A Spatiotemporal Machine Learning Framework for Ecologically-informed Bird Sighting Prediction

Abstract—**Fine-grained bird sighting prediction is crucial for advancing ecological research, informing conservation planning, and enhancing the birdwatching experience while fostering public awareness of biodiversity. The rapid expansion of citizen-based bird observation networks has led to an exponential accumulation of bird sighting records, which can be leveraged to train machine learning models for more precise predictions. However, general-purpose machine learning models often fail to incorporate ecological factors that influence bird activity, resulting in less accurate predictions. In this paper, we present an ecologically informed machine learning framework based on LightGBM that integrates spatiotemporal correlations, ecological context, and dynamic environmental variables to improve bird sighting predictions. The framework captures temporal trends using rolling windows, applies spatial smoothing to account for observation proximity, and models ecological dependencies—such as temperature-food interactions—through interaction terms. Key environmental factors, including habitat classifications, weather conditions, and seasonally adjusted food availability proxies, are dynamically incorporated to enhance ecological relevance. Evaluation results demonstrate significant improvements in predictive accuracy, with increased F1-scores compared to baseline methods. By embedding ecological principles into machine learning models, this framework enables data-driven insights that reflect real-world environmental complexities, providing a powerful tool for biodiversity monitoring and conservation strategies.**

I. Introduction

Birds are vital bioindicators of ecosystem health, providing crucial insights into biodiversity, environmental changes, and the impacts of climate change. Their presence, activity, and distribution patterns reflect the condition of natural habitats, making them essential for ecological research and conservation planning [1]. Fine-grained forecasting of bird activity—predicting the number of birds observable at specific locations on particular days—can enhance habitat preservation efforts, support biodiversity monitoring, and foster public engagement with nature [2]. By offering precise spatial predictions, such models can assist in identifying critical habitats for biodiversity monitoring and conservation planning [3].

Citizen-based bird observation networks, such as eBird [4], provide a global platform for bird enthusiasts to record species observations, including location and time. Crowd-sourced data from these networks have already been leveraged for coarse-grained analyses, such as estimating species distributions [5], modeling population changes in migratory bird species [6], and learning seasonal bird movement patterns [7]. Advancements in machine learning have further enhanced bird identification and data collection, with BirdNET [8] utilizing artificial intelligence to classify bird species from audio recordings. The integration of BirdNET into eBird has led to exponential growth in observations, reaching 226 million records in 2023.[1]. This rapidly expanding dataset presents an unprecedented opportunity to move beyond coarse-grained analyses toward fine-grained ecological insights, such as predicting bird activity at specific locations and times. However, despite its potential, this wealth of data remains largely underutilized.

While existing methods for predicting bird activity have provided valuable insights, they predominantly rely on historical observations and general-purpose predictive models [9]. However, bird activity is influenced by dynamic environmental factors such as habitat changes, food availability, and weather conditions, which these models often fail to incorporate in real time. As a result, they struggle to capture the complexity of bird movement, particularly the spatiotemporal correlations that govern migration patterns and habitat utilization [10].

Additionally, most prior studies focus on broad, geographically dispersed datasets that, while useful for large-scale assessments, often overlook localized ecological contexts that provide more actionable insights for conservation effort [11]. Furthermore, while machine learning approaches have improved species classification, they often lack the ability to integrate ecological principles effectively, limiting their interpretability and generalizability across diverse species and regions [12] . This is particularly evident in the study of complex ecological processes, such as animal movement and habitat utilization, where spatiotemporal correlations are critical but often poorly captured by existing models.

To address these challenges, we present an ecologically informed machine learning framework based on LightGBM that integrates spatiotemporal correlations, ecological context, and dynamic environmental variables for accurately predicting bird sightings. Unlike previous approaches, our framework captures temporal trends using rolling windows, applies spatial smoothing to account for observation proximity, and models ecological dependencies—such as temperature-food interactions—through interaction terms. Key environmental factors, including habitat classifications, weather conditions, and seasonally adjusted food availability proxies, are dynamically incorporated to enhance ecological relevance. While our initial implementation focuses on American Robin sightings in Michigan, the framework is designed for broad applicability, making it adaptable to different bird species and geographical contexts. Our evaluation demonstrates that the proposed framework significantly improves predictive accuracy compared to baseline methods. We achieve higher precision and recall, with

[1] https://tinyurl.com/3whdzujp

a substantial reduction in mean squared error and increased F1-scores. By embedding ecological principles within machine learning predictions, our framework provides valuable insights for biodiversity monitoring and habitat management.

The key contributions of this work are:

- A machine learning framework for bird sighting prediction that incorporates spatiotemporal correlations, ecological context, and dynamic environmental variables. By collaborating with domain experts, the framework integrates general ecological factors influencing bird activity across species and regions, enhancing its accuracy and generalizability.
- The first dataset of American Robin sightings in Michigan, capturing detailed spatiotemporal and environmental patterns. This dataset provides a valuable foundation for fine-grained bird sighting prediction and serves as a benchmark for evaluating ecological models in real-world scenarios.
- Empirical validation demonstrating superior predictive performance over baseline models.

The remainder of this paper is structured as follows: Section II details our proposed methodology, including feature engineering and model architecture. Section III details how we collected dataset for American Robin in Michigan and implemented the framework. Section IV presents our experiment setup, results and analysis. Section V summarizes existing approaches and compares them with our approach, and Section VI concludes with discussions on future directions and applications.

II. Methodology

In this section, we first present the design goals, key challenges, and an overview of the proposed machine learning framework. We then provide a detailed explanation of each step in the framework.

A. Overview: Objective, Challenges, and Solution

Our objective is to develop a method for estimating the probability of observing a given bird species at different locations within a specified region. To accomplish this, we must address the following challenges:

1) **How can we identify the ecological factors that influence bird activity and are available from existing data sources?** Bird activity is driven by a complex interplay of environmental and ecological factors, including temporal dynamics (e.g., seasonal migrations) and spatial characteristics (e.g., habitat connectivity) [13] . Additionally, the availability of relevant data must be considered when representing these factors.
   Solution: We collaborated with an avian domain expert to identify key ecological factors and explored methods for obtaining them from online web services and various data sources.
2) **How can we incorporate these factors to model their impact on bird activity?** Integrating diverse data types, such as habitat classifications, weather conditions, and food availability, requires effective data preprocessing and feature engineering [14].
   Solution: Building on previous studies [13], [14], we incorporate spatio-temporal correlations into our bird activity prediction model. Prior research has demonstrated that integrating both spatial and temporal dependencies improves predictive performance [15]. Temporal features, such as rolling windows and seasonality trends, help capture periodic behaviors like breeding and migration [14]. Similarly, spatial dependencies—arising from habitat connectivity, geographic proximity, and environmental gradients—provide crucial context for understanding bird sighting distribution patterns.
3) **How can we learn accurate predictive models especially with limited training data?** Machine learning models often fail to learn a suitable hypothesis in the presence of limited training data, making it essential to build models that can learn from limited data without compromising their predictive power [16].
   Solution: Our solution employs a LightGBM model, selected for its ability to efficiently handle categorical features and its proven effectiveness in spatiotemporal ecological modeling [17]. Unlike deep learning methods that require extensive training data, LightGBM provides robust predictions even with limited seasonal data. By leveraging a tree ensemble, our model captures complex feature relationships while remaining more transparent than deep neural networks in terms of interpretability, allowing us to get insights into the importance of features explaining the model's predictions. This balance makes LightGBM particularly well-suited for fine-grained, context-specific ecological predictions, ensuring both reliable performance and actionable insights for conservation efforts.

B. Identifying Ecological Factors

Working with our avian behavior expert, we identified several key determinants of bird activity:

- **Habitat Characteristics:** The structure and composition of habitats fundamentally influence bird presence and behavior. The domain expert emphasized how factors such as vegetation density, tree height, and foliage diversity affect nesting site selection and foraging activities. For example, studies have found that tree height, distance from central lawns, and tree coverage were the primary factors that influence the selection of nest sites in urban environments [18].
- **Climate and Weather Conditions:** Temperature, precipitation, and seasonal changes critically influence migration patterns and daily activities of birds. The expert highlighted how adverse weather can alter flight paths and timing, while favorable conditions enhance feeding efficiency following prior work. [19].
- **Food Availability:** The abundance and distribution of food resources emerged as a crucial factor in our expert consultations. Birds adjust their movements and timing

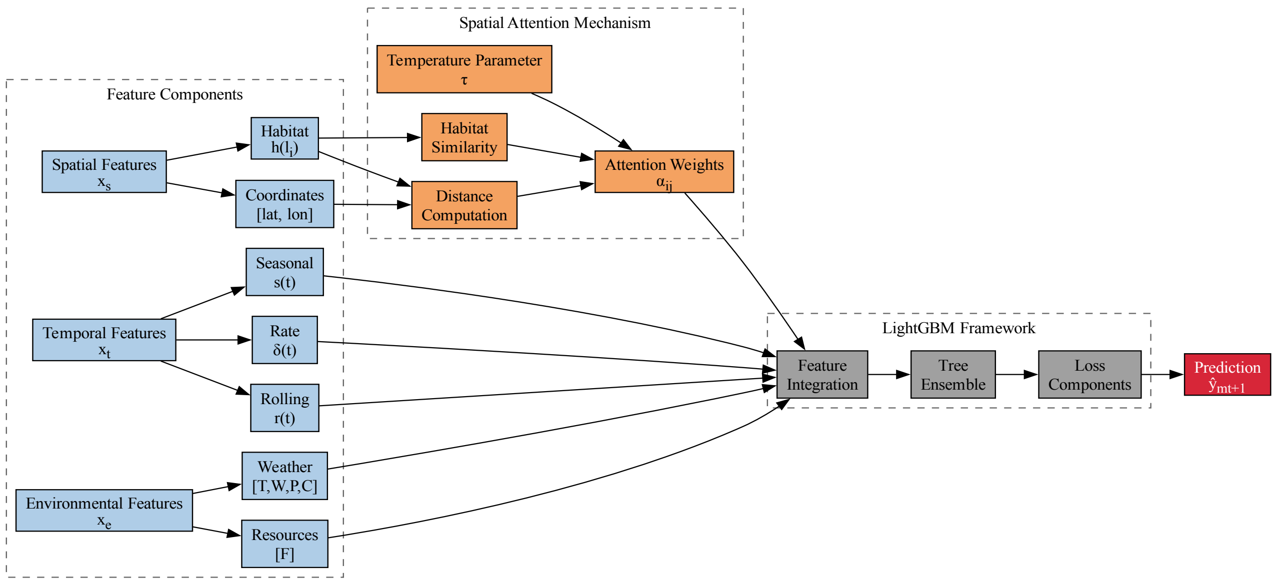

Fig. 1. Dynamic Spatial-Temporal Bird Observation Framework

to exploit areas with higher food availability, particularly during breeding and migration periods [20].

- **Human Activities:** Our expert emphasized how urbanization, light pollution, and noise can significantly disrupt natural behaviors. These human-induced factors create distinct ecological contexts that shape bird activity in region-specific ways, including altered foraging patterns around artificial food sources and adapted habitat use in urban green spaces [18].

While the domain expert identified key factors influencing bird behavior, obtaining comprehensive and reliable data sources for these factors posed a challenge. In particular, real-time food availability and habitat quality lack direct measurement methods. To address this, we approximate these difficult-to-quantify features for a given bird species at a specific location by combining: (1) the location's environmental context (e.g., presence of forest, wetland, open water, or grassland); (2) the bird's habitat preferences; and (3) the quantity and quality of suitable habitat in these contexts at different times of the year. Habitat and food preference data were primarily sourced from *Birds of the World* [21], which provides comprehensive documentation of American Robin habitat use and diet across different landscapes and seasons. This data directly informed the construction of our resource availability index. We additionally validated our habitat-diet modeling assumptions using U.S. Biological Survey records, as detailed by Wheelwright [22].

C. Feature Engineering

Given a spatiotemporal series $X_{\leq t}, y_{m,t}$, where $X_{\leq t} \in \mathbb{R}^{T \times D}$ represents dynamically encoded input features of dimension D collected until time t (T denotes the total time step), $y_{m,t}$ denotes the categorical target variable at each timestep t, the objective of the prediction problem is to estimate future target variables $y_{m,t+1}$ at time $t+1$ given the historical context $X_{\leq t+1}$. The input features $X_{\leq t}$ encompass environmental, spatial, and temporal dimensions, specifically designed to capture bird observation patterns with an ecological focus. The model generates predictions $\hat{y}_{m,t+1}$ by conditioning each step on previously observed states, ensuring temporal consistency. Bird movement patterns are fundamentally driven by three key factors: habitat suitability, temporal cycles, and environmental conditions [23], [24]. Studies have shown that habitat-driven changes significantly impact species distribution over time, necessitating dynamic modeling approaches that incorporate both spatial and temporal habitat factors [24]. Our architecture, as shown in Figure 1, explicitly models these biological drivers through specialized components, each capturing a critical aspect of avian behavior.

The proposed architecture was selected for its ability to integrate multiple drivers of bird activity into a cohesive framework. Spatial features provide critical location-specific context, temporal features capture seasonal trends and localized dynamics, and environmental features model external influences such as weather and resource availability. This multi-component design enables the model to capture complex ecological patterns essential for bird activity prediction.

The input features $X_{\leq t}$ are processed through three specialized components, each addressing a specific dimension of bird activity, as depicted in Figure 1. The spatial component, denoted as x_s represents location-specific attributes and includes geographic coordinates $[lat, lon]$ and direct habitat

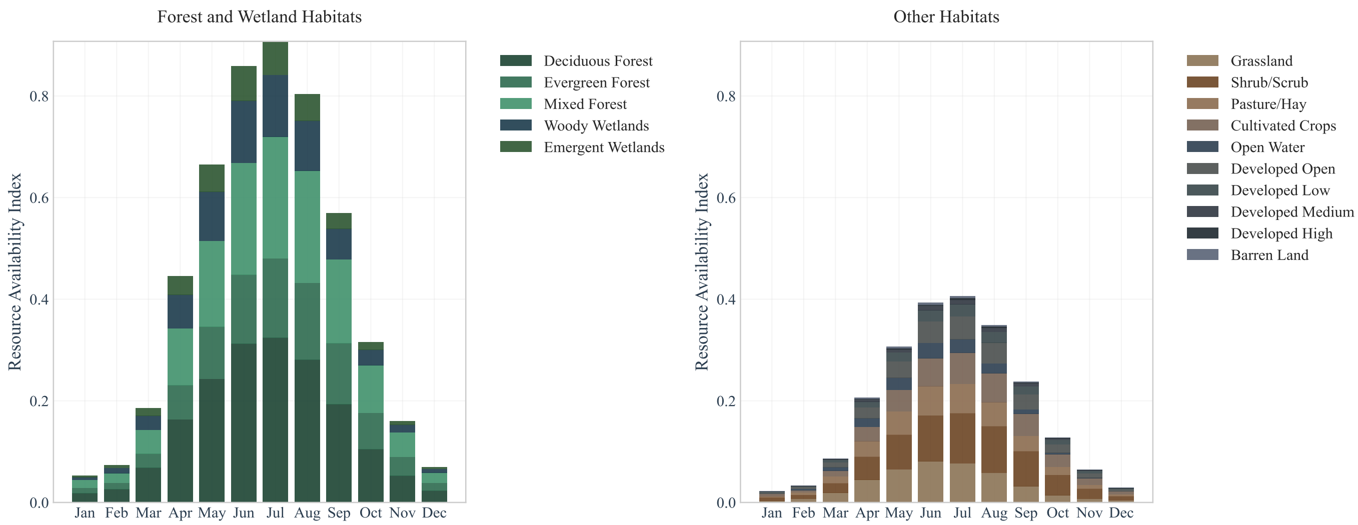

Fig. 2. Food Availability by Habitat and Season

encoding $h(l_i)$, which captures land cover classification from the National Land Cover Database. The use of direct habitat encoding simplifies the model while retaining critical ecological information.

The temporal component, denoted x_t encodes seasonal, local dynamic, and rate-of-change effects. Seasonal trends $s(t)$ are represented using sine and cosine transformations to capture annual periodicity. Localized trends are captured through rolling statistics, $r(t)$, which compute a 7-day rolling mean and standard deviation. Rate-of-change effects, $\delta(t)$, model temporal variations such as daily or weekly changes in bird activity. The 7-day window was selected based on its effectiveness in capturing weekly patterns in bird observation frequency, a practice commonly employed in large-scale bird monitoring platforms such as *eBird*. Additionally, structured data validation approaches, such as those described by Yu et al. [25], reinforce the importance of systematic temporal windows in large-scale citizen science projects to ensure data consistency and quality.

By leveraging a 7-day rolling window, the temporal component captures both circadian rhythms through daily statistics and seasonal migration patterns through annual periodicity transforms, aligning with known behavioral cycles in bird populations [23].

The environmental component, denoted x_e captures external factors influencing bird observations. This includes weather parameters $[T, W, P, C]$, representing temperature, wind speed, precipitation, and cloud cover, respectively. Additionally, a resource availability index F quantifies food and habitat availability, incorporating seasonal dietary shifts derived from ecological studies. Weather parameters directly influence bird activity patterns, with temperature and precipitation affecting foraging behavior, wind conditions impacting flight patterns, and cloud cover influencing visibility and hunting success [19]. The resource availability index captures seasonal variations in food sources that drive bird movement decisions.

The resource availability index F is constructed by combining habitat-specific seasonal patterns with environmental conditions. For each habitat type h at time t, we compute:

$$F(h,t) = w_h \cdot S(t) \cdot E(t) \tag{1}$$

where w_h represents habitat-specific weights derived from NLCD classifications, $S(t)$ captures seasonal food availability patterns documented in ecological literature [21] as a real-valued function in [0,1], and $E(t)$ represents environmental modulators (temperature, precipitation) mapped to a real value between [0,1]. Both S(t) and E(t) are continuous functions that quantify ecological patterns and environmental conditions respectively.

To illustrate how this index reflects known ecological patterns, Figure 2 presents the resource availability index for a specific bird species (Robin) across different location contexts. The figure highlights key ecological differences by dividing habitats into two categories: (1) forests and wetlands, which provide high seasonal food availability, particularly during breeding and migration periods, and (2) developed and agricultural landscapes, which offer lower and more stable but less seasonally variable resources.

This distinction enables clearer comparisons between habitats with fundamentally different ecological functions. Notably, deciduous forests show peak food availability in spring and summer due to increased invertebrate abundance, while mixed forests sustain moderate resource availability into the fall through fruit production. This multi-habitat composition aligns with documented American Robin foraging patterns [21] where different habitats offer complementary resources throughout the annual cycle.

D. Spatial Attention Mechanism

To capture location-specific patterns and spatial dependencies, the model employs a simplified spatial attention mechanism, as shown in Figure 1. For a given pair of locations l_i and l_j, the attention weight α_{ij} is computed using a softmax function as below:

$$\alpha_{ij} = \frac{\exp(-d(l_i, l_j)/\tau + \phi(h(l_i), h(l_j)))}{\sum_{k \in N(i)} \exp(-d(l_i, l_k)/\tau + \phi(h(l_i), h(l_k)))}$$

where $d(l_i, l_j)$ represents the geodesic distance between locations l_i and l_j, $\phi(h(l_i), h(l_j))$ measures habitat similarity using cosine distance and τ denotes the temperature parameter. The term $N(i)$ represents the K nearest neighbors of location i. The softmax function converts the attention weights to probability distribution. The temperature parameter τ controls the sharpness of the attention distribution, where lower values ($\tau = 0.1$ in our implementation) make the distribution more focused on the closest locations, while higher values create a more uniform distribution. We empirically found that $\tau = 0.1$ provides the best balance between local and global spatial dependencies.

The spatial attention mechanism focuses on weighting spatially close locations (lesser the distance $d(l_i, l_j)$, more is the attention weight) and ecologically similar habitats, enabling the model to capture complex spatial dependencies in bird movement patterns. The attention-weighted features, combined with the original temporal features (seasonal $s(t)$, rate $\delta(t)$, rolling $r(t)$) and environmental features (weather parameters and resource availability index), are all fed into the feature integration component of the LightGBM framework, ensuring that both raw and attention-weighted features contribute to the final prediction.

E. Core Predictive Model

Following feature integration, the predictive model is a tree ensemble to learn the best hypothesis for estimating the target variable from the input features. The objective function combines standard cross-entropy loss with penalties for spatial and temporal coherence as below:

$$L(\theta) = L^{\theta}_{ce}(y, \hat{y}) + \lambda_1 L^{\theta}_{s}(x_s) + \lambda_2 L^{\theta}_{t}(x_t),$$

where $L^{\theta}_{ce}(y, \hat{y})$ is the cross-entropy loss for classification with ground truth denoted as y and the model predictions denoted as $\hat{y}$. The spatial penalty $L^{\theta}_{s}(x_s)$ enforces consistency between predictions at spatially close locations, computed as the below Mean squared error (MSE) loss:

$$L^{\theta}_{s}(x_s) = \frac{1}{|N|} \sum_{i,j} \alpha_{ij} (\hat{y_i} - \hat{y_j})^2.$$

In the above equation, $\hat{y_i}$ and $\hat{y_j}$ refers to the model's predictions at locations i and j and α_{ij} being the respective attention weights used to account for the MSE loss between the locational predictions according to the the attention weights.

The temporal penalty $L^{\theta}_{t}(x_t)$ enforces smoothness in predictions across time steps and is defined as:

$$L^{\theta}_{t}(x_t) = \frac{1}{T} \sum_{t} \left[w_1(t)(\hat{y}_t - \hat{y}_{t-1})^2 + w_2(t)(\hat{y}_t - \hat{y}_{t-7})^2 \right].$$

In the above equation, $\hat{y}$, $\hat{y}_{t-1}$ and $\hat{y}_{t-7}$ refers to the model's predictions at time step t, $(t-1)$ and $(t-7)$ respectively. The weights $w_1(t)$ and $w_2(t)$ control the relative importance of day-to-day consistency ($w_1(t) = 0.3$) versus weekly patterns ($w_2(t) = 0.7$). The higher weight on weekly patterns reflects the strong seven-day periodicity observed in bird behavior, while still maintaining smooth daily transitions.

This integrated architecture leverages spatial attention and temporal coherence to capture complex ecological patterns in bird observations. The effectiveness of each component is empirically validated through comprehensive ablation studies and stability analysis, as detailed in Section V.

F. Hyperparameter Settings

The model's hyperparameters were tuned through cross-validation on the training set. For the LightGBM framework, we used: number of trees $= 1000$, learning rate $= 0.01$, max depth $= 8$, min data in leaf $= 20$, and feature fraction $= 0.8$. The spatial attention mechanism uses $K = 12$ nearest neighbors and temperature $\tau = 0.1$. The loss function weights λ_1 and λ_2 were set to 0.3 and 0.5 respectively, balancing the importance of spatial and temporal consistency with the primary classification objective. These values were selected to maximize F1-score while maintaining ecological plausibility of the predictions, as validated by domain experts.

III. Implementation and Evaluation

To evaluate the effectiveness of the methodology, we implement the framework for predicting American Robin sightings in Michigan, using observational data collected from the eBird platform [26]. Michigan provides a suitable study region due to its diverse ecological conditions, ranging from urban environments to forested areas, and its role as a critical stopover for migratory birds.

A. Robin Dataset

The dataset comprises 40,059 American Robin observations across 1,152 unique geographical locations in Michigan, sourced from eBird. We used observations from 2023 (January–December) for training (52.01%, 20,835 observations) and 2024 (January–December) for validation (47.99%, 19,224 observations). The training-validation split was chosen to reflect a real-world forecasting scenario, where past data is used to predict future occurrences. We ensured that seasonal trends and geographical distributions were consistent across both years to minimize biases. Observations are categorized into three classes based on count thresholds: low (1-5 birds), medium (6-15 birds), and high (>15 birds). The dataset exhibits a natural class imbalance, with small bird groups being significantly more common than large gatherings. To address this imbalance, we applied SMOTE to the medium and high classes to improve class representation in model training.

Observations are spatially referenced and temporally indexed, enabling the capture of migration patterns, habitat preferences, and seasonal changes. Data preprocessing included outlier removal ($|z| > 3$) and mean interpolation for continuous variables to preserve temporal trends. Geographical and habitat classifications were sourced from the National Land Cover Database (NLCD) 2019 release [27], while meteorological data–covering temperature, wind speed, precipitation, and cloud cover–was obtained from OpenWeatherAPI. We plan to open-source the dataset along with our prediction model upon publication.

B. Implementation Details

The implementation consists of feature processing and model training phases. For feature processing, we utilized the previously described three-component architecture, with specific implementation choices guided by domain expertise and data availability.

The model was trained using LightGBM, optimized for structured ecological data. The objective function combines cross-entropy loss with spatial and temporal regularization terms as detailed in Section II.E. We performed hyperparameter optimization using Bayesian optimization with 5-fold cross-validation, running 100 trials to ensure robust parameter selection. Results reported in Section IV are averaged over 10 independent runs with different random seeds to account for statistical variations, with standard deviations reported alongside mean performance metrics.

Training utilized early stopping with a patience of 50 epochs and SMOTE balancing to address class imbalance. The SMOTE parameters were selected to maintain ecological validity of the synthetic samples, as verified through domain expert review of the generated data points.

IV. Results and Analysis

This section presents a comprehensive analysis of our model's performance, demonstrating how its architecture effectively captures the complex patterns of bird behavior.

A. Model Performance

The model was evaluated on a spatiotemporal dataset spanning two complete annual cycles, encompassing both breeding and migration periods. Table I presents a detailed performance comparison against baseline models and ablated versions of our architecture.

TABLE I
Performance Comparison of Models

Model	F1-Score	Precision	Recall
Proposed Model	0.822 ± 0.008	0.815 ± 0.007	0.829 ± 0.009
W/O Spatial Attention	0.763 ± 0.009	0.758 ± 0.008	0.769 ± 0.010
XGBoost	0.656 ± 0.011	0.649 ± 0.010	0.663 ± 0.012
Random Forest	0.633 ± 0.010	0.628 ± 0.009	0.639 ± 0.011

The proposed model achieved an F1-score of 0.822 ± 0.008, with precision of 0.815 ± 0.007 and recall of 0.829 ± 0.009, significantly outperforming all baselines. The high precision demonstrates the model's ability to accurately identify true bird presence, particularly critical during migration periods when false positives could mislead ecological studies. The 25.3% improvement over XGBoost and 29.9% over Random Forest underscores the effectiveness of our ecology-driven architecture in capturing the inherent complexity of bird behavior.

B. Feature Importance and Ecological Patterns

To evaluate the contributions of different feature categories, we conducted a detailed feature importance analysis and ablation studies. This section quantifies the ecological relevance of each feature, demonstrating how our model captures real-world seasonal and spatial patterns in bird behavior.

1) Feature Importance Analysis: Feature importance scores, derived from the trained LightGBM model, highlight the dominant factors influencing bird sighting predictions. Temporal features, particularly the 7-day rolling statistics, exhibited the highest predictive power, reflecting the fundamental weekly rhythms observed in American Robin behavior [28]. This aligns with ecological research indicating that birds maintain regular foraging and movement patterns within weekly cycles, even during migration.

Habitat features emerged as the second most significant predictor. The model effectively learns habitat suitability, reinforcing the validity of its spatial component [29]. Weather parameters displayed a strong seasonal dependence, influencing bird observations in different ecological contexts. Temperature had the highest importance during winter, reflecting its role in regulating food availability and metabolic demands [22]. Precipitation played a key role in the breeding season, aligning with its impact on nest success and insect abundance [29]. Food availability followed a clear seasonal trajectory, peaking in spring and summer when birds require high-energy food sources for nesting and raising young.

These results confirm the model effectively captures seasonal cycles, habitat preferences, and weather-driven variations, reinforcing its ecological validity.

TABLE II
Feature Importance Analysis with Peak Seasonal Influence

Feature	Importance Score	Peak Influence Season
7-day Rolling Mean	0.85 ± 0.02	Year-round
Habitat Type	0.76 ± 0.01	Spring
Temperature	0.72 ± 0.03	Winter
Food Availability Index	0.70 ± 0.02	Spring/Summer
Precipitation	0.68 ± 0.02	Spring/Summer

2) Ablation Study: Quantifying Feature Contributions: To further analyze the contributions of different modeling components, we conducted ablation studies by systematically removing spatial and temporal features and evaluating the impact on classification performance. Table III presents the results.

TABLE III
Ablation Study Results: Impact of Removing Spatial and Temporal Features

Component Removed	F1-Score	Precision	Recall
Full Model (All Features)	0.822	0.815	0.829
Without Spatial Attention	0.763	0.758	0.769
Without Temporal Features	0.745	0.741	0.749
Without Both Components	0.687	0.682	0.691

The removal of the spatial attention mechanism resulted in a 5.9% decrease in F1-score, highlighting its role in capturing location-specific patterns and habitat preferences. The more substantial impact of removing temporal features (7.7% reduction) confirms the primacy of temporal patterns in bird behavior, particularly the weekly and seasonal rhythms that drive movement decisions [22]. The 13.5% performance drop when both components were removed demonstrates their synergistic relationship in modeling complex spatiotemporal patterns.

These findings strongly align with established ecological research, supporting the validity of our model's design choices. The performance decline without spatial attention confirms that habitat characteristics and proximity-based spatial correlations are essential for modeling bird activity [29]. Likewise, the deterioration observed when removing temporal features validates the importance of seasonal and migration-related trends.

3) Ecological Interpretation of Feature Importance: Each feature's seasonal importance closely aligns with biological expectations. Temperature is most critical in winter, when thermoregulation and food scarcity significantly impact bird behavior [22]. Food availability peaks in spring and summer, consistent with the energy demands of nesting and juvenile rearing. Precipitation is a key predictor in the breeding season, affecting nesting success and invertebrate abundance [29].

The strong alignment between feature importance scores and known ecological trends demonstrates that our model captures real-world behavioral patterns rather than overfitting statistical artifacts. These results validate the effectiveness of integrating spatiotemporal correlations, habitat structure, and dynamic environmental features in bird sighting predictions.

C. Limitations and Future Directions

As the first attempt to incorporate spatio-temporal features with ecological principles in bird sighting prediction and demonstrating strong performance, the proposed model could be extended in several promising directions for future research. While our current temporal modeling effectively captures seasonal patterns and weather effects, extending this approach could incorporate longer-term climate trends. Future work could explore dynamic temporal modeling approaches, leveraging climate projections and anomaly detection to enhance long-term predictive capabilities.

Our model effectively utilizes eBird data, one of the most comprehensive bird observation datasets available. While its crowd-sourced nature enables large-scale data collection, it may introduce observational biases. Future research could integrate additional data sources such as automated acoustic sensors and radar-based tracking systems, complementing citizen science observations with automated monitoring data.

While we demonstrate the framework's effectiveness using American Robin data in Michigan, the approach is designed for broad applicability. The model's architecture can be adapted to different species and regions, opening opportunities to study diverse migratory patterns and habitat preferences across species. This extensibility makes our framework a valuable foundation for broader ecological modeling applications.

V. Related Work

Bird activity prediction has been a focal point in ecological research, with applications ranging from biodiversity monitoring to conservation planning. Much of the existing work on bird prediction has focused on coarse-grained applications, such as estimating species distributions [5], modeling population changes in migratory bird species [6], and learning seasonal bird movement patterns [7].

For such applications, species distribution models (SDMs) and generalized additive models (GAMs) are widely used to predict bird presence or absence based on environmental variables like temperature, precipitation, and vegetation cover [30], [31]. These models are effective for large-scale studies but lack the resolution to capture fine-grained temporal and spatial dynamics, such as daily or hourly bird activity patterns [2]. For example, studies using SDMs have successfully predicted bird distributions across continents but struggle to account for localized factors like microhabitat preferences or short-term environmental changes [32].

Similarly, general-purpose machine learning approaches, such as random forests and neural networks, have been applied to model bird migration routes and stopover sites [33], [34]. While these methods improve predictive accuracy, they remain limited to coarse-grained outputs and do not address fine-grained bird sightings.

In contrast to these existing approaches, as far as we know, our work presents the first framework that explicitly integrates spatiotemporal features with ecological principles for fine-grained bird sighting prediction. By combining attention mechanisms with domain-specific constraints, our method achieves both the temporal resolution and ecological validity needed for accurate daily predictions.

VI. Conclusion

This paper advances spatiotemporal modeling for ecological systems through a novel architecture that integrates domain-specific constraints with modern machine learning techniques. Our framework's superior performance, achieving an 82.2% F1-score while maintaining interpretability, demonstrates that explicitly modeling ecological principles can significantly improve predictive accuracy. The success of our spatial attention mechanism in capturing habitat dependencies suggests broader applications for attention-based approaches in spatiotemporal prediction tasks where domain expertise can inform attention weights. Looking ahead, as ecological datasets continue to expand, our model provides a robust foundation for frameworks that seamlessly integrate domain knowledge with learning algorithms, playing a crucial role in advancing both machine learning methodology and ecological understanding.

References

[1] R. D. Gregory, A. van Strien, P. Voříšek, A. W. G. Meyling, D. G. Noble, R. P. Foppen, and D. W. Gibbons, "Developing indicators for european birds," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 360, no. 1454, pp. 269–288, 2005.

[2] A. Johnston, D. Fink, M. D. Reynolds, W. M. Hochachka, B. L. Sullivan, N. E. Bruns, E. Hallstein, M. S. Merrifield, S. Matsumoto, and S. Kelling, "Abundance models improve spatial and temporal prioritization of conservation resources," *Ecological Applications*, vol. 25, no. 7, pp. 1749–1756, 2015.

[3] R. Virkkala, N. Leikola, H. Kujala, S. Kivinen, P. Hurskainen, S. Kuusela, J. Valkama, and R. K. Heikkinen, "Developing fine-grained nationwide predictions of valuable forests using biodiversity indicator bird species," *Ecological Applications*, vol. 32, no. 2, p. e2505, 2022.

[4] B. L. Sullivan, C. L. Wood, M. J. Iliff, R. E. Bonney, D. Fink, and S. Kelling, "ebird: A citizen-based bird observation network in the biological sciences," *Biological conservation*, vol. 142, no. 10, pp. 2282–2292, 2009.

[5] A. Johnston, W. M. Hochachka, M. E. Strimas-Mackey, V. Ruiz Gutierrez, O. J. Robinson, E. T. Miller, T. Auer, S. T. Kelling, and D. Fink, "Analytical guidelines to increase the value of community science data: An example using ebird data to estimate species distributions," *Diversity and Distributions*, vol. 27, no. 7, pp. 1265–1277, 2021.

[6] J. Walker and P. D. Taylor, "Using ebird data to model population change of migratory bird species." *Avian Conservation & Ecology*, vol. 12, no. 1, 2017.

[7] M. Fuentes, B. M. Van Doren, D. Fink, and D. Sheldon, "Birdflow: Learning seasonal bird movements from ebird data," *Methods in Ecology and Evolution*, vol. 14, no. 3, pp. 923–938, 2023.

[8] S. Kahl, C. M. Wood, M. Eibl, and H. Klinck, "Birdnet: A deep learning solution for avian diversity monitoring," *Ecological Informatics*, vol. 61, p. 101236, 2021.

[9] J. Shamoun-Baranes, W. Bouten, L. Buurma, R. DeFusco, A. Dekker, H. Sierdsema, F. Sluiter, J. Van Belle, H. Van Gasteren, and E. Van Loon, "Avian information systems: developing web-based bird avoidance models," *Ecology and Society*, vol. 13, no. 2, 2008.

[10] D. Fink, W. M. Hochachka, B. Zuckerberg, D. W. Winkler, B. Shaby, M. A. Munson, G. Hooker, and S. Kelling, "ebird: A human/computer learning network for biodiversity conservation and research," *BioScience*, vol. 61, no. 9, pp. 689–697, 2011. [Online]. Available: https://academic.oup.com/bioscience/article-abstract/61/9/689/395051

[11] E. S. Bridge, K. Thorup, M. S. Bowlin, P. B. Chilson, R. H. Diehl, R. W. Fléron, P. Hartl, R. Kays, J. F. Kelly, D. C. Douglas *et al.*, "A movement ecology paradigm for unifying organismal movement research," *Trends in Ecology & Evolution*, vol. 26, no. 8, pp. 415–422, 2011. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0169534711000871

[12] R. Nathan, W. M. Getz, E. Revilla, M. Holyoak, R. Kadmon, D. Saltz, and P. E. Smouse, "A movement ecology paradigm for unifying organismal movement research," *Proceedings of the National Academy of Sciences*, vol. 105, no. 49, pp. 19 052–19 059, 2008. [Online]. Available: https://www.pnas.org/content/105/49/19052

[13] F. A. La Sorte, D. Fink, W. M. Hochachka, and S. Kelling, "Convergence of broad-scale migration strategies in terrestrial birds," *Proceedings of the Royal Society B: Biological Sciences*, vol. 283, no. 1823, p. 20152588, 2016. [Online]. Available: https://royalsocietypublishing.org/doi/10.1098/rspb.2015.2588

[14] K. G. Horton, B. M. Van Doren, F. A. La Sorte, E. B. Cohen, H. L. Clipp, D. Sheldon, A. Farnsworth, and J. F. Kelly, "Phenology of nocturnal avian migration has shifted at the continental scale," *Nature Climate Change*, vol. 10, pp. 63–68, 2020. [Online]. Available: https://www.nature.com/articles/s41558-019-0648-9

[15] C. K. Wikle and M. B. Hooten, "A general science-based framework for dynamical spatio-temporal models," *TEST*, vol. 19, no. 3, pp. 417–451, 2010. [Online]. Available: https://link.springer.com/article/10.1007/s11749-010-0209-z

[16] G. Guillera-Arroita, J. J. Lahoz-Monfort, and J. Elith, "Is my species distribution model fit for purpose? matching data and models to applications," *Global Ecology and Biogeography*, vol. 24, no. 3, pp. 276–292, 2015. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/geb.12268

[17] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu, "LightGBM: A highly efficient gradient boosting decision tree," in *Advances in Neural Information Processing Systems*, vol. 30, 2017. [Online]. Available: https://proceedings.neurips.cc/paper/2017/file/6449f44a102fde848669bdd9eb6b76fa-Paper.pdf

[18] Z. Ding, A. Guo, M. Lian, Y. Wang, W. Ying, H. Jiang, X. Zhou, C. Qian, J. Lai, and J. Cao, "Landscape factors influencing bird nest site selection in urban green spaces," *Frontiers in Ecology and Evolution*, vol. 11, p. 1258185, 2023.

[19] O. Gordo, "Why are bird migration dates shifting? a review of weather and climate effects on avian migratory phenology," *Climate Research*, vol. 35, no. 1-2, pp. 37–58, 2007.

[20] C. Both, "Food availability, mistiming, and climatic change," *Effects of climate change on birds*, pp. 129–147, 2010.

[21] E. N. Vanderhoff, P. Pyle, M. A. Patten, R. Sallabanks, and F. C. James, "American robin (turdus migratorius), version 1.0," *Birds of the World*, 2020. [Online]. Available: https://doi.org/10.2173/bow.amerob.01

[22] N. T. Wheelwright, "The diet of american robins: an analysis of us biological survey records," *The Auk*, vol. 103, no. 4, pp. 710–725, 1986.

[23] B. Helm and M. Liedvogel, "Avian migration clocks in a changing world," *Journal of Comparative Physiology A*, pp. 1–26, 2024.

[24] E. L. Porzig, N. E. Seavy, T. Gardali, G. R. Geupel, M. Holyoak, and J. M. Eadie, "Habitat suitability through time: using time series and habitat models to understand changes in bird density," *Ecosphere*, vol. 5, no. 2, pp. 1–16, 2014.

[25] J. Yu, S. Kelling, J. Gerbracht, and W.-K. Wong, "Automated data verification in a large-scale citizen science project: A case study," in *2012 IEEE 8th International Conference on E-Science*. IEEE, 2012, pp. 1–8.

[26] S. Kelling, W. M. Hochachka, D. Fink, M. Riedewald, R. Caruana, G. Ballard, and G. Hooker, "ebird: A human/computer learning network for biodiversity conservation and research," in *Proceedings of the Twenty-Fourth AAAI Conference on Artificial Intelligence*. AAAI Press, 2010, pp. 1902–1909. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/18963

[27] J. Dewitz and U. G. Survey, "National land cover database (nlcd) 2019 products (ver. 2.0, june 2021)," 2021. [Online]. Available: https://data.usgs.gov/datacatalog/data/USGS:60cb3da7d34e86b938a30cb9

[28] R. K. Swihart and S. G. Johnson, "Foraging decisions of american robins: somatic and reproductive tradeoffs," *Behavioral Ecology and Sociobiology*, vol. 19, pp. 275–282, 1986.

[29] D. N. Bonter, B. Zuckerberg, C. W. Sedgwick, and W. M. Hochachka, "Daily foraging patterns in free-living birds: exploring the predation–starvation trade-off," *Proceedings of the Royal Society B: Biological Sciences*, vol. 280, no. 1760, p. 20123087, 2013.

[30] J. Elith and J. R. Leathwick, "Species distribution models: Ecological explanation and prediction across space and time," *Annual Review of Ecology, Evolution, and Systematics*, vol. 40, pp. 677–697, 2009.

[31] A. Guisan and N. E. Zimmermann, "Predictive habitat distribution models in ecology," *Ecological Modelling*, vol. 135, no. 2-3, pp. 147–186, 2000.

[32] O. J. Robinson, V. Ruiz-Gutierrez, and D. Fink, "Integrating citizen science data with expert surveys increases accuracy and spatial extent of species distribution models," *Diversity and Distributions*, vol. 24, no. 10, pp. 1471–1485, 2018.

[33] W. M. Hochachka, D. Fink, R. A. Hutchinson, D. Sheldon, W.-K. Wong, and S. Kelling, "Data-intensive science applied to broad-scale citizen science," *Trends in Ecology & Evolution*, vol. 22, no. 2, pp. 43–47, 2007.

[34] S. Kelling, D. Fink, F. A. La Sorte, A. Johnston, N. E. Bruns, and W. M. Hochachka, "Using semistructured surveys to improve citizen science data for monitoring biodiversity," *BioScience*, vol. 69, no. 3, pp. 170–179, 2019.