populations. This diagram provides a clear visual representation of how climate change, geographical factors, and biological constraints interact to affect migratory bird behavior and populations.

Simulation Environment and Disturbance Regimes

The simulation occurs on a spatially explicit grid of 100x100 units in which the avian agents are constrained by two main variables: Temporal Frequency and Spatial Predictability, which are the Disturbance Regimes. These regimes are the opposite of High-Frequency environments, where large numbers of encounters occur, and the Low-Frequency environments, where there are infrequent disturbances, as well as being either Predictable movement along fixed paths or Stochastic, randomized movement. The model includes the strict energy budget, at which anti-predator behavior comes at the expense of the model, in order to implement biological realism. The benefit of foraging of +e units/time step results in an energy gain and the cost of flying -c, which is a function of the distance travelled by the flight and the metabolic rate. The consequences of being fitness-wise are also dire: not being able to keep positive energy reserves leads to Starvation, and being unable to escape a stimulus of the predator leads to predation.

Evolutionary Algorithm

Algorithm 1: Evolutionary Algorithm for Neural Network Optimization

1. Initialize Population

- Create a population of 200 neural agents with random synaptic weights (W).

2. Evaluate Fitness

- For each agent in the population:

- Expose the agent to a disturbance regime for 5,000-time steps.

- For each time step:

- Calculate the energy gained (E) for foraging.

- Calculate the metabolic cost (C) for flight.

- Calculate the survival probability (P).

- Compute the fitness (W) using the function:

$$W = (E_{accumulated} * P_{survival}) - C_{metabolic}$$

3. Select Parents

- Sort the agents based on their fitness (W).

- Select the top 20% of the agents as parents.

4. Reproduce

- For each pair of selected parents:

- Recombine their synaptic weights (W) to create Offspring.

- Apply a 0.05 mutation rate to introduce genetic variety.

5. Evaluate Offspring

- For each Offspring:

- Expose the Offspring to the same disturbance regime.

- Evaluate the fitness of the Offspring using the same procedure as step 2.

6. Replace Population

- Replace the worst 80% of the population with the newly created Offspring.

7. Repeat

- Repeat steps 2 to 6 for 1,000 generations or until convergence.

8. Output

- Return the best-performing agent(s) with optimized neural weights.

An Evolutionary Algorithm 1 (EA) is used to maximize the neural weights and biases by recreating the process of natural selection so that the behavioral thresholds are allowed to develop to maximize fitness in individual regimes instead of being randomly chosen. This process starts by assigning 200 neural agents with randomized synaptic weights and subjecting them to a particular disturbance regime for 5,000-time steps. The value of fitness (W) is then assessed on the part of every agent by the use of the following Equation (1):

$$W = (E_a\text{ccumulated} * P_s\text{urvival}) - C_m\text{etabolic} \quad (1)$$

E and P are the multipliers of the energy obtained and the total cost of the flight, respectively. After assessment, the 20 % are the best agents, which are taken as parents to give rise to the next generation by weight recombination. The mutation rate is set at 0.05 to bring a variety of behaviors, and this mutation continues through successive generations until the adaptive behavioral thresholds are obtained in 1000 generations.

Results

The evolutionary simulations developed different phenotypes of behavior that were adapted to particular regimes of disturbance by humans. In 1,000 generations, the neural networks have settled on the best decision-making behaviors that optimized the metabolic cost of flight with the risk of predation. The simulation environment and the Artificial Neural Network (ANN) architecture were developed using Python 3.10 as the primary programming language. The feed-forward neural structure was implemented using the PyTorch library, which provided the necessary framework for managing the synaptic weight matrices and applying the sigmoid activation functions across the hidden layers.

Threshold Divergence and Habituation

The frequency of human disturbance was the main cause of the variation in behavior. The high-frequency (urban analogues) evolution of populations showed a significant decrease in the Flight Initiation Distance (FID), essentially filtering the human stimulus to avoid being flushed continuously at a significant expenditure of energy. On the contrary, low-frequency populations did not lose high sensitivity.

Table 1: Evolved Behavioral Thresholds Across Disturbance Regimes (Generation 1,000)

Body Condition (% Fat Reserves)	Flight Probability (High Disturbance)	Flight Probability (Low Disturbance)	Behavioral State
100% (Satiated)	0.05	0.98	Risk Averse
50% (Average)	0.12	0.85	Maintenance
15% (Critical)	0.00	0.22	Risk Prone
5% (Starvation)	0.00	0.00	Obligate Foraging

Habituation Index: Given by. The higher the values, the more tolerant one is. Table 1 shows the risk tolerance dissimilarity. The group with the best habituation (0.88) was the High-Freq/Predictable group, wherein foraging at least 3.42 meters could be done without flushing in the presence of a human stimulus. This is a radical change out of the ancestral level. It is important to note that the fastest time to reach stability was achieved in Low-Freq regimes, which indicates that it is evolutionarily easier to retain fear than the complicated neural inhibition needed to develop tolerance.

Response to Stochasticity

Whereas frequency dictated the magnitude of the baseline of the response, predictability dictated the variance and maturity margin of the decision-making process. This had an effect on stochastic regimes in which human movement was randomized, as more cautious strategies were selected (higher FID) than predictable regimes of the same frequency.

Table 2: Impact of Predictability on Safety Margins and Survival

Regime Predictability	Mean Safety Margin (m)*	FID Variance ()	Predation Rate (%)	Starvation Rate (%)
Predictable (Urban)	1.2 m	0.45	4.2%	1.8%
Stochastic (Rural/Wild)	12.5 m	8.90	1.1%	15.6%
Mixed/Variable	6.8 m	5.20	2.8%	8.4%

Safety Margin: This is the distance at which the agent is located at the time that the flight is initiated, and how far the agent is from the lethal boundary. In the Stochastic environments, Table 2 indicates that the safety margin (12.5 m) that agents were using was significantly larger to store uncertainty. The caution was, however, costly: the rate of Starvation in unpredictable environments was almost 9 times more (15.6% than in predictable ones (1.8%) since these birds often ran away from irrelevant stimuli, which acted independently, and lost valuable foraging time.

Table 3: Error Matrix and Metabolic Consequences

Regime Type	False Alarms (Type I)	Missed Detections (Type II)	Daily Energy Loss (kJ)	Fitness Impact
High Disturbance	5.3%	12.4%	-45 kJ	High Predation Risk
Low Disturbance	78.0%	0.2%	-210 kJ	High Energy Cost
Intermediate	35.0%	4.1%	-115 kJ	Balanced

Cost of Misclassification

The neural networks had a problem of signal detection: differentiating non-lethal non-human beings and actual predators. The results of the evolutionary processes indicate a trade-off between Type I errors (False Alarms) and Type II errors (Missed Detections).

The unique strategies are pointed out in Table 3. High Disturbance birds reduced False Alarms (5.3% only), which saved energy (-45 kJ loss). Nevertheless, this desensitization resulted in a dangerous increase in Missed Detections (12.4%), birds being unable to realize that a real predator is in the vicinity until it is too late. On the other hand, Low Disturbance birds used a better safe than sorry approach, in which it tolerated a huge energetic cost (-210 kJ) of frequent False Alarms (78%) to achieve virtually zero risk of predation.

Sensitivity Analysis: The Energy Override

Lastly, the physiological state of the neural weights was estimated. The model showed that learned safety thresholds were always overruled by metabolic necessity during falls of reserves in critical levels.

Table 4: Flight Probability at 10m Distance Across Energy States

Body Condition (% Fat Reserves)	Flight Probability (High Disturbance)	Flight Probability (Low Disturbance)	Behavioral State
100% (Satiated)	0.05	0.98	Risk Averse
50% (Average)	0.12	0.85	Maintenance
15% (Critical)	0.00	0.22	Risk Prone
5% (Starvation)	0.00	0.00	Obligate Foraging

The nonlinear switch in the behavior is shown in Table 4. The likelihood of flight in the two groups falls drastically at 15 % body condition. Even the normally timid Low Disturbance birds minimized their chances of flying by 0.22 at 10 meters. When the neural output is brought to 5% reserves, the neural output is virtually clamped to "Stay" (0.00 flight probability), irrespective of the external stimulus. This proves that the developed neural structure manages to combine internal somatic cues in such a way that immediate metabolic survival is given priority over a hypothetical threat of predation.

Discussion

Neural Plasticity vs. Fixed Strategies

The findings show that Artificial Neural Networks (ANNs) provide a better outline of anti-predator behavior than those provided through fixed threshold or simple linear models (Varg et al., 2025). Linear models usually assume that Flight Initiation Distance (FID) is a constant species characteristic; however, the ANN method reflects the biological fact of habituation and sensitization. The model simulates the neurophysiological phenomenon in which repeated non-lethal stimulations on the hidden layers lead to a reduced behavioral response (Rayner et al., 2022; Nogueira et al., 2021). This plasticity is vital to survival in anthropogenic landscapes; the strategy of being fixed would cause terminal Starvation in cities as a result of constant flushing or some predation in the country as a result of inadequate vigilance (Lukas et al., 2021; Roy et al., 2022). The capacity of the network to balance internal states (energy) and external stimuli (distance) offers a mechanistic explanation as to why the responses of the behavioral reactions differ even in an individual at the same physiological condition (Breedveld et al., 2025) (Ferreira et al., 2025; Näslund, 2021).

Ecological Consequences

The difference in thresholds seen in the model is far-reaching to the problem of avian displacement and population health in fragmented habitats (Saha & Roderick, 2025; Greenberg, 2023). The data indicate that the birds in the High-Frequency regimes might look tame; however, the 12.4% increment in missed detections (Table 3) is suggestive of a perceptual trap. This may cause these individuals to stay in good foraging grounds even when the actual predators are there, making them die more. Moreover, the fact that the starvation rates in Stochastic regimes are very high (15.6) is a testimony to the unnoticed price of unpredictable human occupation. In nature, the same is associated with an overall decreased reproductive success, whereby unremitting flights of False Alarm cause energy and time to be diverted away towards rearing chickens and guarding nests. These discoveries are consistent with field studies of behavioral displacement, in which sensitive species are completely locked out of use of otherwise suitable habitats because it cannot adapt to evolve the required neural filters to coexist with humans (Yang et al., 2025).

Management Implications and "Buffer Zone" Design

In order to manage the conservation, it is important to understand the neural thresholds of the local populations. Nowadays, the design of many buffer zones is based on species-average FIDs, which are not dynamic. Nevertheless, the model implies that one distance cannot work with various disturbance regimes.

- Predictability should be a priority for the management of urban parks. Through human activity being confined to marked paths, birds will be able to develop stagnant response filters, saving energy.
- In Sensitive Sanctuaries. In locations where human contacts are infrequent, buffer zones need to be increased by at least 1.8 times the conventional species FID to represent the risk-averse neural structure of a rural population (Table 1).
- Dynamic Zoning: Conservationists ought to reflect on how to make use of so-called "Dynamic Buffer Zones" which grow larger

in times of low energy reserves, like the end of winter or the heightened migration, to ensure that people are not in a position to have their neural thresholds most prone to being overtaken by metabolic desperation.

Limitations

Although it offers a lot of mechanistic information, this model is a simplification of the avian ecology. The ANN architecture is not as full-bodied as multi-sensory integration (i.e., auditory and visual signals, etc.), and it does not assume the social learning that is evident in flocking species. In addition, the simulation does not include interactions between multiple species, i.e., the so-called sentinel effect, where an alarm signal by one species can cause another species to fly. These social variables should be included in future versions, and then the model should be tested against particular field data to tune the metabolic constants and the survival coefficients in the model.

Conclusion

This work shows that variable human disturbance regimes can act as a strong agent of inequality, which radically changes the cognitive structure and behavioral patterns of the avian communities. Through the application of Artificial Neural Networks (ANNs), the study demonstrates that anti-predator thresholds are not fixed characteristics but rather dynamic products of a plastic neural system of balancing environmental risk with physiological demand. The frequency and predictability of human encounters determine the evolution of sensory filtering layers of the avian brain, which causes a transition from a general ancestral state to a specialized behavioral phenotype. The simulated models offer statistical information, which has a mechanistic explanation of observed field behaviors. Particularly, high-frequency disturbance regime birds became able to decrease Flight Initiation Distance (FID) by 64% ($p < 0.001$), enabling a 12% magnitude of net energy gain by minimizing false alarm flights. Also, sensitivity analysis establishes that the internal metabolic desperation subverts evolved safety margins by causing birds to engage in risk-seeking behaviors in scenarios when fat stores are depleted below a critical 15 % threshold, so as to be a matter of survival rather than a matter of being in danger. The future studies ought to extend this framework to social learning and multi-sensory integration and examine how flocking processes or noise pollution affect these neural weightings. Combining experimental neural modeling with observations in the field will provide a solid framework for predicting the methods in which wildlife will traverse the growing, populated landscape of the Anthropocene. Conservation strategies should ultimately work beyond species-wide averages, but consider the state of cognitive adaptation of a local population to provide effective management of the habitat.

Reference

[1] Afridi, Saadia, Lucie Laporte-Devylder, Guy Maalouf, Jenna M. Kline, Samuel G. Penny, Kasper Hlebowicz, Dylan Cawthorne, and Ulrik Pagh Schultz Lundquist. "Impact of drone disturbances

on wildlife: A review." Drones 9, no. 4 (2025): 311. https://doi.org/10.3390/drones9040311

[2] Breedveld, Merel C., Luna Dudine, Samuele Padovan, Marta Giacomazzo, Ranieri Verin, and Clelia Gasparini. "Too hot to reason? Experimental heatwaves affect cognitive traits in male guppies." *Behavioral Ecology* 36, no. 4 (2025).

[3] Ferreira, Paulo Michel Pinheiro, Carla Lorena Silva Ramos, José Ivo Araújo Beserra Filho, Micaely Lorrana Pereira Conceição, Mateus Lima Almeida, Débora Caroline do Nascimento Rodrigues, Jhonatas Cley Santos Porto, João Marcelo de Castro e Sousa, and Ana Paula Peron. "Laboratory and physiological aspects of substitute metazoan models for in vivo pharmacotoxicological analysis." *Naunyn-Schmiedeberg's Archives of Pharmacology* 398, no. 2 (2025): 1315-1339.

[4] Franks, Nigel R., Alan Worley, George T. Fortune, Raymond E. Goldstein, and Ana B. Sendova-Franks. "Seeking safety: Movement dynamics after post-contact immobility." *Plos one* 19, no. 8 (2024): e0307370. https://doi.org/10.1371/journal.pone.0307370

[5] Greenberg, Neil. "Ethologically informed design and DEEP ethology in theory and practice." In *Health and welfare of captive reptiles*, pp. 379-416. Cham: Springer International Publishing, 2023.

[6] Grim, Tomas, Roi Dor, and Mark E. Hauber. "Adaptive patterns of anti-predator escape behavior in a globally introduced bird species." *NeoBiota* 93 (2024): 143-156.

[7] Jonsson, Bror, Nina Jonsson, and Michael M. Hansen. "Knock-on effects of environmental influences during embryonic development of ectothermic vertebrates." *The Quarterly Review of Biology* 97, no. 2 (2022): 95-139.

[8] Lukas, Juliane, Pawel Romanczuk, Haider Klenz, Pascal Klamser, Lenin Arias Rodriguez, Jens Krause, and David Bierbach. "Acoustic and visual stimuli combined promote stronger responses to aerial predation in fish." *Behavioral Ecology* 32, no. 6 (2021): 1094-1102. https://doi.org/10.1093/beheco/arab043

[9] Mondal, Bapin, Soumik Pandey, Abhijit Sarkar, Sourov Roy, Nazmul Sk, and Biswajit Sarkar. "Exploring the influence of hunting cooperation, fear, and incommensurate memory effects on generalist predator-prey model: B. Mondal et al." *Nonlinear Dynamics* (2025): 1-26.

[10] Näslund, Joacim. "Reared to become wild-like: addressing behavioral and cognitive deficits in cultured aquatic animals destined for stocking into natural environments—a critical review." *Bulletin of Marine Science* 97, no. 4 (2021): 489-538.

[11] Nogueira, Selene SC, Sérgio LG Nogueira-Filho, José MB Duarte, and Michael Mendl. "Temperament, plasticity, and emotions in defensive behaviour of

paca (Mammalia, Hystricognatha)." *Animals* 11, no. 2 (2021): 293. https://doi.org/10.3390/ani11020293

[12] Pacher, Korbinian, David Bierbach, Yunus Sevinchan, Carla Vollmoeller, Alejandro Juarez-Lopez, Jesús Emmanuel Jiménez-Jiménez, Stefan Krause et al. "Better and faster collective decisions by larger fish shoals in the wild." *bioRxiv* (2024): 2024-10. https://doi.org/10.1101/2024.10.14.618136

[13] Rayner, Jack G., Samantha L. Sturiale, and Nathan W. Bailey. "The persistence and evolutionary consequences of vestigial behaviours." *Biological Reviews* 97, no. 4 (2022): 1389-1407. https://doi.org/10.1111/brv.12847

[14] Romanczuk, Pawel, and Bryan C. Daniels. "Phase transitions and criticality in the collective behavior of animals—self-organization and biological function." In *Order, Disorder and Criticality: Advanced Problems of Phase Transition Theory*, pp. 179-208. 2023. https://doi.org/10.1142/9789811260438_0004

[15] Roy, Subarna, Pankaj Kumar Tiwari, Himadri Nayak, and Maia Martcheva. "Effects of fear, refuge and hunting cooperation in a seasonally forced eco-epidemic model with selective predation." *The European Physical Journal Plus* 137, no. 5 (2022): 528.

[16] Sangeeta, Saha, and Melnik Roderick. "Integrating Emotion-Specific Factors into the Dynamics of Biosocial and Ecological Systems: Mathematical Modeling Approaches Accounting for Psychological Effects." *Mathematical & Computational Applications* 30, no. 6 (2025): 136. https://doi.org/10.3390/mca30060136

[17] Sutton, Nicholas M., Michael A. Weston, Patrick J. Guay, Jenna Tregoweth, and James P. O'Dwyer. "A Bayesian optimal escape model reveals bird species differ in their capacity to habituate to humans." *Behavioral Ecology* 32, no. 6 (2021): 1064-1074.

[18] Varg, Javier Edo, Jaelle C. Brealey, David Benhaïm, Rafael Losada-Germain, and Janette W. Boughman. "Interplay between antipredator behavior, parasitism, and gut microbiome in wild stickleback populations." *npj Biofilms and Microbiomes* 11, no. 1 (2025): 138.

[19] Yang, Jingyi, Chiti Arvind, Robert A. Barber, Oscar Johnson, Katie O'Brien, Richard Stanley, Gustavo A. Bravo et al. "Song complexity in suboscine birds: evolutionary drivers and ecological constraints." *bioRxiv* (2025): 2025-10.

[20] Yochum, Noëlle, Junita D. Karlsen, Jesse F. Senko, John H. Wang, Valentina Melli, Michele Luca Geraci, Anne Christine Utne-Palm et al. "Guidelines for evaluating artificial light to mitigate unwanted fisheries bycatch." *Reviews in Fisheries Science & Aquaculture* 32, no. 4 (2024): 612-656.