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Engineering Informatics for Aviation Safety: Machine Learning-Based Prediction of Bird Strikes Using a Model-Based CPSS Design¹

Bird strikes on aircraft present a growing concern to wildlife preservation efforts and pose safety and economic challenges in aviation and urban design that amalgamate a sociotechnical system. Recent evidence suggests that artificial light at night is a contributing factor to bird strikes, especially during migration seasons, when birds are more likely to be disoriented by bright urban lighting. In this article, we explore the interplay of factors influencing bird strikes and present a machine learning-based predictive modeling approach informed by cyber-physical-social systems (CPSS). We emphasize the CPSS paradigm as a lens for modeling a range of systems engineering problems where evolving geospatial, temporal, and societal constraints characterize the environment. We underscore the interactions between the cyber, physical, and social spaces in model development and feature selection, providing a model-based system design with clear interpretations for public policy design and decision-making. Through exploratory data analysis and predictive modeling, we identify significant patterns and trends in bird strikes and develop a model to predict bird strikes at a given time and location, with implications for urban planning, lighting design, and aviation safety. We emphasize the potential of these predictive models to inform decisions in public policy and aerospace safety, aiming to mitigate bird strikes while accounting for ecological and industrial factors through model-based systems design. We envision this providing an actionable step toward designing evolving cyber-physical-social systems and engineering informatics for public policy.

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1 Frame of Reference

Societal problems are characterized by a plethora of interconnected factors that collectively contribute to their complexity. To address these problems effectively, it is necessary to implement public policies anchored in informed approaches. In the intersection of ecological conservation, aviation safety, and urban design, the increasing threat of bird strikes and the adverse effects of artificial lights at night (ALANs) necessitate a transdisciplinary approach guided by “systems engineering,” “engineering informatics,” and “design” to guide public policies through

decision options. Through model-based systems design, we demonstrate the interaction between the social and technical variables of the sociotechnical system, highlighting the utility of cyber-physical-social systems (CPSS) in addressing the complexities inherent in such interconnected issues. In this article, we extend our previous work presented at the ASME IDETC-CIE 2024 conference [1].

Exemplifying a highly connected societal issue, bird strikes on airplanes, helicopters, and even spacecraft during takeoff are influenced by many anthropogenic and ecological variables and present a growing challenge in aviation safety and urban design. When examining the factors influencing bird strikes, a crucial aspect involves comprehending the interaction among ecological factors (driven by bird migration patterns and wildlife preservation), urban design, and aviation safety. Bird migration patterns and behavioral changes due to the impact of ALAN principally account for the social space, whereas wildlife preservation, urban

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design, and aviation safety incorporate social and physical spaces for model-based system design. This requires an understanding of intricate system interactions to facilitate well-informed decisions, aiming not only to reduce bird strikes but also to enhance human safety. Since design choices may impact ALAN-induced bird strikes in future scenarios, we address this as a predictive model for systems design.

In this article, we aim to contribute to the progression of a machine learning-based predictive modeling approach in “systems engineering,” “engineering informatics,” and “design” by addressing a challenge rooted in a complex system that involves “birds as objects” to design public policies. We explore various domains of interaction with the overarching goal of designing enhanced policies. Before examining the main approach, it is critical to understand the background and significance of bird strikes. In this section, we provide background on bird strikes, identify research gaps, and introduce the promising potential of predictive modeling for policy design.

1.1 Overview of Bird Strikes and Their Significance. Bird strikes, defined as incidents where birds collide with a moving vehicle, have emerged as a concern for both wildlife conservation and aviation safety. Historically, these events were considered rare occurrences, but with the expansion of global air traffic and changes in natural habitats, they have become increasingly common, posing a threat to both avian populations and human safety.

Severe strikes can cause critical flight issues, posing safety risks to passengers and crew. In 2009, US Airlines Flight 1549 took off from New York and was shortly after struck by a flock of birds, resulting in the loss of all engine power. The pilot landed the flight successfully in the Hudson River with no injuries to passengers or crew, in an incident that quickly became known as “the Miracle on the Hudson” [2].

Furthermore, the significance of bird strikes extends beyond the immediate risk to flight safety. From an ecological perspective, these incidents highlight the broader issue of how human activities, such as aviation and urban development, can intersect with and impact wildlife. Birds, especially migratory species, face numerous threats from habitat loss, climate change, and urbanization. The specific challenge of ALAN contributes to this by disorienting birds during their flight, making them more prone to collisions with aircraft [3].

The implications of bird strikes are multifaceted. Economically, they cause substantial damage to aircraft, leading to high repair costs and operational delays. Moreover, bird strikes have resulted in human injuries and fatalities, highlighting safety concerns in aviation. For wildlife, the loss of birds, particularly those from already declining species, exacerbates the challenges of conservation efforts [4]. Adaptation measures are expensive for both birds and people; implementing mitigation strategies demands significant financial and operational costs, while birds are otherwise forced to alter their behaviors and natural habitats.

This interaction of factors underscores the need for a multifaceted approach to addressing bird strikes. Understanding the role of ALAN in this context provides a tangible point of intervention. Thus, by examining the impact of artificial lights on bird behavior and the resulting increase in strike incidents, we can begin to design public policies and interventions that mitigate these risks. The objective in designing such policies is twofold: first, to enhance aviation safety by reducing the frequency/severity of bird strikes, and second, to contribute to wildlife conservation efforts by minimizing one of the anthropogenic risks to bird populations.

1.2 Discussion of Artificial Light at Night as a Contributing Factor. ALAN represents a pervasive environmental change affecting ecosystems worldwide. ALAN is the introduction of artificial light into previously dark nighttime environments; it disrupts natural light cycles, profoundly influencing the behavior,

physiology, and distribution of wildlife, including birds. The impact of ALAN on avian species is multifaceted, affecting their migration patterns, foraging behaviors, predator–prey interactions, and reproductive cycles as well [5].

The theoretical underpinnings linking ALAN to changes in bird behavior derive from the connection between light and the biological rhythms of many species. Birds, like many other organisms, rely on natural light cues for critical behaviors, including navigation and timing of their migrations. The disorientation caused by bright, artificial lighting, especially in urban areas, can change environmental cues that induce certain behaviors. This behavioral change can lead to increased incidences of bird strikes [5]. These strikes not only pose a significant threat to avian populations but also present safety and economic challenges in aviation and urban environments [4]. Researchers in this area have begun to shed light on the extent of ALAN’s impact on wildlife. Studies have shown that nocturnally migrating birds, attracted or disoriented by intense light sources, are particularly at risk. This phenomenon is exacerbated during migration seasons when large numbers of birds are on the move, making them more vulnerable to collisions with illuminated structures [6].

1.3 Application to Public Policy Design and Mitigation Strategies. Through the approach suggested in this model-based system design, we envision assisting decision-makers in making better-informed decisions by designing effective policies. This is carried out through careful consideration of multiple domains, including ecological conservation, aviation safety, and urban development. Our findings, derived from data exploration and random forest regression modeling, have potential applications in formulating bird-strike-mitigation strategies. By identifying key predictors of bird strikes, aviation authorities and wildlife conservationists can implement targeted measures, such as altered flight paths and lighting adjustments during high-risk periods identified by the model.

The utility of this model for public policy design carries implications for the formulation of bird-strike mitigation strategies. By pinpointing key predictors of bird strikes through our model and predicting them as the geographical location changes, aviation authorities and wildlife conservationists can deploy targeted engineering measures. For instance, the model’s insights can inform flight path scheduling and facilitate adjustments to lighting systems during high-risk periods, thereby providing a tangible application of engineering solutions to mitigate the impact of bird strikes on aviation safety and ecological preservation.

Moreover, through the suggested model-based design, we offer designers an approach to grasp the interconnections among diverse variables within complex systems, facilitating a comprehensive understanding of interactions at the element level and their subsequent impact on the entire system. Through this model, we assist designers in comprehending the emergent effects stemming from the intricate interplay of multiple interactions. This proposed method and its application have additional potential for computational automation, empowering designers to create adaptive policy frameworks. These policies would dynamically evolve in response to fluctuations in variable parameters, guided by shifts in the environment that were not included in initial predictive variables.

This real-time adaptive approach is designed to support decision-making for aviation industries, urban planning departments, and wildlife conservationists. It enables them to make more informed decisions at the nexus of wildlife conservation and the prevention of inadvertent flight hazards. The result is a suite of intelligent solutions to mitigate the impacts of ALAN through effective public policies.

1.4 Organization of the Article. Our focus in this article is on predictive modeling, aiming to bridge the gap between empirical evidence and actionable policies. By leveraging data on bird

migration, light pollution, and bird-strike records, we develop a model that can predict the likelihood of strikes at any given time and location. This predictive capacity is crucial for designing interventions that are both effective and efficient, targeting resources to times and places where the risk of bird strikes is the highest. Through this work, we contribute to the ongoing dialog between conservationists, aviation professionals, and policymakers, seeking solutions that balance human needs with the imperative of wildlife preservation.

1.4.1 Organization of the Article

- In Sec. 2, we provide a critical review of related work in geospatial and CPSS modeling and illustrate the novelty of our approach.
- In Sec. 3, we detail the methods employed in integrating multiple data sources and outline our approach to predictive modeling.
- In Sec. 4, we present the results of our exploratory data analysis (EDA) and the outcomes of our predictive modeling efforts, highlighting key findings and their implications.
- In Sec. 5, we discuss the interpretation of our results, explore possible limitations of our method, and suggest directions for future research.
- In Sec. 6, we offer closing remarks by summarizing the significance of our findings and their potential impact on public policy and conservation efforts.

In the following sections, we articulate and address the identified research gaps, contributing to a deeper understanding of ALAN's impact on bird strikes and offering actionable insights for mitigation strategies.

2 Review of Related Work

To model and predict bird strikes effectively, we propose examining the intersection of geospatial predictive modeling and the CPSS paradigm. We provide a critical review of existing literature by surveying current predictive modeling techniques for geospatial data and assessing their capabilities and limitations. Subsequently, we discuss the CPSS paradigm and explore how it has been applied to model emergent behavior arising from dynamic interactions within an environment characterized by cyber, physical, and social components. By synthesizing insights from these areas, we identify gaps in existing research and underscore the need for a novel modeling approach that can adapt to evolving geospatial conditions and societal demands.

2.1 Predictive Modeling for Geospatial Data. Predictive modeling for geospatial data has been extensively explored across various domains, such as environmental monitoring, urban planning, and transportation systems, including in the context of wicked problems [7]. Traditional statistical methods like spatial regression and kriging have been used to model spatial dependencies and predict outcomes based on geographical variables [8,9]. With the advent of machine learning, techniques like decision trees, random forests, support vector machines, and neural networks have been applied to handle complex nonlinear relationships in spatial data [8].

For instance, random forests have been used to predict land-use changes [10], while neural networks have been employed to forecast weather patterns and urban growth [11]. In environmental science, spatiotemporal models have been developed to predict pollution dispersion and habitat suitability for wildlife [12].

2.1.1 Comparative Analysis of Existing Approaches. While traditional statistical methods offer interpretability and are effective for linear relationships, they often struggle with high-dimensional data and complex interactions [13]. Machine learning models provide better predictive performance in such scenarios

but may lack transparency, making it difficult to interpret the results [8]. Ensemble methods like gradient boosting and random forests can strike a balance by offering improved accuracy and some level of interpretability [14].

Deep learning models such as convolutional neural networks have shown promise for handling spatial data by capturing spatial hierarchies. However, they most often require large datasets and significant computational resources [15]. Moreover, most existing models alone do not inherently account for the dynamic and evolving interplay between social behavior [16] and the physical environment in model representations.

2.1.2 Limitations in Predicting Emergent Behavior. From our review of the literature, we posit that a significant limitation of the current predictive models is their inability to capture emergent behavior arising from the complex interactions between the evolving physical environment and social behavior. Bibri noted this limitation of capturing the property of emergence in the context of smart cities, where a decision-support framework for urban planning is proposed [7]. Similarly, Kovács-Györi et al. noted the limitations of existing approaches for capturing the self-organizing aspect of urban systems, providing an example of stigmergy in which pedestrians build pathways that urban planners did not initially account for, subsequently inspiring the revision of structures based on new information patterns [8]. Kovács-Györi et al., in this case, highlighted the need for a geodata strategy, as alone these models typically are based on only static relationships captured over a given time frame, and thus often fail to adapt to changes over time or incorporate emergent social influences effectively. This limitation can hinder their applicability in scenarios where human behaviors, technological factors, and environmental conditions evolve and interact dynamically, such as in the case of bird strikes being influenced by urban lighting and subsequent mitigation measures.

2.2 CPSS as a Paradigm for Modeling Emergent Behavior. CPSS integrates computational resources (cyber), physical components (physical), and human behaviors (social) to create a holistic modeling framework. The CPSS paradigm has been applied in smart grids, intelligent transportation systems, and healthcare to model and manage complex systems effectively [17,18].

In previous work, Allen et al. discussed the design of evolving CPSS (E-CPSS), highlighting the need for models that can adapt over time and incorporate changes in technology, physical environment, and society [19]. This evolution is important for accurately predicting and managing emergent behaviors in complex systems. In the context of predictive modeling, this entails dynamic updates to the model over time to adapt and respond to changes in the environment while balancing computational complexity and real-world constraints [16].

2.2.1 Approaches for Integrating Cyber, Physical, and Social Spaces. Integrating the cyber, physical, and social spaces of the CPSS requires methods that can handle heterogeneous data sources and dynamic interactions. Multi-agent systems have been used before, with agents representing entities within each space, and interacting according to predefined rules [20]. Machine learning models are also designed to process data streams and update predictions in real time.

Kordabad addressed the management of computational complexity in CPSS [21] and illustrated an example of geospatial modeling relating to crime rate prediction in Los Angeles, CA, offering strategies to handle high dimensionality. These approaches, outlined in the literature, form a basis for enabling the modeling of systems where geospatial and societal factors are in constant flux.

2.3 Research Gap Identification. Current geospatial predictive models excel in specific domains but, overall, often lack the inherent capacity to account for the dynamic and interdependent

nature of evolving factors within their model representations [7,8,22]. Moreover, while CPSS offers a theoretical framework for such integration, practical applications in predictive modeling remain limited. Few studies have explicitly implemented a CPSS-based predictive technique, and fewer have applied them to real-world environmental and public policy concerns.

2.3.1 The Need for a Modeling Approach Applicable to Evolving Geospatial, Socially Informed Circumstances. Upon reviewing the literature, we suggest that a modeling approach is needed to handle the complexities of evolving geospatial data intertwined with social behaviors and technological influences. Such an approach could be universally applicable to problems characterized by dynamic interactions between societal factors and physical environments; we outline its potential generalizability in Sec. 5.3.

In the context of ALAN and bird strikes, our CPSS-based predictive model incorporates bird migration patterns (social/biological), urban lighting data (physical), and computational platforms (cyber) to predict and mitigate incidents most effectively. Moreover, if this model were continually updated with additional data over time, it would constitute an evolving CPSS. This integration can provide stakeholders with actionable, easily interpretable insights and facilitate informed decision-making across urban design, aviation safety, and wildlife conservation. We discuss our method in detail in Sec. 3.

3 Method

In this section, we detail our method for model-based system design to develop policies aimed at mitigating the impact of ALAN on bird strikes, thereby achieving a parallel objective of safeguarding human lives from aircraft accidents. We describe our conceptual map, which illustrates the interconnectedness of the challenge within the CPSS paradigm.

3.1 Impact of ALAN on Bird Strikes as a Complex System. In Fig. 1, we illustrate our conceptual map for a model-based, data-driven system design approach to designing public

policy aimed at mitigating the impact of ALANs on bird strikes and reducing potential aviation incidents. The influence of nighttime artificial lighting disrupts bird flights by disturbing melatonin production, leading to disorientation [5]. This light pollution not only affects flight orientation but may also induce variations in flight timing. Consequently, birds undergo behavioral changes, altering their migratory patterns and leading to detours, delayed departures, or stopovers in suitable habitats.

We approach this as a system with interacting component-level variables that cause system-level impacts through emergent behavior. Analyzing the interactive effects of light pollution on behavioral shifts in birds holistically is imperative. The focus extends beyond the critical analysis of ALAN's direct impact on bird strikes; it also encompasses an understanding of emergent effects arising from interactions among various variables. Further elucidation of this approach is provided in the subsequent sections, delving into the intricacies of systems engineering principles and policy design considerations. Through the proposed approach, we aim to do the following:

- (1) Analyze the interaction between component-level variables and assess their impact on the emergent behavior of the system.
- (2) Analyze interactions between transdisciplinary variables comprising diverse social and technical domains.
- (3) Utilize model-based system design for better-informed decision-making.
- (4) Investigate and discern the primary variables with the most significant impact on bird strikes.

In this article, we integrate multiple data sources to investigate the impact of ALAN on bird strikes and train a model to predict strikes, leveraging the Federal Aviation Administration (FAA) Wildlife Strike Database (DS1 in Fig. 1), a light pollution geographic information system (GIS) map (DS2 in Fig. 1), and Bird-Cast migration forecasts (DS3 in Fig. 1).

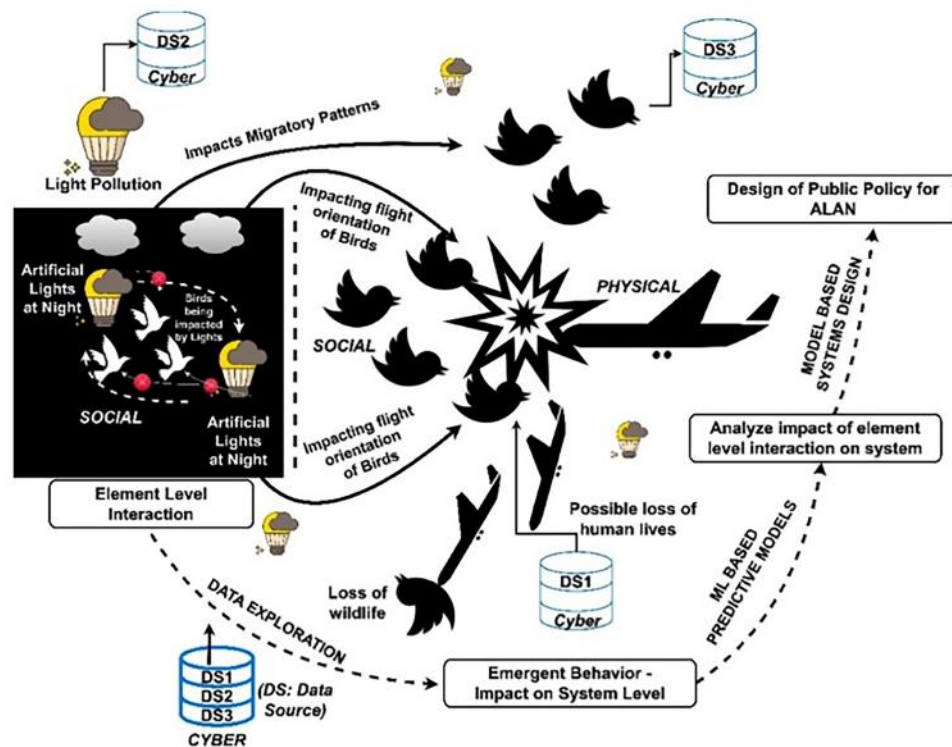


Fig. 1 Conceptual map: policy design for the impact of ALAN on birds as a CPSS

3.2 Addressing ALAN as Model-Based System Design. We introduce our model-based system design approach in Fig. 2, where a spectrum of variables provides invaluable insights for system design. In this intricate system, the exchange of information is not immediately apparent, given the diverse social and technical domains encompassing aviation, wildlife, and light emission. However, our method accounts for the nuanced interactions among these variables through robust data exploration methods. The primary aim is to empower policymakers by providing comprehensive, data-driven insights derived from our model-based system design. These insights, derived from the intricate web of interconnected variables, serve as a cornerstone for designing well-informed policies that harmonize the complexities of aviation, wildlife preservation, and urban lighting.

This model-based system design, as shown in Fig. 2, is supported by the conceptual map that is presented in Fig. 1. This is embodied in the CPSS paradigm. The aircraft, represented in Fig. 1, constitute the major elements of physical space, whereas light pollution, birds, and changes in their behavior are the primary entities of social space. The geographical and urban planning factors contribute to both social and physical spaces. The data sources presented as DS1, DS2, and DS3 in Fig. 1 and explained in detail in Sec. 3.3 form the cyber space that enables data-driven design for this model-based system.

In Fig. 3, we outline our approach to predictive modeling through a sequence of steps, including problem identification, data source selection, EDA, and predictive model construction. This is further expanded in the following sections.

3.3 Description of Data Sources. We use the FAA Wildlife Strike Database to provide initial EDA findings on the distribution of bird strikes, including trend analysis, species-specific analysis, and temporal patterns (Sec. 4.1). In Secs. 4.2 and 4.3, we incorporate the light pollution GIS map and BirdCast migration forecasts to perform statistical tests and build a model to predict bird-strike occurrences. By examining the confluence of these data sources, we seek to contribute to a broader understanding of ALAN's impacts, with a specific focus on the role of spatiotemporal predictive modeling in informing public policy design.

3.3.1 Federal Aviation Administration Wildlife Strike Database. The Federal Aviation Administration Wildlife Strike Database [23] provides a comprehensive record of bird-strike incidents reported to the FAA, with over 286,000 reported strikes from 1990 to 2023. Approximately 97% of all recorded strikes with aircraft in the United States involve birds, though strikes with other animals such as deer and coyotes have also been reported [24]. Bird strikes are voluntarily reported, primarily by pilots and airport personnel. Records generally include details on the date,

time, location, species involved, and the extent of damage to the aircraft. This dataset serves as the foundation of our analysis, offering insight into the frequency and distribution of bird strikes in the United States.

3.3.2 Geographic Information System Light Pollution Map. Light pollution data are represented through a GIS raster that maps the intensity and distribution of light pollution across North America [25,26], sourced from NASA Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band VN2 yearly composites of cloud-free satellite data in 2020. This map includes color bands ranging from 0 to 14, with each band corresponding to a discrete light pollution category. In Table 1, we provide unit conversions of raster bands to both magnitudes per square arcsecond and brightness ratio, based on the color scale derived from David Lorenz's Light Pollution Atlas [25]. The magnitudes per square arcsecond reflect standard astronomical brightness, while the artificial/natural brightness ratio provides a comparative measure of artificial light pollution. We use this data to quantify light pollution levels at each bird-strike location, enabling us to perform correlation analyses and train a predictive model.

3.3.3 BirdCast Migration Forecasts. The BirdCast project entails forecasts of bird migration in North America, providing valuable data on the movement of birds, especially during peak migration periods, using input data from the NEXRAD weather surveillance radar network across the continental United States [27,28]. Data for this project were graciously provided by Alexander Tedeschi, Andrew Farnsworth, Adriaan Dokter, and Julia Wang at the Cornell Lab of Ornithology. We use 2023 forecast data, captured each day at 0600Z, to train our predictive model. These data are divided into GeoTIFF files for each month, with

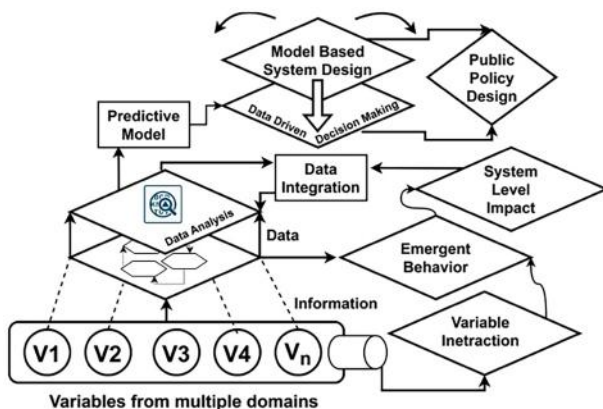


Fig. 2 Addressing bird strikes through a model-based, data-driven system design

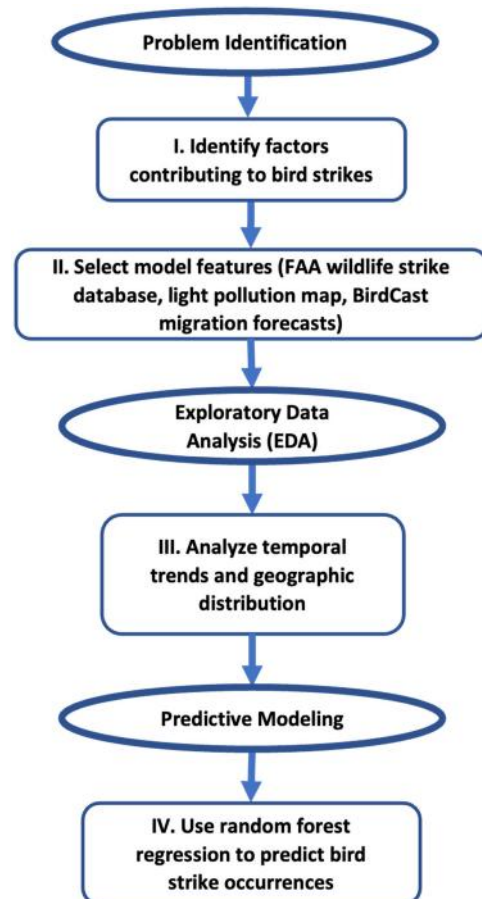


Fig. 3 Diagram of predictive modeling approach

Table 1 Dual-unit representation of light pollution data [25]

Raster band	Magnitudes per square arcsecond (mag/arcsec ²)	Brightness ratio (Artificial/Natural)
0	22.00–21.99	<0.01
1	21.99–21.93	0.01–0.06
2	21.93–21.89	0.06–0.11
3	21.89–21.81	0.11–0.19
4	21.81–21.69	0.19–0.33
5	21.69–21.51	0.33–0.58
6	21.51–21.25	0.58–1.00
7	21.25–20.91	1.00–1.73
8	20.91–20.49	1.73–3.00
9	20.49–20.02	3.00–5.20
10	20.02–19.50	5.20–9.00
11	19.50–18.95	9.00–15.59
12	18.95–18.38	15.59–27.00
13	18.38–17.80	27.00–46.77
14	<17.80	>46.77

each layer containing a time dimension. For any single day, there are four raster bands:

- *U* (birds' ground speed component west to east in m/s)
- *V* (birds' ground speed component south to north in m/s)
- *MTR* (migration traffic rate in birds/km)
- *VID* (vertically integrated density in birds/km³)

Moreover, there are four extra bands corresponding to the kriging variance of each variable. Kriging variance in the context of BirdCast reflects the uncertainty in predictions of bird migration intensity across different geographic locations. BirdCast uses kriging, a geostatistical interpolation technique, to estimate bird migration patterns from sparse observational data; the NEXRAD network does not have complete coverage of all airspace. The kriging variance provides a measure of the expected error or uncertainty of these estimates, indicating how much confidence we can have in the predicted migration intensities at locations where direct observations are not available [29]. This helps researchers to better understand and predict bird movements.

3.4 Methods for Preparing and Integrating Data. The foundational step in our EDA and modeling involved preparing and integrating three data sources: the FAA Wildlife Strike Database, a light pollution GIS map, and BirdCast migration forecasts. This process is guided by a systematic approach to ensure the integrity and usability of the combined dataset for analysis and predictive modeling.

3.4.1 Geo-Referencing Light Pollution Geographic Information System Raster. To integrate the light pollution data with the bird-strike database effectively, the light pollution GIS raster was georeferenced [30] using QGIS software. Geo-referencing involved assigning real-world coordinates to each pixel of the raster image, aligning with the WGS 84—EPSG:4326 coordinate reference system. This step enables the spatial joining of light pollution data with bird-strike incidents by matching latitude and longitude values, providing geospatial context for the analysis.

3.4.2 BirdCast Migration Forecast Integration. The BirdCast migration forecasts, offering insights into bird migration patterns, were integrated by leveraging PYTHON's GIS libraries (rasterio and pyproj) to process GeoTIFF files. This integration allowed us to join datasets by latitude, longitude, and day of the year, enriching the analysis with temporal and spatial dimensions of bird migration in relation to light pollution.

3.5 Exploratory Data Analysis Techniques. Our EDA begins with a deep dive into the FAA wildlife strike dataset, aiming to unveil patterns and anomalies that could inform our

subsequent predictive modeling efforts. Using PYTHON libraries such as pandas and matplotlib, we conduct a series of analyses focusing on temporal trends, geographical distributions, and species-specific strike rates.

- **Temporal trends:** We analyze bird-strike occurrences over time, identifying peak periods that correspond with migratory seasons [31]. Through this analysis, we observe a notable increase in strikes during spring and fall migrations.
- **Geographic distribution:** Utilizing GIS tools, we map bird strikes against light pollution levels, uncovering hotspots where high ALAN levels coincide with increased strike incidences. This spatial analysis highlighted urban areas as zones of elevated risk.
- **Species-specific analysis:** By examining the species involved in reported strikes, we discern patterns indicating that certain migratory birds are more susceptible to ALAN-related incidents. This insight underscores the need for species-specific strike-mitigation strategies.

Visualizations, including maps, bar plots, and line plots, are provided in Secs. 4.1 and 4.2 to illustrate spatial and temporal relationships between bird strikes and light pollution. These visual tools enhance our understanding of the data and guide our model design choices, detailed in Sec. 3.6.

3.6 Statistical and Machine Learning Techniques for Predictive Modeling. Building on the foundational data joins and EDA detailed in the preceding sections, we employ a combination of statistical tests and machine learning techniques to understand the impact of ALAN and to develop a predictive model of bird-strike incidents. Through this approach, we aim to harness the predictive power of our integrated datasets to forecast bird-strike risk with greater precision and identify effective mitigation strategies.

3.6.1 Correlation Analysis. Kendall's τ and Spearman's ρ rank correlation coefficients are calculated to explore the strength and direction of the relationship between bird strikes and light pollution levels [32]. This allows us to quantify the impact of ALAN on bird strikes and determine its predictive strength in model construction.

3.6.2 Predictive Modeling With Random Forest Regression. Focusing on a random forest regression model, implemented using PYTHON's scikit-learn library [33], allows us to model the continuous outcome variable representing the frequency of bird strikes under varying conditions. This model was chosen for its balance between model performance and interpretability, as well as being able to handle nonlinear relationships between predictors and the target variable [34].

- **Model development:** The random forest was trained using features identified as significant through our statistical tests, including time of day and light pollution level.
- **Feature importance:** Using our model, we provide insight into feature importance, highlighting which variables most significantly affect bird-strike rates and aiding in the prioritization of mitigation efforts.

The training dataset, as outlined in Table 2, contains one dependent variable (*y*) and seven predictors (*X*). Data are grouped by

Table 2 Training dataset for predictive model

Number of strikes (<i>y</i>)	Month of the year (<i>X</i>)	Day of the month (<i>X</i>)	Latitude (<i>X</i>)
Longitude (<i>X</i>)	Light pollution level (<i>X</i>)	Migration traffic rate (<i>X</i>)	Bird density (<i>X</i>)

Table 3 List of variables and their distribution

Count: 72,545	Mean	Standard deviation	Minimum value	Maximum value
Number of strikes (y)	3.29	4.69	1	99
Latitude (X)	37.4503	5.54	24.5561	49.1939
Light pollution level (X)	11.69	1.77	0	14
Migration traffic rate (X)	881.56	2830.06	0	79,147.52
Bird density (X)	22.69	58.42	0	1368.47

latitude, longitude, and day of the year, for a total of 72,545 records in the dataset. Moreover, in Table 3, we outline the ranges and distributions of key variables, illustrating their connections. The mean number of strikes at a given location, for instance, is 3.29, with a range between 1 and 99. Additionally, the range of latitude and longitude values demarcates the geographic scope of our dataset.

This listing helps illuminate how each variable contributes to our model, the inter-variable relationships, and the model's collective influence on accuracy. Understanding the variability within these variables is useful for evaluating the fidelity of our predictive model and the interpretability of performance metrics, as it affects both the training process and the generalizability of our predictions.

3.6.3 Evaluation and Validation. To ensure the reliability and applicability of our model, we implement the following evaluation and validation strategies:

- **Performance metrics:** Mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), R-squared (R^2), and weighted mean absolute percentage error (WMAPE) are used to quantify the model's accuracy in predicting bird-strike rates, offering clear measures of predictive performance.
- **Cross-validation:** We implemented k-fold cross-validation with $k = 5$ to assess the model's generalizability across different subsets of the data, ensuring robustness against overfitting.
- **Hyperparameter tuning:** To avoid overfitting and enhance predictive accuracy, we employed 250 decision trees in the random forest and tuned the maximum tree depth to 25, the minimum samples for splitting to 2, and the minimum samples per leaf to 5. The model was developed using an 80–20 train–test split.

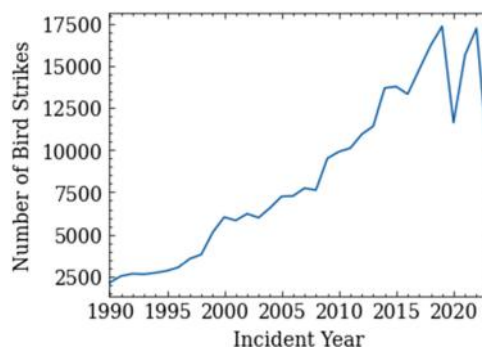
4 Results

Our focus in EDA is on temporal trends and the geographic distribution of bird-strike occurrences, while our predictive modeling efforts provide a starting point for policymakers to make informed predictions of bird strikes given relevant environmental, temporal, and geographic predictors.

4.1 Exploratory Data Analysis Findings. Our EDA focused on extracting patterns and trends from the FAA wildlife strike dataset. Below, we discuss the findings revealed in the figures.

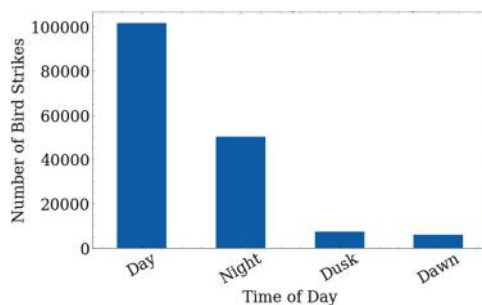
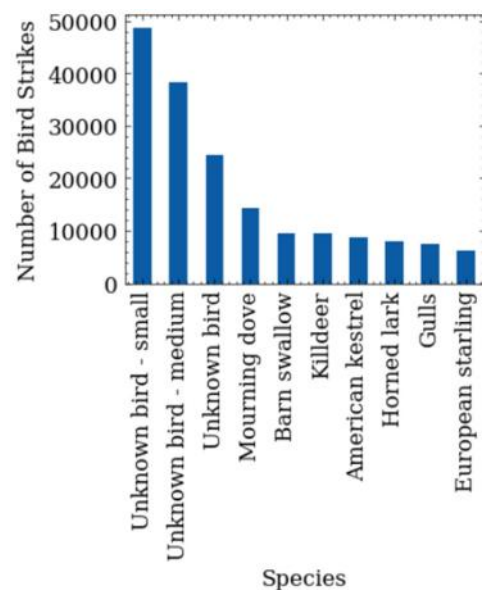
In Fig. 4, we observe an overall upward trend in bird strikes from 1990 to 2023, with the exception of 2020, a year with significantly reduced airport traffic due to COVID-19-related public transportation protocols. The overall upward trend underscores growing challenges in aviation safety and wildlife management, warranting further investigation into contributing factors such as environmental changes or aviation industry growth.

In Fig. 5, we observe differences in voluntarily reported time-of-day data for bird strikes in the FAA database, with four discrete categories including “Day,” “Night,” “Dusk,” and “Dawn.”

**Fig. 4 Yearly bird strikes trend (1990–2023)**

We observe that 61.5% of bird strikes occurred during the daytime, 30.4% at night, and 8.1% at dawn or dusk.

Through our species-specific analysis in Fig. 6, we observe that certain bird species are more frequently involved in strikes. The most frequently represented values in the bar plot are “Unknown bird—small,” “Unknown bird—medium,” and “Unknown bird.” Following these are specific species, including mourning dove, barn swallow, killdeer, and American kestrel. We observe that smaller bird species are most represented in this bar plot and are more commonly affected by aviation-related bird strikes.

**Fig. 5 Recorded bird strikes by time of day (1990–2023)****Fig. 6 Species-specific analysis (top ten species involved in bird strikes)**

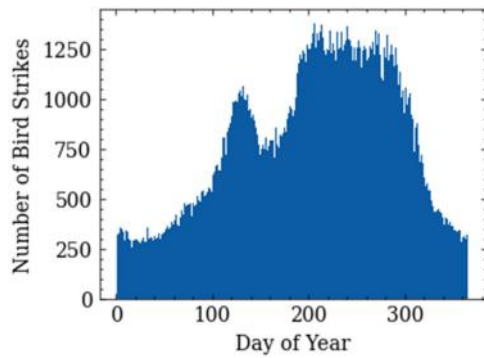


Fig. 7 Distribution of bird-strike occurrences by day of year (1990–2023)

In Fig. 7, time-series analysis across the day of the year from 1990 to 2023 illustrates seasonal trends in bird strikes, with peaks during migration periods in spring and fall. This pattern reflects the natural behaviors of bird populations and their movement across regions, emphasizing the need for seasonal considerations in airport flight operations and wildlife management to mitigate the risk of bird strikes.

In Fig. 8, we present a geographic analysis of bird strikes, revealing hotspots across the United States. Larger circles indicate a

higher number of bird strikes at a given location. Airports situated near migration routes and urban centers are identified as particularly vulnerable. We also observe noteworthy differences between daytime and nighttime strikes. This spatial analysis is critical for prioritizing intervention areas and guiding the deployment of resources for bird-strike prevention.

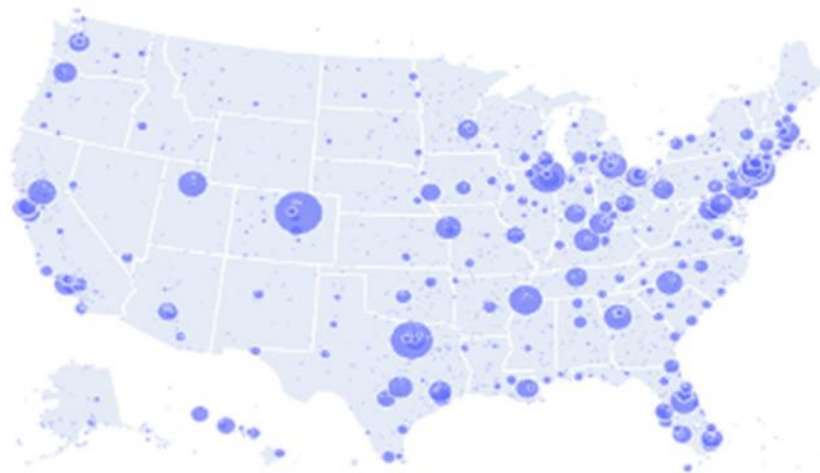
4.2 Correlation Analysis of Bird Strikes and Light Pollution.

In this section, we present the findings from our correlation analysis, focusing on Kendall's τ and Spearman's ρ rank correlation coefficients to investigate the relationship between light pollution and bird-strike incidents.

- Kendall's τ coefficient is calculated to be 0.33, with a p -value less than 0.01, indicating a statistically significant correlation that is not due to random chance.
- Spearman's ρ correlation coefficient is calculated to be 0.42, with a p -value less than 0.001, indicating a statistically significant correlation. This outcome corroborates the findings from Kendall's τ , highlighting a robust association between variables.

In Fig. 9, we plot discrete light pollution level categories (0–14) against strike records in the FAA wildlife strike database, observing higher strike counts as light pollution levels increase (see Table 1 for conversions to $\text{mag}/\text{arcsec}^2$ and the artificial light brightness ratio). These findings corroborate our correlation tests and suggest that light pollution is a significant factor influencing

All Recorded Strikes



Daytime Strikes



Nighttime Strikes



Fig. 8 Recorded bird-strike locations in the United States (1990–2023)

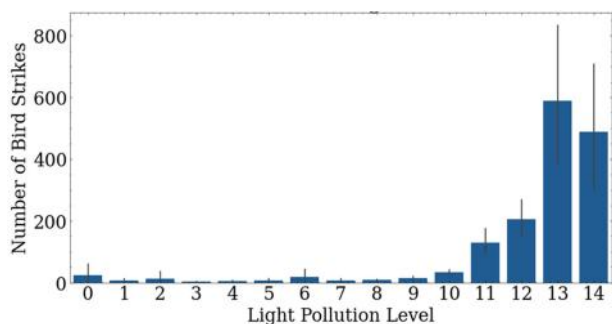


Fig. 9 Bar plot of light pollution levels against bird-strike count

bird strikes, with higher levels of light pollution associated with higher rates of these incidents.

4.3 Predictive Modeling Outcomes. In this subsection, we discuss the outcomes of the random forest regression model and its potential applicability in a public policy design context.

4.3.1 Model Performance Metrics

- MSE: 4.16
- RMSE: 2.04
- MAE: 1.16
- R^2 : 0.80
- WMAPE: 35.40%

These metrics indicate the model's average predictive error and fit quality, given the distribution and skew of the dependent variable bird strikes, with an R^2 of 0.80, suggesting that approximately 80% of the variance in bird strikes can be explained through the model.

4.3.2 K-Fold Cross-Validation. Using K-fold cross-validation, we evaluate the model across different subsets of the dataset to minimize the potential bias of a single train-test split. The average MSE and MAE across the folds were 4.02 and 1.15, respectively. These results closely align with the initial evaluation, suggesting consistent model performance across various data segments.

4.3.3 Monthly Performance Metrics. In Table 4, we provide monthly averages of the model's performance metrics across all years in the training data. The average absolute and squared errors vary from month to month, indicating differences in prediction accuracy over time. For example, January has an average absolute error of 0.62 and a squared error of 1.15, while May has

Table 4 Monthly averages of performance metrics in the training dataset

Month	Average absolute error	Average squared error
January	0.62	1.15
February	0.60	0.99
March	0.71	1.31
April	0.89	2.41
May	0.99	3.32
June	0.88	2.50
July	1.03	3.23
August	1.05	3.08
September	1.05	3.41
October	1.03	3.45
November	0.87	2.32
December	0.68	1.33

slightly higher errors, with an average absolute error of 0.99 and a squared error of 3.32.

Overall, across the monthly absolute errors and absolute squared errors in the dataset:

- The **average absolute error** is approximately 0.87, suggesting that, on average, model predictions deviate from the actual number of strikes by about 0.87 strikes.
- The **average squared error** is approximately 2.38, reflecting the average squared deviation of the predictions from the actual values, adjusted for the scale of the dataset.

4.3.4 Relevance to Public Policy Design. Through Figs. 10–12, we interpret the random forest model via evaluations of permutation importance, feature importance, and SHapley Additive exPlanation values (SHAP). Based on the contributions of each feature to the model, we observe that light pollution has the strongest predictive value across two of the three evaluation criteria (permutation importance in Fig. 10 and SHAP values in Fig. 12). The distribution of SHAP values further indicates that higher levels of light pollution are associated with increased bird strikes.

Additionally, latitude, longitude, and month are the strongest predictors by measure of feature importance in Fig. 11. We also observe that day, bird density, and migration traffic rate have comparatively low impact across all selected evaluation criteria.

The random forest regression model's predictions provide actionable insights for policymakers and conservation efforts. For instance, using the model, we can identify specific time frames and geographic areas with increased bird-strike risk, enabling preemptive action to mitigate them. These insights may guide the development of comprehensive public policies that balance the needs of urban development, aviation safety, and wildlife conservation.

5 Discussion

In this section, we interpret the results of our data analysis and predictive modeling efforts, discuss their applicability to public policy design, and outline directions for future work.

5.1 Results Interpretation. The findings from our investigation into the impact of ALAN on bird strikes, underscored by predictive modeling, provide insights into the complexities of wildlife preservation within human-modified landscapes. By elucidating the relationship between ALAN and bird strikes, we aim to shed light on broader ecological and safety implications, offering a foundation for informed public policy and urban planning decisions.

5.1.1 Contextualizing Within Aviation Safety and Urban Planning. Our analysis reveals a correlation between increased light pollution and the incidence of bird strikes, highlighting the risks to avian populations and underscoring the safety and economic challenges facing the aviation industry. By mapping bird-strike occurrences against light pollution levels, we have identified high-risk zones that often coincide with urban areas and major flight paths. This suggests that mitigating the effects of ALAN could significantly enhance aviation safety by reducing the frequency of bird strikes.

Moreover, based on the temporal and geographic patterns identified in our EDA, we emphasize the need to consider bird migration dynamics in urban planning and aviation safety strategies. The peaks in bird strikes during migration seasons underscore the importance of temporal adjustments in lighting policies, potentially dimming or redirecting lights during these critical periods to minimize disorientation among migratory birds.

5.1.2 Practical Applications for Designing Public Policy. The model-based system design that leverages predictive modeling is a potential tool for policymakers, enabling forecasts of bird-strike occurrences at any given time and location with a high degree of

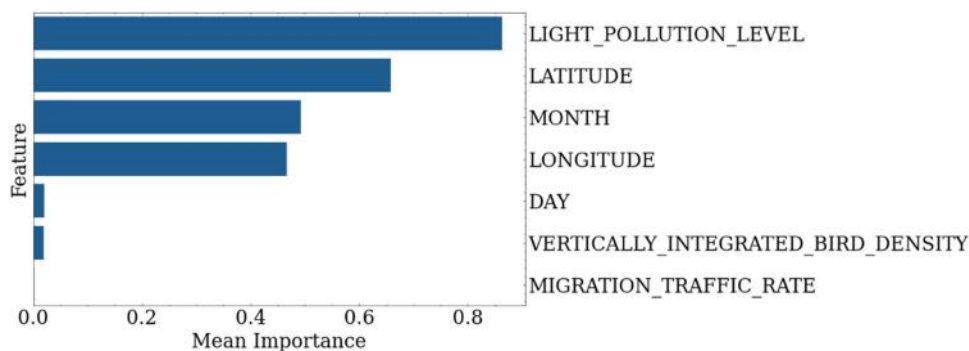


Fig. 10 Permutation importances in the random forest model

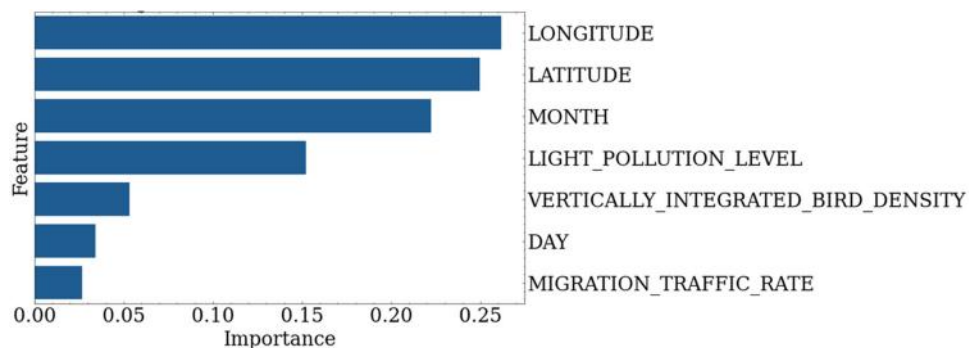


Fig. 11 Feature importances in the random forest model

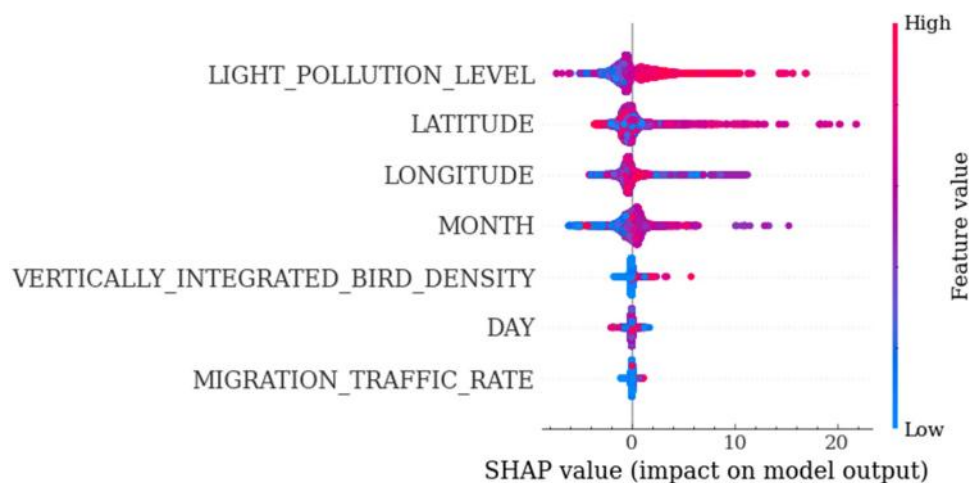


Fig. 12 SHAP values in the random forest model (beeswarm plot)

accuracy. Through this approach, designers will be able to advance principles of systems engineering and model-based system design to develop effective public policies. By integrating various data sources and framing them within the CPSS paradigm, we provide a basis for selecting relevant predictors of bird strikes. This anchors in the idea of information models for social problems, where the focus is on the effective use of multiple information sources and their integration to enable designers to understand the causes of emergent system behavior, resulting in fundamental developments in the design of systems for social problems. This integrated approach facilitates the design of targeted mitigation strategies, such as

- Incorporating predictive modeling into urban planning processes to implement mitigation efforts at high-risk locations and timeframes.
- Adjusting urban lighting schemes during migration periods to reduce attraction or disorientation of migratory birds.
- Planning new developments or modifying existing structures to mitigate the impact of light pollution on surrounding ecosystems.

Our findings are relevant to developing public policies that balance human needs with wildlife conservation, as demonstrated

through these practical applications. By informing such policies with predictive modeling, we can proactively address the challenges posed by ALAN, enhancing both aviation safety and biodiversity conservation.

5.2 Limitations. In this article, we contribute new insights into the relationship between ALAN and bird strikes, utilizing predictive modeling and cyber-physical-social system design to inform public policy and conservation strategies. However, it is crucial to acknowledge the limitations that accompany our findings to pave the way for future research and application enhancements.

5.2.1 Analysis of General Light Pollution Rather Than Specific Light Sources. One limitation of our analysis is that it does not discriminate between different types of lighting sources. Specifically, our GIS light pollution map captures light pollution observed from satellite data, including artificial lighting sources and industrial sources such as flaring from oil and gas sites [35]. This means that our correlation analysis and predictive model do not directly incorporate ALAN as a variable, but instead use general satellite-observed light pollution to approximate its impact. In future work, emphasis could be placed on refining the model by controlling for other sources of light pollution, enabling a more direct assessment of the impact of ALAN.

5.2.2 Feature Selection in Predictive Model. Our predictive model, while robust, is constrained by the variables included. Factors such as altitude and airport traffic can also significantly influence the occurrence of bird strikes. Including these additional predictors may enhance the model's accuracy and applicability. Researchers may consider integrating these and other relevant variables, especially in untested environments outside the geographic scope of our research, to construct a comprehensive model that captures additional factors influencing bird strikes.

5.2.3 Assessing the Performance of the Model Over Time. As the incidence of bird strikes may decrease due to effective interventions informed by our model, the resulting data sparsity could challenge the model's ongoing accuracy and relevance. The diminishing frequency of bird strikes, while a desired outcome, may lead to the underrepresentation of certain conditions or outliers in future datasets, potentially skewing the model predictions. To counteract these challenges, strategies such as integrating synthetic data could be employed to enhance the dataset, ensuring robust predictive capabilities despite fewer real-world incidents. Additionally, implementing adaptive feedback mechanisms that recalibrate the model based on the outcomes of mitigation efforts can help maintain accuracy, as noted in the design method for evolving CPSS (Sec. 2.2). Through these approaches, we can ensure that our model remains dynamic, responsive to change, and facilitates continuous improvement and relevance in predicting bird strikes under varied conditions.

5.2.4 Other Considerations and Areas for Future Work

- **Spatial and temporal resolutions:** The granularity of data used in our analysis might not capture variations in light pollution (2020 data) or bird migration patterns (1/day forecast data) over the time period of bird strikes we studied (1990–2023). Higher-resolution data could provide more precise insights into the spatial and temporal dynamics of bird strikes.
- **Voluntary reporting bias:** Reliance on the FAA Wildlife Strike Database, which is based on voluntary reporting, may introduce bias. Not all bird strikes are reported, especially those that do not result in significant damage. Efforts to adopt more systematic data-collection methods could reduce this bias.
- **Generalizability across regions:** Our study focuses on the United States, and while the model shows promise, its applicability to other geographical regions remains to be tested.

Different migratory patterns, species diversity, and urban lighting standards could affect the model's relevance in other contexts.

5.3 Generalizability of the Modeling Approach. In exploring the interplay between ALAN and bird strikes, our modeling approach has demonstrated effectiveness in predicting complex phenomena driven by dynamic interactions among model representations. Through the salient features of this method, grounded in the CPSS paradigm and a model-based system design for geospatial data, we present opportunities for application across various domains facing similar challenges. In this section, we highlight these features and discuss their applicability in example scenarios relating to adaptive manufacturing systems, ecology, and civil engineering.

5.3.1 Salient Features of the Method. We posit that our modeling approach is characterized by several key features that contribute to its adaptability and effectiveness in complex systems:

- **Holistic integration** provides relevant model features by combining cyber, physical, and social components to capture complex interactions and emergent behaviors.
- **Model-based system design.** The focus is on understanding the system's dynamics and relationships to inform model construction [36] and policy design.
- **Geospatial and temporal modeling** incorporates spatial and temporal data to enhance predictive accuracy and relevance [37].
- **Potential for continued adaptability with E-CPSS** allows the model to evolve over time with new data, maintaining accuracy in changing environments.
- **Actionable insights for decision-making** provide interpretable results that inform policy and design interventions across domains.

5.3.2 Extended Modeling Application: Adaptive Manufacturing Systems. Adaptive manufacturing systems [38,39] operate in environments characterized by fluctuating demand, supply chain uncertainties, and evolving consumer behavior, which create emergent complexities akin to those in our bird-strike setting. Thus, applying our modeling approach in this domain has the potential to enhance responsiveness and efficiency.

In the context of adaptive manufacturing, the CPSS paradigm may be loosely mapped as follows, depending on enterprise needs: 1. The cyber component includes data analytics platforms that process real-time market data, inventory levels, and production metrics; 2. The physical component encompasses manufacturing equipment, production processes, and logistics networks; and 3. The social component involves market trends, regulatory environments, and stakeholder objectives.

Integration with geospatial components involves incorporating location-specific data, such as regional demand variations, distribution routes, and supplier locations. Temporal dynamics are also accounted for by factoring in seasonal demand and market trends. For example, manufacturers of seasonal goods can integrate historical sales data and economic indicators to forecast demand accurately, enabling them to adjust manufacturing schedules and inventory levels in real time, thereby reducing the costs of overstocking or understocking. Similar approaches for just-in-time manufacturing, including digital twins and real-time analytics, have been discussed in Refs. [36,40,41]. Although our method also offers the added benefit of providing a framework for modeling emergent behavior with geospatial data, as identified in the research gaps.

The evolving CPSS concept plays a crucial role in this adaptive manufacturing scenario by allowing models to update with new sales data, market indicators, and supply chain information. This dynamic adaptation helps anticipate changes in demand driven by factors such as inflation, production challenges, or shifting

consumer preferences. As a result, manufacturers can respond to unexpected events by dynamically updating models and strategies.

Applying our approach in adaptive manufacturing could offer several benefits, including increased efficiency by aligning production closely with actual demand, enhanced responsiveness by quickly adapting to market changes, and improved decision-making through data-driven insights to inform strategic planning.

5.3.3 Extended Modeling Application: Engineering. The intersection of wildlife movement and human infrastructure presents complex challenges that could benefit from our modeling approach. Predictive models have previously been used in informing the design and placement of structures like wildlife crossings [42], and our method may help support the long-term efficacy and adaptability of these approaches.

In road ecology, the CPSS paradigm may involve a formulation with 1. Computational models processing wildlife movement data, traffic patterns, and environmental conditions (cyber); 2. Road networks, natural habitats, and physical barriers (physical); and 3. Human activities such as land development, transportation policies, and conservation initiatives (social). Integrating geospatial data could allow us to map wildlife migration routes, collision hotspots, and habitat connectivity, while accounting for temporal dynamics, including seasonal migration periods, breeding seasons, and variations in traffic over time.

The evolving CPSS aspect can enable adaptive modeling by updating predictions as new wildlife movement data becomes available or as environmental conditions change, for example, due to climate change. This proactive planning may anticipate shifts in wildlife patterns and adjust infrastructure plans accordingly.

For instance, engineers and ecologists could use our approach to identify high-risk areas by combining data on wildlife movements, road locations, and automobile traffic volumes. This informs the design of effective wildlife overpasses or underpasses that align with animal behavior and movement patterns. Continuous post-implementation data collection allows for assessing the effectiveness of these structures and making necessary adjustments.

The benefits of applying our modeling approach in road ecology could include enhanced safety by reducing wildlife-vehicle collisions, conservation goals by maintaining habitat connectivity, and efficient resource use by allocating funds and efforts where they will have the most significant impact.

6 Closing Remarks

In this article, we uncover interactions between ALAN and bird strikes as a CPSS, with implications for public policy and aviation safety. Through the development of a predictive model, we have illuminated the impact of ALAN on increasing the incidence of bird strikes, particularly in areas with high levels of light pollution and during critical migration periods. Moreover, we have taken steps to address the previously identified research gaps.

6.1 Summary of Results. Our findings confirm that ALAN is a contributing factor to bird strikes, with clear correlations between increased light pollution levels and the frequency of these incidents. The predictive model developed as part of this research provides a valuable tool for forecasting bird strikes at any given time and location in the United States, enabling policymakers and conservationists to implement targeted mitigation strategies. By integrating data from the FAA Wildlife Strike Database, a light pollution GIS map, and BirdCast migration forecasts, we have demonstrated the potential of predictive modeling in informing more effective and proactive approaches to aviation safety.

6.2 Implications for Public Policy and Lighting Design. The insights gained from our research have implications for public policy and lighting design. By adopting bird-friendly lighting technologies and incorporating ALAN considerations into the

planning process, policymakers can play a critical role in reducing the negative impacts of artificial lighting on avian populations. Furthermore, the development and enforcement of lighting standards that minimize unnecessary exposure to ALAN can significantly contribute to the preservation of biodiversity in urban environments. Thus, in summary, we propose an approach for system designers to design public policies through model-based system design by allowing them to:

- (1) Analyze the interaction between component-level variables and assess their impact on the emergent behavior of the system.
- (2) Analyze interactions between transdisciplinary variables comprising diverse social and technical domains.
- (3) Utilize model-based system design for better-informed decision-making.
- (4) Investigate and discern the primary variables with the most significant impact on bird strikes.

6.3 Looking Ahead. With this work, we provide an actionable step for engineering informatics in aviation safety, and more generally, toward designing E-CPSS for public policy. By adopting an informed, proactive approach to public policy design, we can mitigate the adverse effects of ALAN and foster a safer, more sustainable coexistence between human and avian populations. Further, we envision designing adaptive systems that support self-adaptive public policies, enabling decision-makers to make better-informed decisions pivoted on the integration of preserving wildlife, preventing flight accidents, and informed urban planning for a sustainable tomorrow.

For inquiries about accessing our dataset and using our data to build upon our work, please contact the corresponding author.

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Conflict of Interest

There are no conflicts of interest. This article does not include research in which human participants were involved. Informed consent was not applicable. This article does not include any research in which animal participants were involved.

Data Availability Statement

Data provided by a third party listed in the Acknowledgment.

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