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Research Article

Wildlife Hazard Management – An Intuitive Web-Based Risk Matrix for Airport Stakeholders

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Abstract

The purpose of this study is to employ Tableau and R to create a web-based system for early wildlife hazard alerts at airports, addressing the critical need for timely and accurate wildlife risk assessments. The historical data displays specific time, season, altitude, size, and frequency related to wildlife reports in the United Stated for wildlife management and planning. A user-friendly risk assessment tool, utilizing the Shiny platform, offers airport stakeholders color-coded risk levels by analyzing wildlife hazard report frequencies and sizes. This research distinguishes itself by integrating advanced data visualization techniques and a dynamic risk matrix tool, enhancing proactive wildlife hazard management. The proposed tool is demonstrated through its application at Los Angeles (LAX) and Sacramento (SAC) International Airports, and algorithm is shared to readers for implementation across various airport settings. This paper enhances understanding of wildlife hazard reports, empowering airport stakeholders to make proper decisions for proactive wildlife control, ultimately improving airport safety and sustainability.

Keywords

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Wildlife Hazard
Bird Strike
Risk Management
Shiny

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1. Introduction

In 2019 alone, there have been reported to be 17,228 wildlife strikes on aircraft and over 227,000 between 1990 and 2019 in the United States (Federal Aviation Administration [FAA], 2021). Wildlife hazards, predominantly associated with avian animals, pose a potential life-threatening issue, especially during takeoff and landing, with a majority of incidents occurring below 2000 ft above ground level (AGL) (Dolbeer, 2013). Noteworthy incidents like the U.S. Airways Flight 1549 in 2009 ("The Miracle on the Hudson") emphasize the criticality of wildlife hazard management near busy airports (National Transportation Safety Board [NTSB], 2010). Challenges extend to general aviation airports, exemplified by a 2016 runway incident at Lancaster Airport, Philadelphia, involving a Beechcraft and a deer, resulting in aircraft structural damage and an emergency landing (Kunkle, 2021). This issue is not confined to the United States, affecting other countries, particularly those with emerging economies and increasing airline services (Aircraft Accident Investigation Bureau of India, 2014). The study underscores the necessity of persistent wildlife hazard

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management for continual and significant benefits to airport safety.

This study introduces an innovative, web-based risk matrix tool to enhance airport wildlife hazard management. This tool uses historical data visualization and risk assessment, offering stakeholders an intuitive and user-friendly platform to understand wildlife risk levels effectively. Building on the fundamental risk assessment methodologies, the developed Shiny application serves as an interface that allows airport operators to dynamically interact with wildlife strike data without requiring extensive coding knowledge.

2. Literature review

Airport safety experts believe that initiating a proactively approach to reduce the likelihood and severity of wildlife events around airports is imperative. Believing in this main theory, airports comply with mandatory policies and seek to develop a system or tool that could effectively help operators mitigate wildlife hazards around airports. Per 14 CFR 139.337, Wildlife Hazard Management, it requires airports to report wildlife strikes and implement a wildlife hazard management plan including assessment and controls (14 CFR 139.337, n.d.). Currently, data collection practices are normally conducted via the Form 5200-7 for airports (FAA, 2013) and pilot reports through the FAA web-based reporting system (FAA, n.d.), which enable the Administrator to archive wildlife hazard reports and monitor the potential impact that could arise.

Airport Wildlife Safety Management System

Clearly, the assurance of airport safety has evolved from a reactive to a proactive fashion. The rationality of a proactive wildlife safety management is to detect hazards or threats and mitigate them before resulting in an accident. To be more proactive in promoting aviation safety, in 2010, the *Airline Safety and Federal Aviation Administration Extension Act 2010* was passed and ratified to mandate airline Safety Management Systems (SMS) implementation including Safety Policy, Safety Risk Management, Safety Assurance and Safety Promotion. Since August 30, 2010, the FAA Order 5200.11 has started to mandate airport Safety Risk Management (SRM) noting that from June 1, 2011, all categories of hub airports, from June 1, 2012, all FAR 139 airports, from June 1, 2013, all towered airports and from June 1, 2014, all National Plan of Integrated Airport Systems (NIPIAS) airports must conduct SRM (FAA, August 30, 2010). That said, the SRM process could be used to enable airports to identify wildlife hazards, determine potential risks, and design appropriate risk mitigation strategies in a systemic manner (FAA, 2007, p. 5).

In the Transportation Research Board (TRB) Airport Collaborative Research Program (ACRP) *Synthesis* 37 *Lessons Learned from Airports Safety Management Systems Pilot Studies* (Transportation Research Board [TRB], 2012), the researchers surveyed on FAA pilot study airports revealed that there are challenges associated with the implementation of SMS such as the usage of risk matrix while available documents and manuals are conceptually simple. While the FAA is maintaining a voluntary wildlife hazard reporting system, the risk matrix is nebulous to the airport managers when deciding the risk level. In 2015, the TRB published a handbook, *Applying an SMS approach to wildlife hazard management*, that promulgates a proactive and risk-based method to manage wildlife (TRB, 2015). The advanced Wildlife Hazard Management Risk Assessment Tool (WHaMRAT) was introduced and the risk severity table was provided to airport operators to calculate severity score (Table 1). However, the likelihood or probability score was up to a subjective assumption.

Approaches of Wildlife Hazard Management

U.S. Department of Agriculture (USDA) estimates that about thirty-eight wildlife strikes are reported to the FAA every day. Around ninety-seven percent of wildlife strikes involve birds (U.S. Department of Agriculture, [USDA], 2017). DeVault, Blackwell, Seamans, and Belant (2016) extracted wildlife hazard records from the Federal Aviation Administration National Wildlife Strike Database for Interspecific Avian Hazards. Their research presented comprehensive descriptive statistics on wildlife reports, encompassing details such as species involved, seasonal variations, group sizes, corresponding bird masses, and the extent of damage caused by the strikes. The findings underscored the need for prioritized control measures, guided by the severity of wildlife, to enhance aviation safety. ICAO has also identified that certain land uses near airports, such as parking lots, theaters, food outlets, and golf courses, contribute to wildlife hazards. To mitigate wildlife hazards, the advocated strategies include technical and managerial formats. Technical formats such as installing fences, bar wired roofs, perched light poles, ultrasound repellents, wildlife radars, etc. On the managerial side, making the nearby wetlands around airports inhabitable is the key such as cutting grass and trees, draining water, and covering up the storm drainage system (FAA, 2020).

Annex 14 of ICAO focuses on assessing and mitigating wildlife hazards in and around airports, which mandates member states to assess the extent of wildlife hazards, implement wildlife reduction measures, and prevent attraction sites (Blackwell, Devault, Fernandez-Juricic, and Dolbeer, 2009). Despite the implementation of various wildlife detection and control initiatives, the lingering potential threat persists and intermittently results in damages.

Table 1. Advanced-Version WHaMRAT, Severity scores.

	Severity	Guild	Severity	Guild	Severity
Waterbirds		Shorebirds		Rodents	
Waterbirds < 300g	1	If flocks < 20	4	Rodents < 100g	1
Waterbirds 300-999g	2	If flocks ≥ 20	5	Rodents 100-599g	2
Waterbirds 1000-1999g	3	Shorebirds < 300g	1	Rodents 600-1999g	3
Waterbirds 2000-3999g	4	Shorebirds 300-999g	2	Rodents 2000-9999g	4
Waterbirds > 4000g	5	Gulls/Terns		Rodents > 10000g	5
Seabirds		If flocks < 10	4	Lagomorphs	
Seabirds < 300g	1	If flocks ≥ 10	5	Lagomorphs 100-599g	2
Seabirds 300-999g	2	Gulls/Terns < 300g	1	Lagomorphs 2000-9999g	4
Seabirds 1000-1999g	3	Gulls/Terns 300-999g	2	Bats	
Seabirds 2000-3999g	4	Gulls/Terns 1000-1999g	3	Bats < 100g	1
Pelicans/Comorants		Pigeons/Doves		Bats 100-600g	2
Pelicans 1000-1999g	3	If flocks < 20	4	Mesomammals	
Pelicans 2000-3999g	4	If flocks ≥ 20	5	Mesomammals 100-599g	2
Pelicans > 4000g	5	Pigeons/Doves < 300g	1	Mesomammals 600-1999g	3
Waders		Pigeons/Doves 300-999g	2	Mesomammals 2000-9999g	4
If flocks ≥ 5	5	Parrots		Mesomammals > 10000g	5
Waders 300-999g	2	Parrots < 300g	1	Canids	
Waders 1000-1999g	3	Parrots 300-999g	2	Canids 2000-9999g	4
Waders 2000-3999g	4	Parrots 1000-3999g	3	Canids > 10000g	5
Waders > 4000g	5	Aerial Foragers	1	Felids	
Waterfowl		Woodland Birds	1	Felids 600-1999g	3
If flocks < 5	4	Corvids		Felids > 2000g	5
If flocks ≥ 5	5	If flocks < 15	2	Hooved	
Waterfowl 300-999g	2	If flocks ≥ 15	5	Hooved > 10000g	4
Waterfowl 1000-1999g	3	Corvids < 300g	1	Bears	
Waterfowl 2000-3999g	4	Corvids 300-999g	2	Bears > 10000g	5
Waterfowl > 4000g	5	Corvids 1000-1999g	3	Criteria for Score	Severity
Raptors/Vultures/Owls		Grassland Birds	1	0-99g	1
Raptors < 300g	1	Blackbirds/Starlings		100-599g	2
Raptors 300-999g	2	If flocks < 100	4	600-1999g	3
Raptors 1000-1999g	3	If flocks ≥ 100	5	2000-9999g	4
Raptors 2000-3999g	4	Miscellaneous		Greater than 10000g	5
Raptors > 4000g	5	Miscellaneous < 300g	1		
Upland Game Birds		Miscellaneous 300-999g	2		
Upland Game Birds < 300g	1	Miscellaneous 1000-1999g	3		
Upland Game Birds 300-999g	2	Miscellaneous > 4000g	5		
Upland Game Birds 1000-1999g	3	Criteria for Score	Severity		
Upland Game Birds 2000-3999g	4	Less than 300g	1		
Upland Game Birds > 4000g	5	300-999g	2		
Cranes	5	1000-1999g	3		
		2000-3999g	4		
		Greater than 4000g	5		

Note: TRB. (2015). ACRP Report 145, pps. 50-51.

Aviation Safety Models and the Purpose of the Study

There are leading risk management models often used by aviation researchers and practitioners such as SHELL (Software, Hardware, Environment, and Liveware) (Edwards, 1972), James Reason's Swiss Cheese (Reason, 1990), Bowtie barrier-based risk assessment (FAA, 2017), Heinrich's Safety Pyramid (1959), and Human Factors Analysis and Classification System (HFACS) (Wiegmann & Shappell, 2017), just to name a few. However, tracking wildlife animals such as foxes, raccoons, deer, and various bird species are often challenging until they make an appearance in the vicinity of airport facilities or after the post-strike investigation. Having said that, when formulating strategic plans to address wildlife issues, modern safety researchers strive to identify and mitigate potential hazards at the project's outset using a risk matrix. Lu, Schreckengast and Jia (2011) delivered a low-cost airport hazard reporting system using MySQL and On-Line Analytic Processing (OLAP) data mining skills for the budget-constrained airports. However, the hazard report was simply stored and presented on a map while the corresponding risk was not calculated. Fu, Lu and Ji (2023) applied MATLAB to propose a Risk Assessment Matrix of Operational Safety (RAMOS) for aviation safety enthusiasts. Yet coding and troubleshooting become particularly intricate, especially when updating the two independent variables—probability and severity—in response to new archived reports. Following the aforementioned studies, a study centers on advanced wildlife hazard analytics involving examining independent variables to customize a risk matrix besides presenting data dashboards is imperative.

Our approach enhances proactive risk assessment by leveraging diverse factors, contributing to a more robust system for ensuring airport safety. Thus, to propose another layer of proactive defense, identifying an airport's potential wildlife hazards and preparing countermeasures would be plausible.

To do so, the purpose of this study is twofold: (1) to display descriptive data visualization based on archived wildlife reports between January 1, 2000, and October 17, 2023, and (2) to design and propose a user-friendly wildlife risk matrix tool for stakeholders. Utilizing Tableau and R for data visualization provides a clear and interactive platform for stakeholders (including airport operators, air traffic management, drone pilots, regulatory officials, etc.) to understand the distribution and frequency of wildlife strikes. The risk matrix tool, developed using the Shiny platform, offers an intuitive interface for airport operators to assess risk levels based on historical data. This tool aims to enhance proactive wildlife hazard management by allowing users to interact dynamically with the data, making informed decisions without extensive coding knowledge.

3. Technical Methodology

This project serves a dual purpose in shaping a wildlife hazard reference figures/tables and facilitating a wildlife risk matrix exercise. It aims to achieve the following objectives: (1) Utilizing Tableau and R language (Appendix I) to create visualizations of wildlife hazard reports. These visualizations offer vital insights and information crucial for stakeholders, enabling informed decision-making processes. The visualization tools present an intuitive overview of wildlife strike data extracted from the FAA wildlife strike database from January 1, 2000, to October 17, 2023. (2) The Shiny Online (Appendix II) is used to generate coding and risk level for two selected airports, Los Angeles and Sacramento International Airports to showcase the proposed risk matrix tool.

4. Result and Finding

To give a holistic view of airport wildlife hazards in the U.S., between January 1, 2000, and October 17, 2023, the total case count of wildlife strike reports in the United States is 258,218, which include 147,282 (57.25 %) near-miss, 2,756 (1.06%) substantial damage 58 (.0224%) destroyed cases and others.

Near miss. The top five airports for receiving near-miss wildlife reports, as indicated in Figure 1 below, are Dallas/Fort Worth (6,930, 4.70%), Austin-Bergstrom (2,588, 1.76%), Houston George Bush (2,280, 1.55%), Dallas Love Field (1,822, 1.24%), and Houston William-Hobby Airports (1,570, 1.07%).

Despite unspecified species, Mourning Doves (2,709, 1.84%) are associated with the highest number of near-miss reports, followed by Rock Pigeons (821, 0.56%), Killdeer (760, 0.51%), and Barn Swallows (646, 0.44%) (Fig. 2).

Figure 3 below illustrates that the majority of near-miss cases occurred during the Approach phase, followed by incidents during Landing Rolls, Climb, and Take-off Run phases.

Minor damage cases. For the cumulative count of minor damage, it tallies up to 6,013 (2.328%) from January 1, 2000, to October 17, 2023. To streamline readers' comprehension, the authors focus on airports that contribute a minimum of 30 wildlife hazard reports for the initial data analysis. The findings reveal that within the contiguous United States, California, Florida, and Texas stand out as the states experiencing the most frequent wildlife strikes resulting in minor damages (Fig. 4), with recorded cases of 502, 470, and 339 incidents, respectively. Furthermore, there are two notable peaks in case counts observed during the months of April and October regarding minor damage cases (Fig. 5).

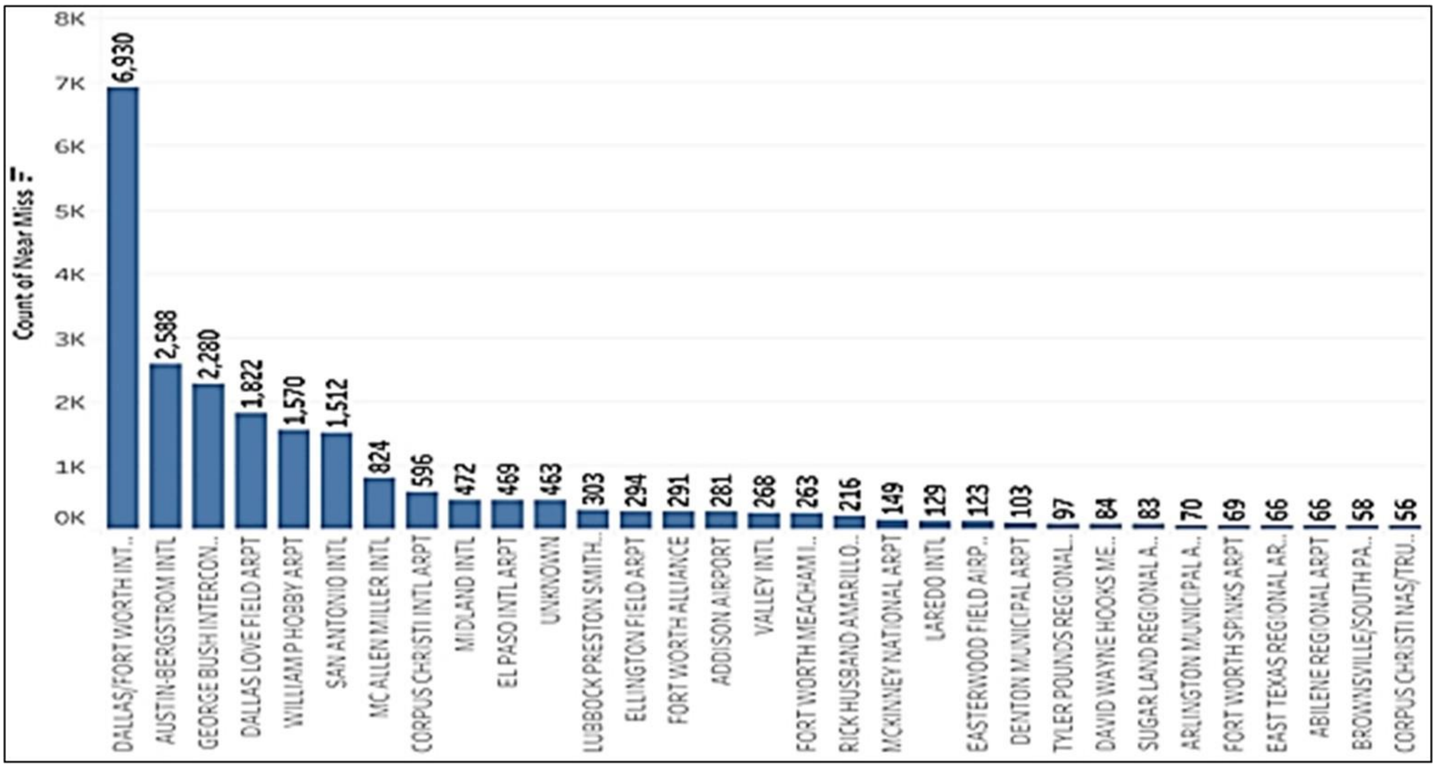

Fig. 1. Near Miss Cases - Airport

Note: Species equal to or more than 50 reports.

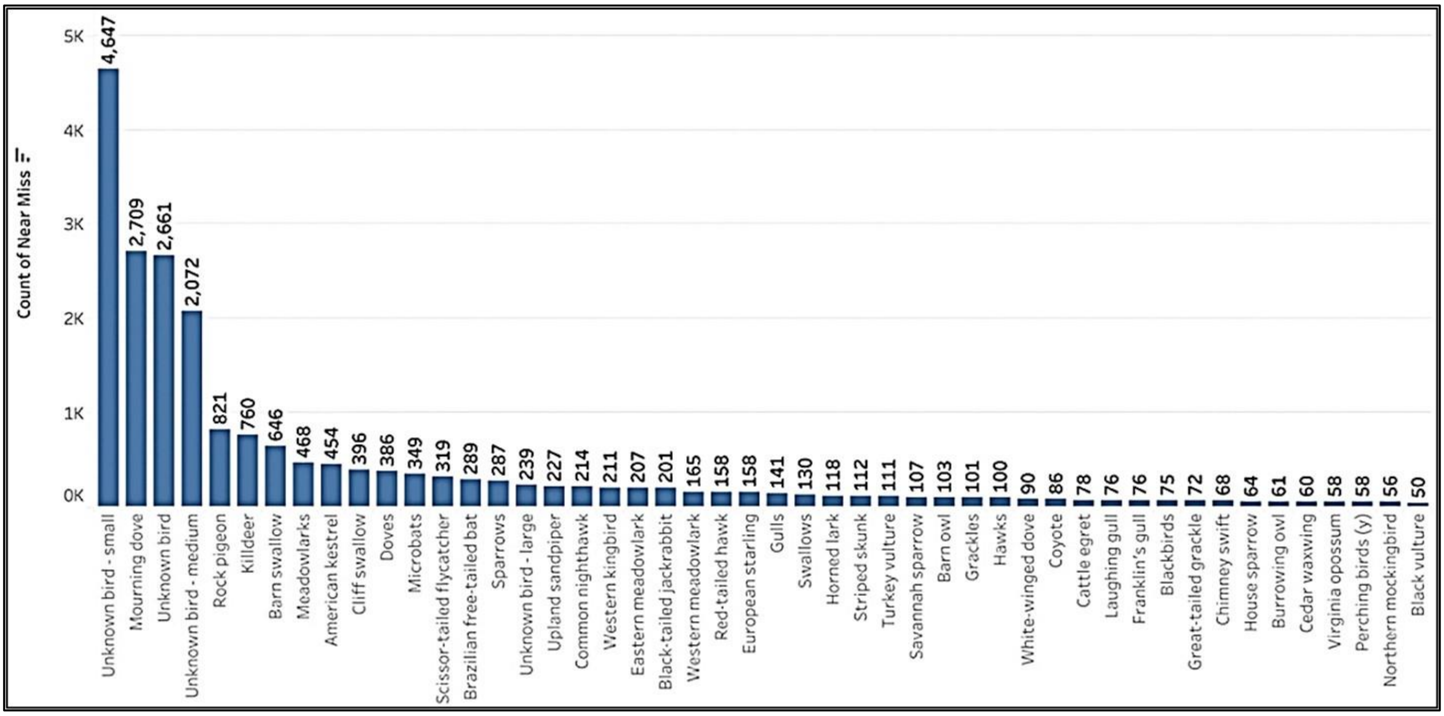

Fig. 2. Near Miss Cases - Species

Note: Species equal to or more than 50 reports.

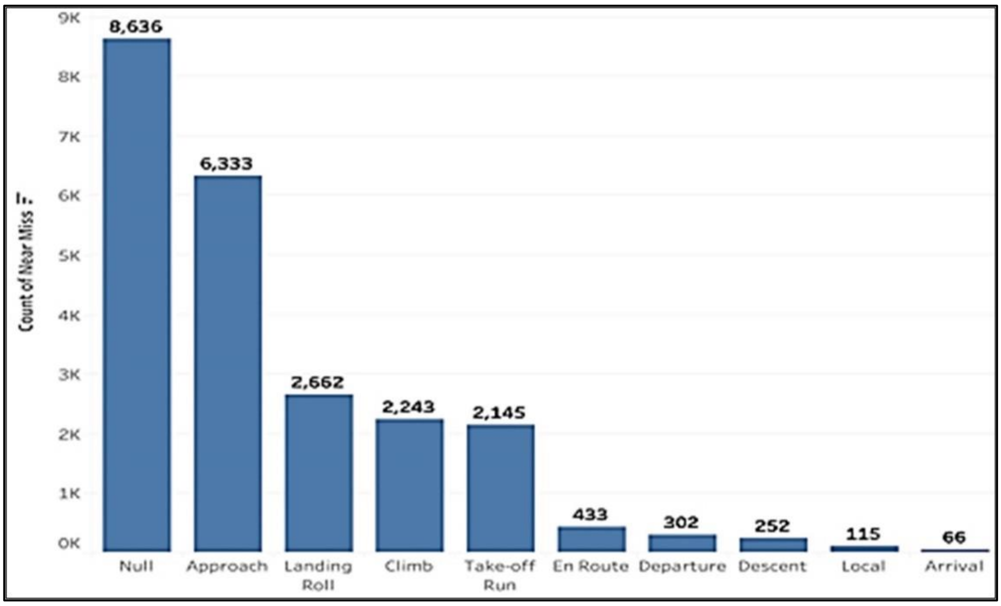

Fig. 3. Near Miss Cases – Flight Phases

Note: This figure excludes “null” data and species equal to or more than 50 reports.

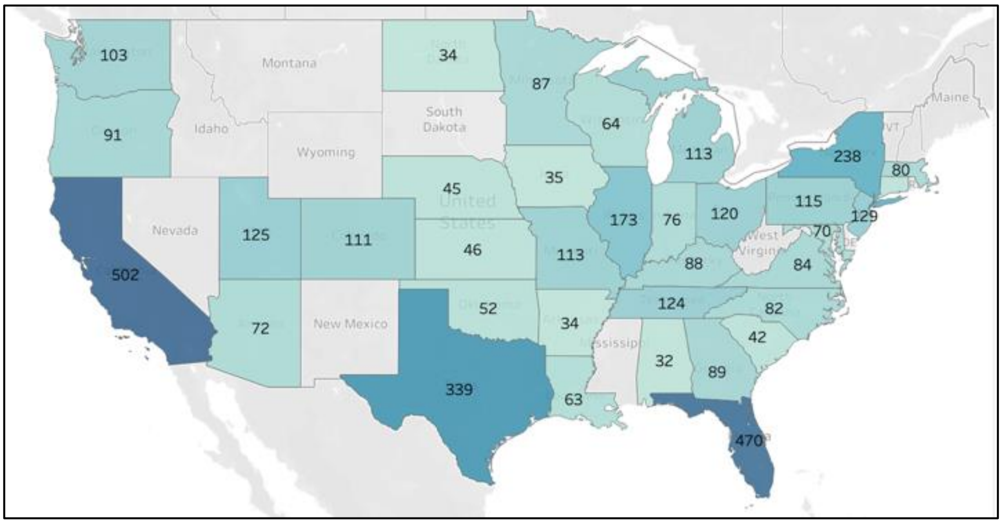

Fig. 4. Minor Damage Count – States

Note: This figure exclusively accounts for reports that are equal to or exceed 30 in count.

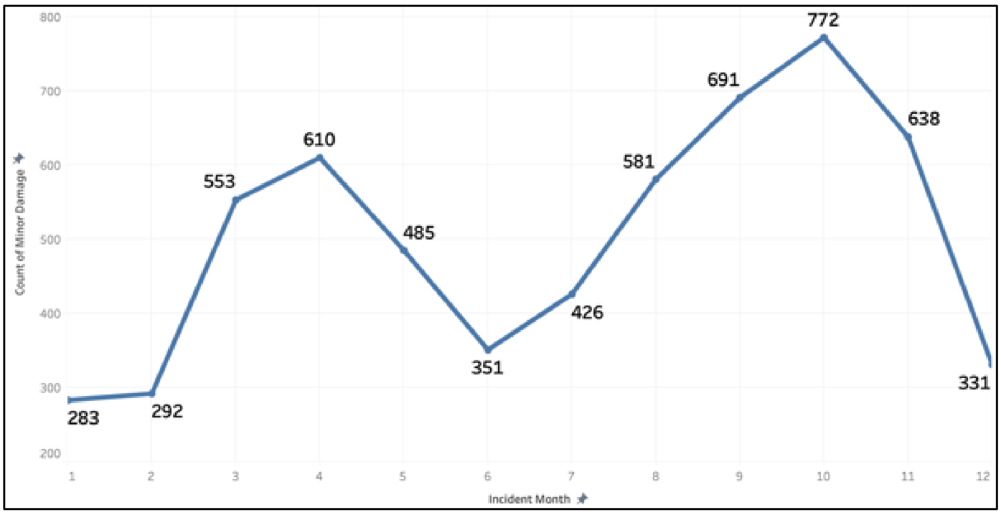

Fig. 5. Minor Damage Count – Month

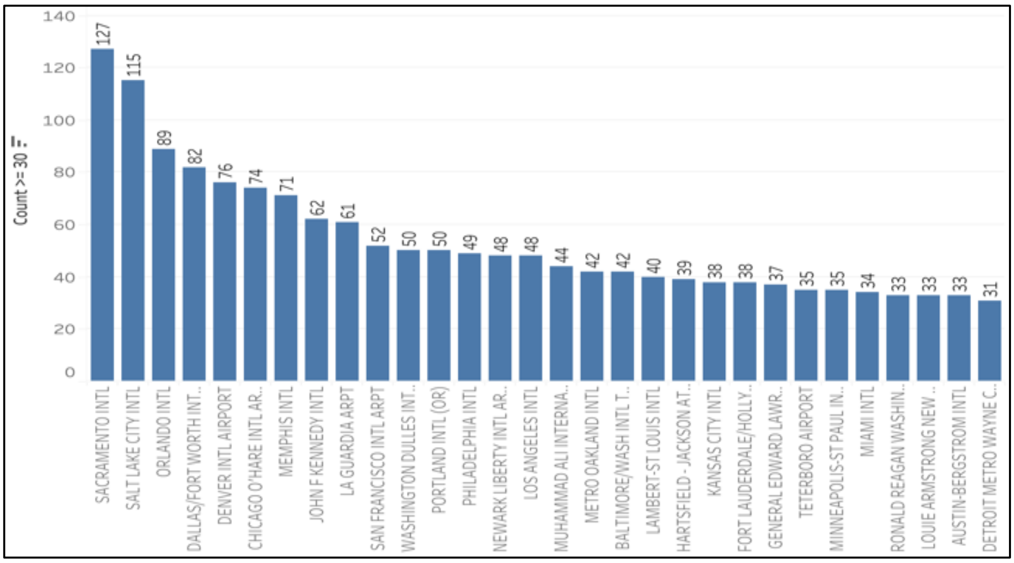

Fig. 6. Minor Damage Cases - Airports

Note: This figure exclusively accounts for reports that are equal to or exceed 30 in count.

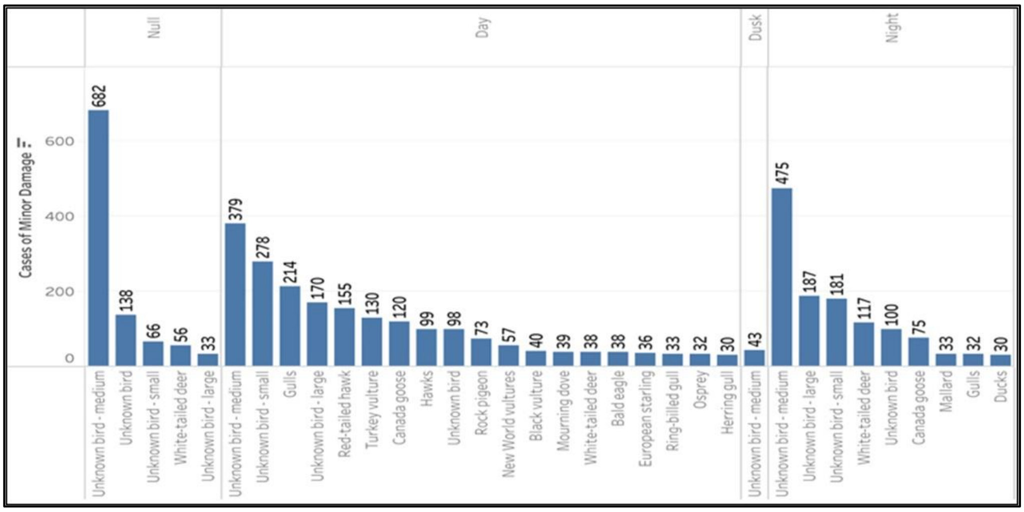

Fig. 7. Minor Damage Cases - Time

Note: This figure exclusively accounts for reports that are equal to or exceed 30 in count.

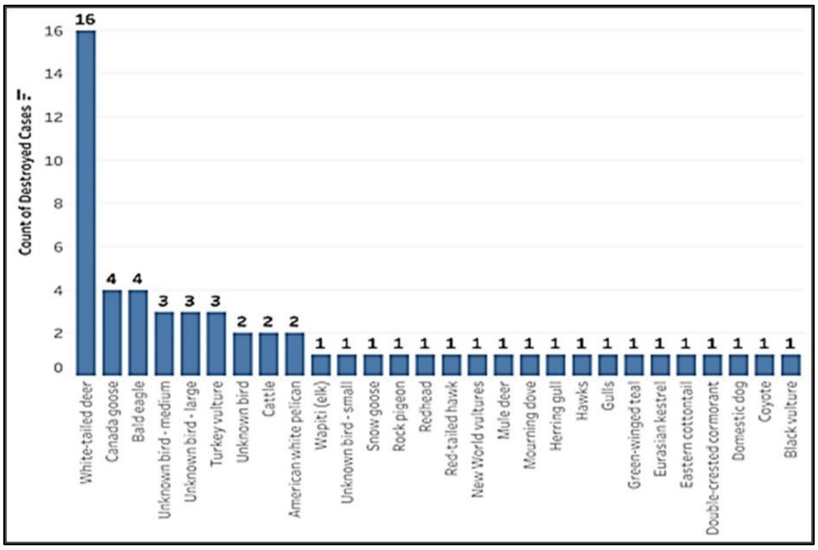

Fig. 8. Destroyed Cases – Species

Note: Excluding "unknown" species

In terms of individual airports, Sacramento International Airport stands out with the highest frequency of occurrences, totaling 127 cases. It is closely followed by Salt Lake City, Orlando, Dallas/Fort Worth, Denver, and Chicago, recording 115, 89, 82, 76, and 74 cases, respectively (Fig. 6).

Although some reports do not specify the species of wildlife involved, the majority of wildlife hazard cases are attributed to Gulls, Red-tailed Hawks, Turkey Vultures, and Canada Goose during daylight hours. Interestingly, during nighttime, White-tailed Deer and Canada Goose are identified as the primary causes of most minor damage incidents (Fig. 7).

Destroyed. The total count of destroyed cases is 58. In instances resulting in destroyed aircraft, White-tailed Deer are responsible for fourteen (16) cases, representing 27.58% of the accidents, followed by Canada Goose and Bald Eagle, each accounting for 6.89% of the accidents (Fig. 8). While the height of accidents involving While-tailed Deer is 0~9 ft AGL, collisions happened at altitude of 8,800 ft AGL (Canada Goose) and 2,137 ft AGL (Bald Eagle) (Fig. 9).

For the categories of operations, Business and Privately-Owned operations encountered most destroyed accident due to wildlife collisions (Fig. 10). The data highlights a significant trend where most destroyed accidents occurred during the En Route flight phase, closely followed by Climb, Landing Roll, Take-off Run, and Approach (Fig. 11). Interestingly, there isn't a discernible specific high-risk time of day associated with these severe damage incidents (Fig. 12).

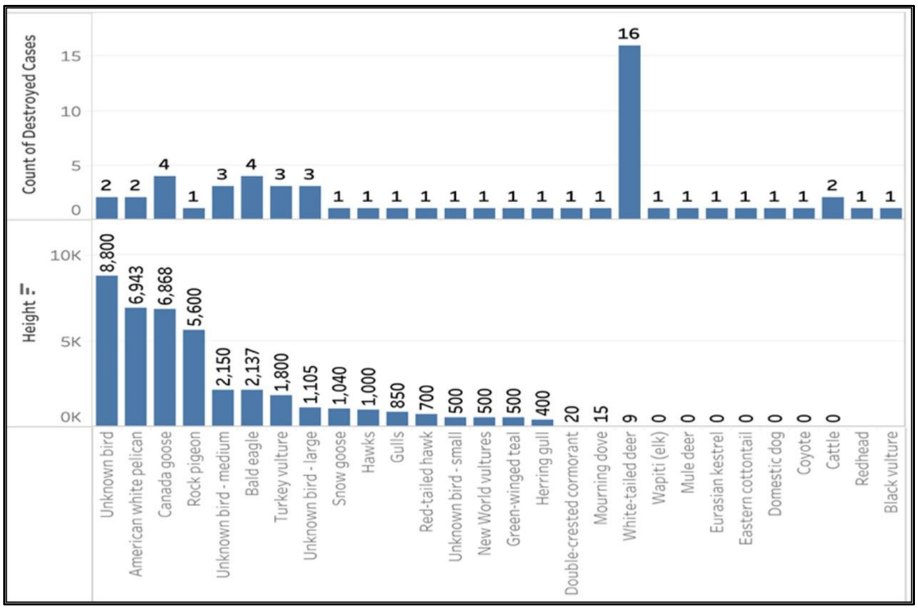

Fig. 9. Destroyed Cases – Heights and Species

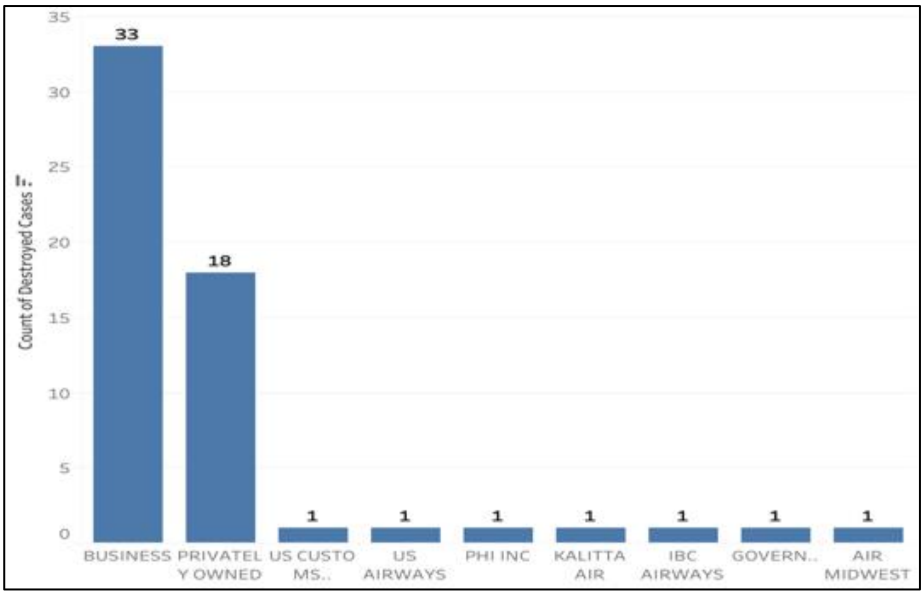

Fig. 10. Destroyed Cases – Operators

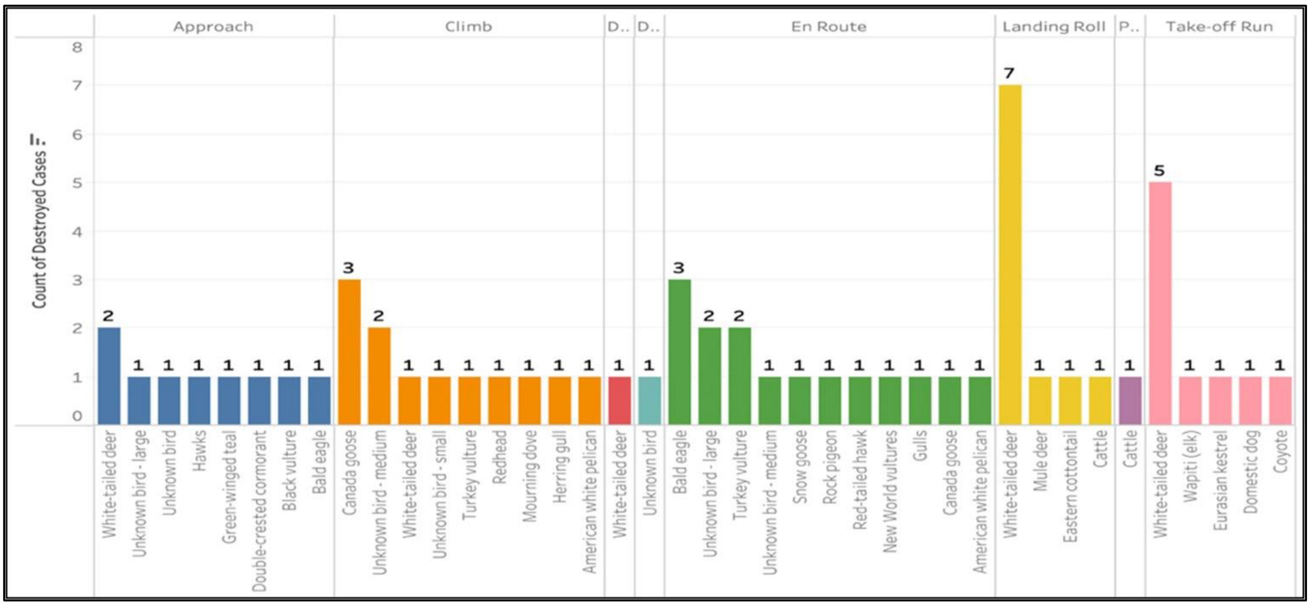

Fig. 11. Destroyed Cases – Phases of Flight and Species

The most substantial financial impacts from wildlife-related accidents are observed at LaGuardia Airport (KLGA) in New York, incurring costs of $49.068 million involving Canada Goose. Moreover, significant financial losses of $15.68 million at Troy Municipal Airport (KTOI) in Troy, Alabama, and $8.125 million at Astoria Regional Airport (KAST) in Oregon are linked to encounters with White-tailed Deer and Wapiti, respectively (Table 2).

Probability and Severity of the Risk Matrix

To demonstrate the convenience and practicality of the designed risk matrix, two Californian airports, Los Angeles International Airport (LAX) and Sacramento International Airport (SAC), are selected for a comparative analysis of wildlife incidents due to the high volume of wildlife hazard reports in California. The similar process can be applied to other interested airport stakeholders.

To identify the probability to estimate risk, Figure 13 shows the hourly cumulative wildlife incidents at Sacramento International Airport (SAC) and Los Angeles International Airport (LAX). It is clear that that both airports experience the lowest number of incidents during the early hours of the day, from midnight to about 05:00. This is likely due to reduced air traffic during these hours. Starting from 06:00, as air traffic begins to increase, so does the number of wildlife strikes, with a noticeable uptick at both airports. A particularly interesting pattern emerges at SAC, where there is a substantial increase in wildlife strike incidents starting from around 17:00, reaching a peak at midnight. This suggests that wildlife activity around SAC is significantly higher during these hours, which could be due to a variety of factors such as nocturnal wildlife behavior, feeding patterns, or the presence of species that are more active during dusk and the early night hours. LAX exhibits a more evenly spread pattern of wildlife strike incidents over the day, with the most significant peak occurring at 07:00. This morning surge may be attributed to the convergence of heightened airport traffic as flights typically ramp up for the day and the early morning wildlife activities. This observation could suggest that the strategies employed should differ in timing and approach due to the distinct patterns of wildlife activity at each location.

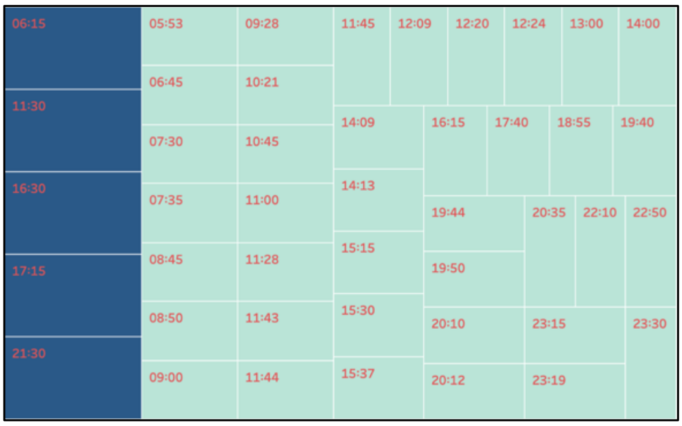

Fig. 12. Destroyed Cases – Time of the Flight

Table 2. Destroyed cases – Financial Losses

Species	Airport ID	
Canada goose	1C9	85.554
	KLGA	49.068.000
Coyote	KOGS	2.242.500
Eastern cottontail	NC30	113.022
Hawks	O41	35.250
Herring gull	KROC	1.852.500
Mourning dove	KLPR	1.794.000
Unknown bird - large	KCPR	234.000
Unknown bird - medium	4IA2	296.100
Unknown bird - small	KCPS	1.191.000
Wapiti (elk)	KAST	8.125.000
White-tailed deer	KLRO	49.472
	KMBT	47.640
	KOZS	253.575
	KRRT	1.157.000
	KTNT	971.750
	KTOI	15.684.500
	Y96	225.900

Note: KLGA – US Airways flight 1549 accident; KTOI – Ark Air Learjet 60 accident

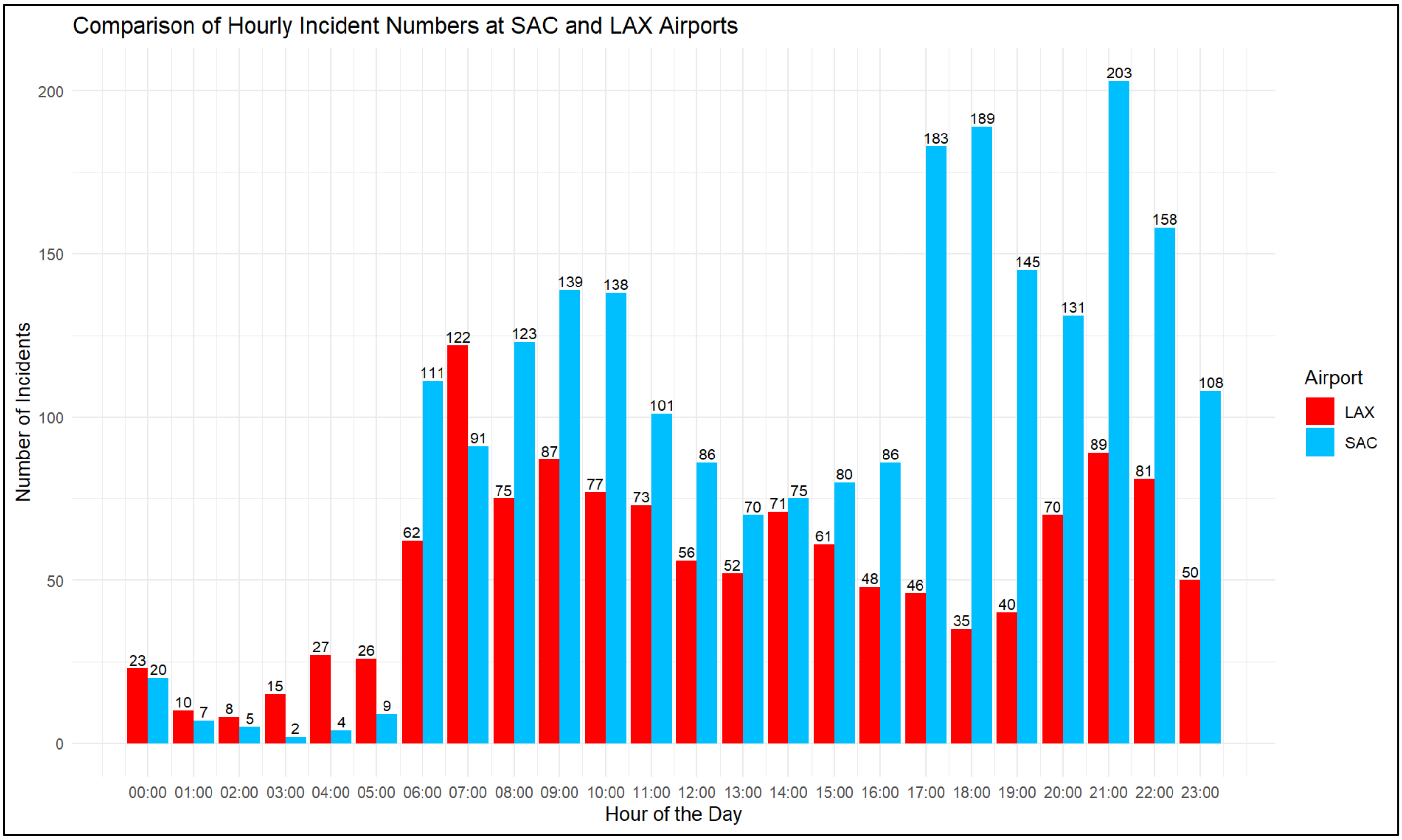

Fig. 13. Hourly Incidents – Comparison between LAX and SAC

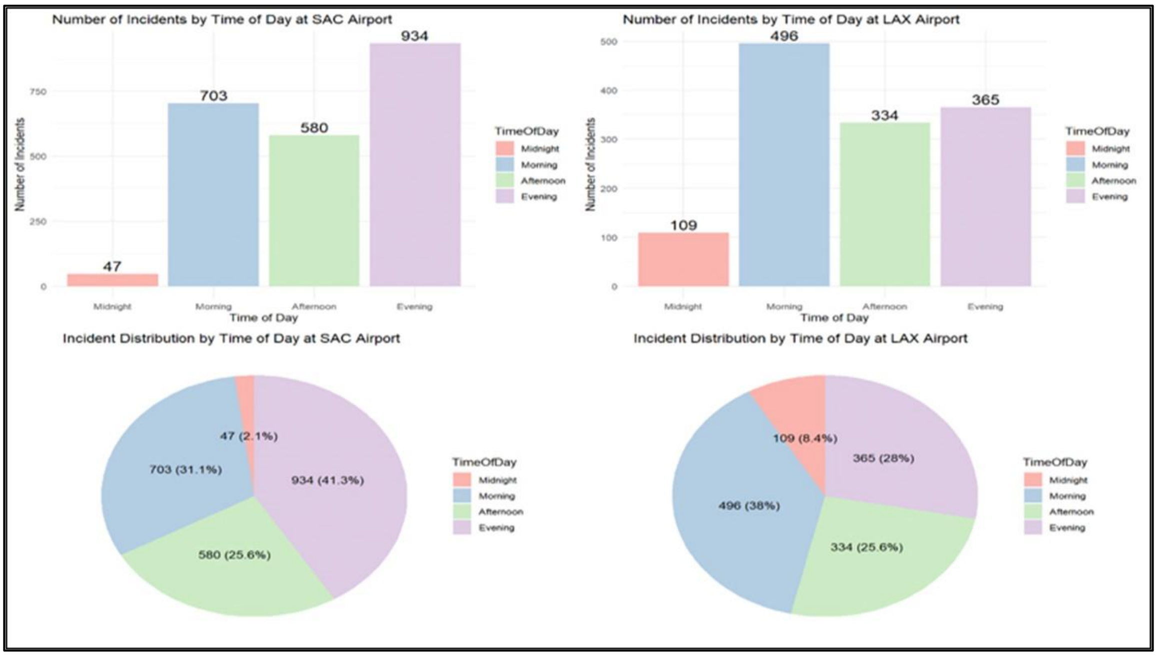

Fig. 14. Number of Incidents – Time of Day Comparison between LAX and SAC

To have better understanding of the time distribution of the incidents at these two airports for proper risk calculation, the following analysis split the time into four different sections: Midnight (00:00-05:59), Morning (06:00-11:59), Afternoon (12:00-17:59), and Evening (18:00-23:59). The following charts shows the number and percentage of incidents at two airports (Fig. 14).

To provide better understanding of the time distribution of wildlife strikes, Figure 15 below depicts a multi-dimensional analysis of wildlife strike incidents at LAX, the data for LAX shows a dramatic percentage increase in evening from February to April, followed by a significant decrease until June (Fig. 15). Midnight incidents at LAX remain consistently low hinting at reduced risks during these hours.

At SAC, Figure 16 presents the percentages of incidents occur within specific time periods (Morning, Afternoon, Evening, and Midnight) across different months of the year. Evening incidents peak notably in April and October, suggesting that these periods have the highest relative occurrence of wildlife strikes during this time of day. This observation plays an important role in deciding wildlife strike probability.

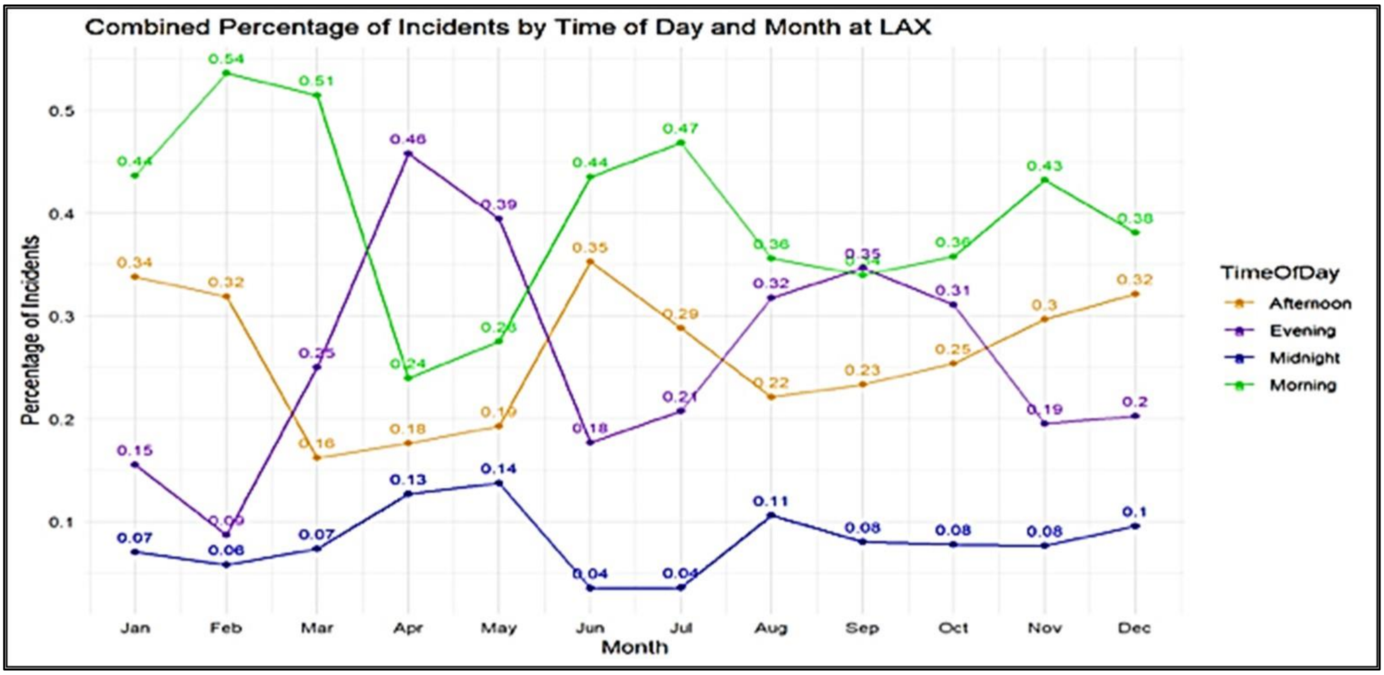

Fig. 15. Probability Density of Incidents by Time of Day – LAX

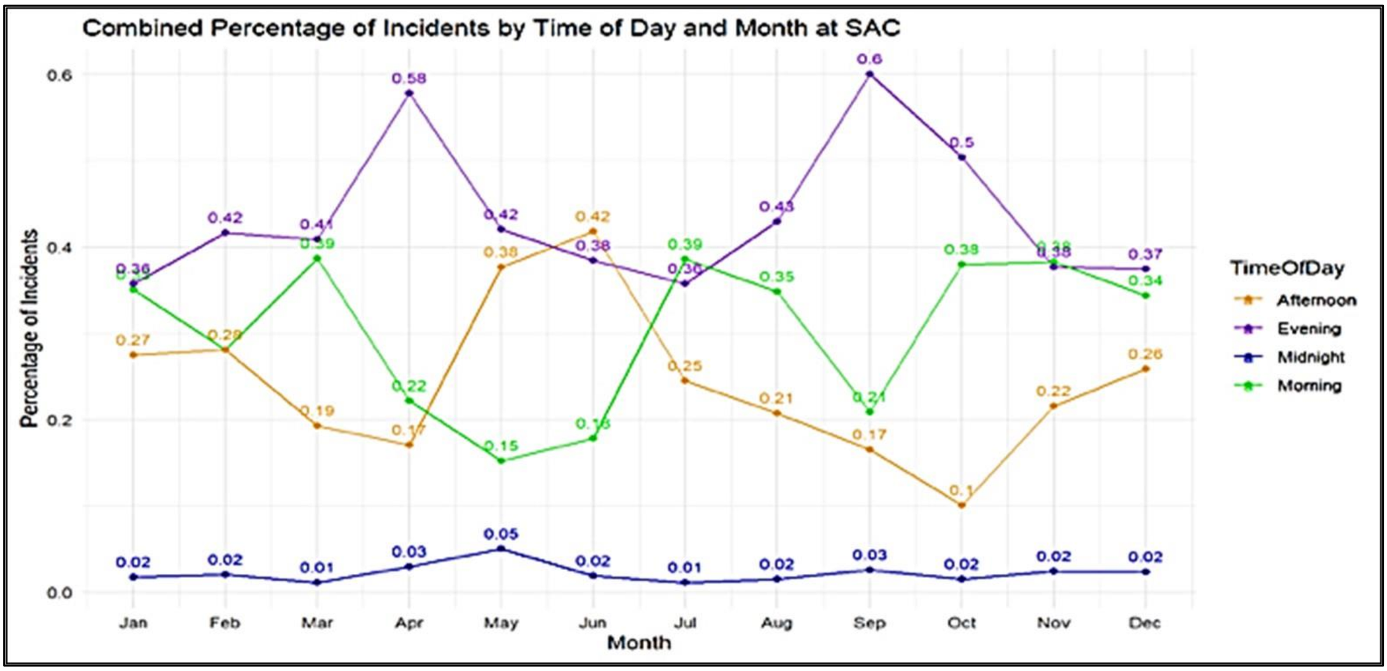

Fig. 16. Probability Density of Incidents by Time of Day – SAC

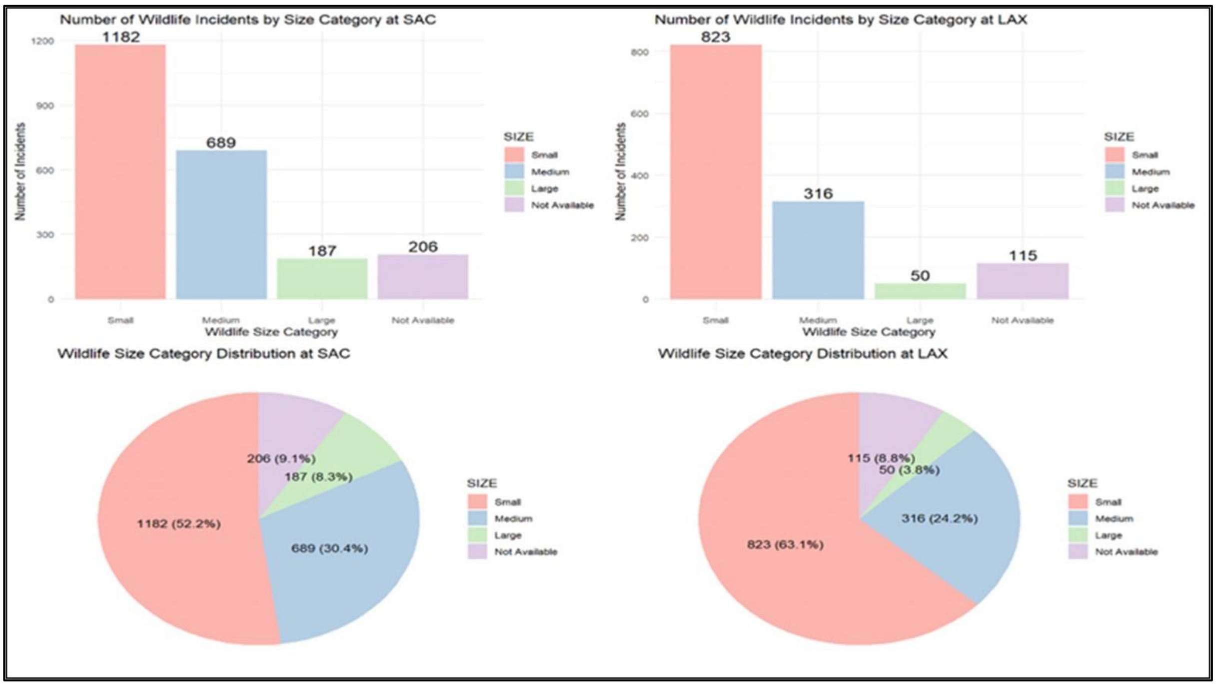

Fig. 17. Incidents by Size – Comparison between LAX and SAC

To decide the severity levels, the size of species is crucial while conducing risk analysis. At SAC, the majority of wildlife incidents involve small-sized animals, with a count of 1,182 incidents representing 52.2% of the total. Notably, SAC has a considerable proportion of medium-sized wildlife strike incidents, accounting for 30.4% with 689 incidents. Large wildlife strike incidents are fewer, with 187 incidents making up 8.3%, and incidents with size not available at 9.1% with 206 incidents. In comparison, LAX also has the highest percentage of incidents involving small-sized avian animals at 63.1%, totaling 823 incidents. However, the percentage of medium-sized wildlife strike incidents is lower than SAC, at 24.2% with 316 incidents. The data reveals that while both airports have the highest incidence with small-sized avian animals, SAC has a notably higher percentage of incidents involving medium-sized avian animals compared to LAX (Fig. 17).

Finding both probability and severity enables the researchers to estimate risk level as risk (R) is theoretically equal to the product of probability (P) and severity (S). Our approach helps identify risk level where resource can be allocated to initiate preventive measures during times of greater risk. It may also guide decisions beforehand on flight scheduling, maintenance activities, and staffing, all aimed at minimizing the magnitude of wildlife strikes. This level of process enhances the airport's risk assessment and management plans, ultimately contributing to safer airport operations and reducing financial losses.

Risk Analysis Web-based Tool – An Exercise

In addition to conducting a visualized analysis of wildlife strike incidents, we developed a specialized website using the free Shiny framework to enable airport operators to dynamically interact with the data and assess risk levels (Wildlife Strikes - Risk Analysis, 2024). While a specialized coding algorithm is developed, this demonstrative platform allows users to select an airport (in this paper, we use SAC or LAX) and month to view a tailored risk analysis for different wildlife size categories.

The Shiny application is structured into two sections: the UI, which is the front end that users interact with, and the server function, which processes the data and generates the output. In the UI, dropdown menus facilitate the selection of an airport and month, creating a user experience that is both intuitive and efficient. The server side uses reactive expressions to filter the data according to these user inputs, ensuring that the displayed information is both relevant and specific to the selected parameters. The codes are presented in Appendices I and II for dissemination among the interested public.

The risk level calculation is a critical feature of the application, providing a quantifiable measure of risk by multiplying the frequency of wildlife strike incidents (probability) by the object's size (severity), with small being 1, medium being 2, and large being 3). While the frequency and object's size are both coded into a corresponding risk level, the overall risk scores could fall into three different risk levels—low (Green), moderate (Yellow), and high (Red). Colored bars are represented in an interactive Plotly bar chart on the main panel of the website so stakeholders could take a prompt risk recognition and decide whether a control is required. Figures 18 and 21 exemplifies the color-coded risk level associated with the selected month at LAX and SAC.

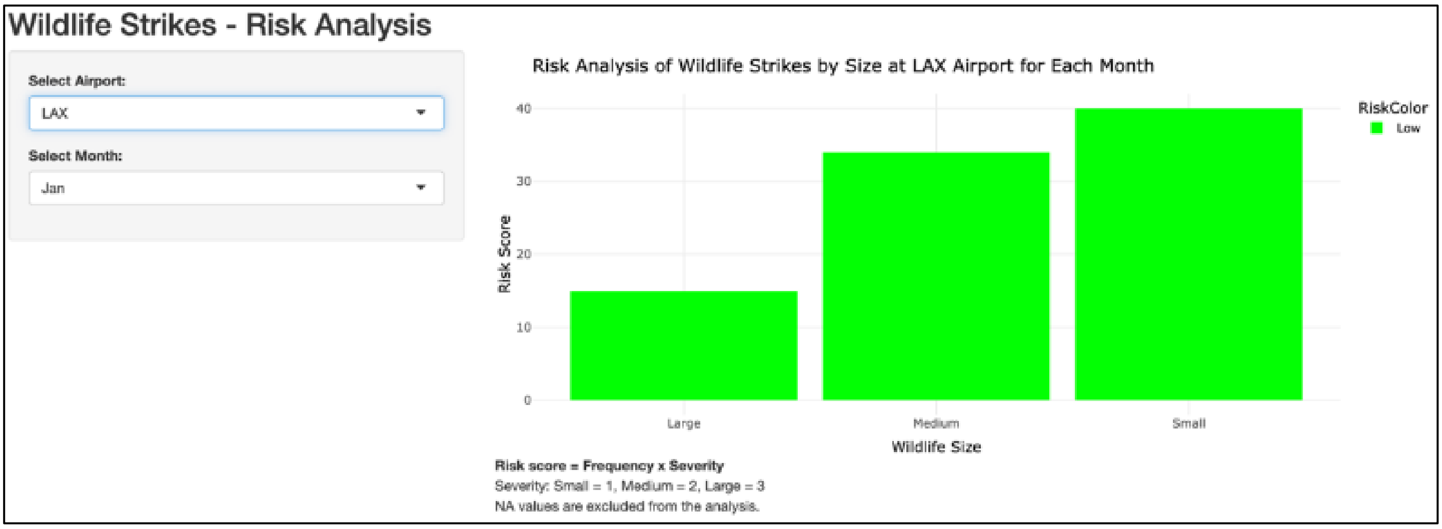

Fig. 18. Wildlife Risk Level – LAX in January

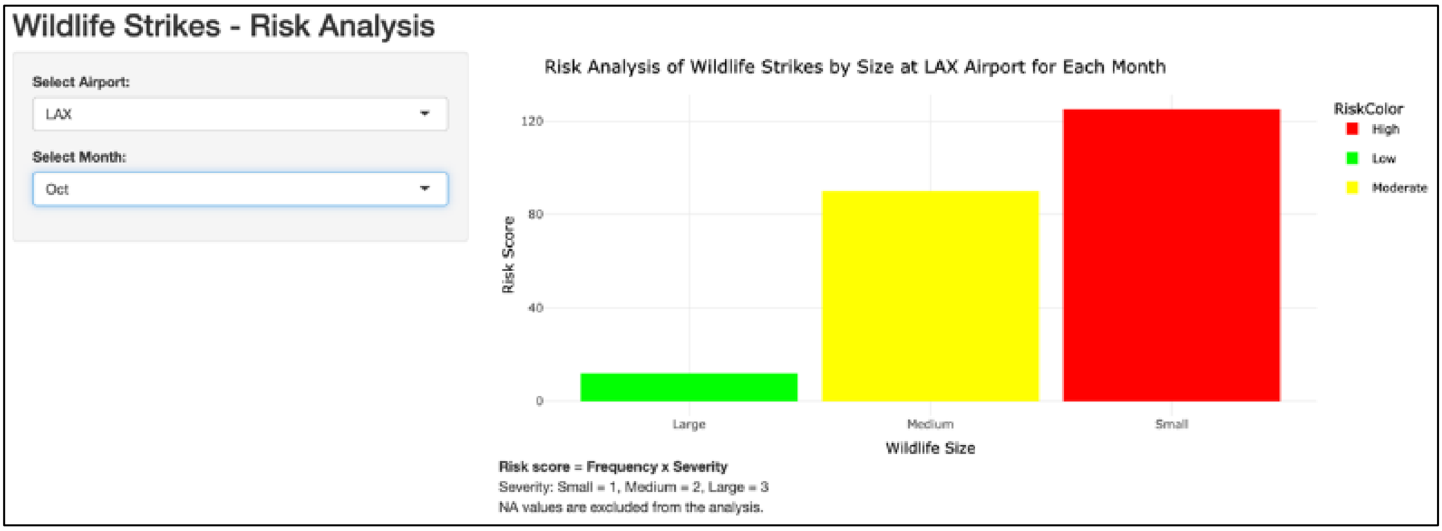

Fig. 19. Wildlife Risk Level – LAX in October

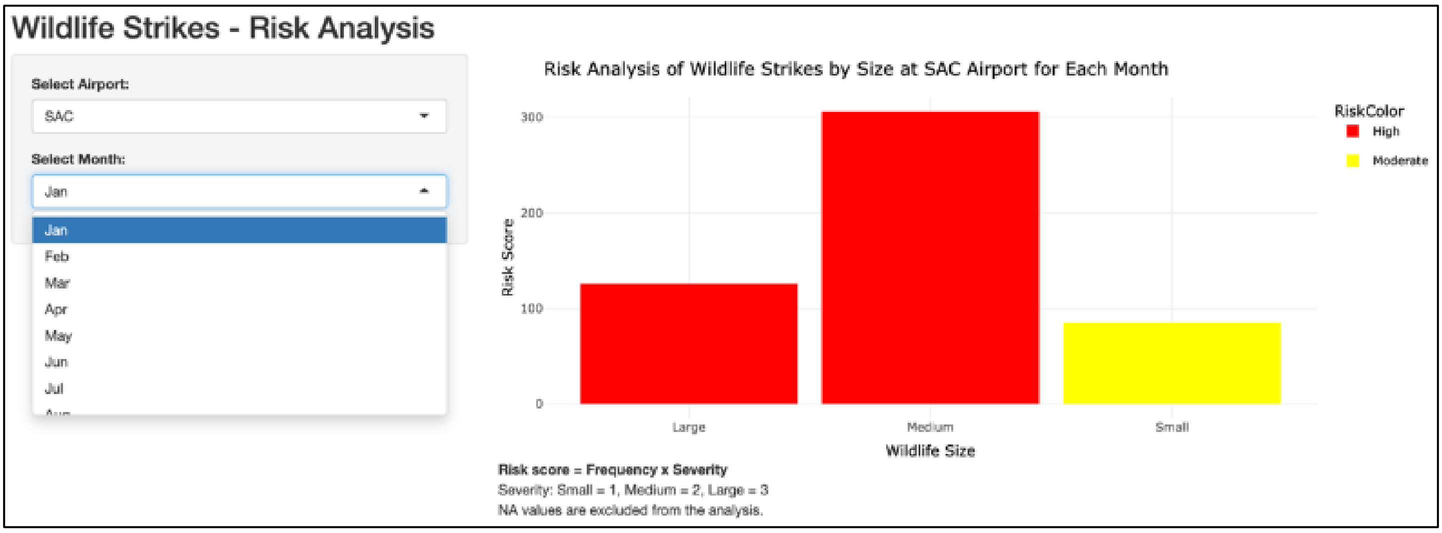

Fig. 20. Wildlife Risk Level – SAC in January

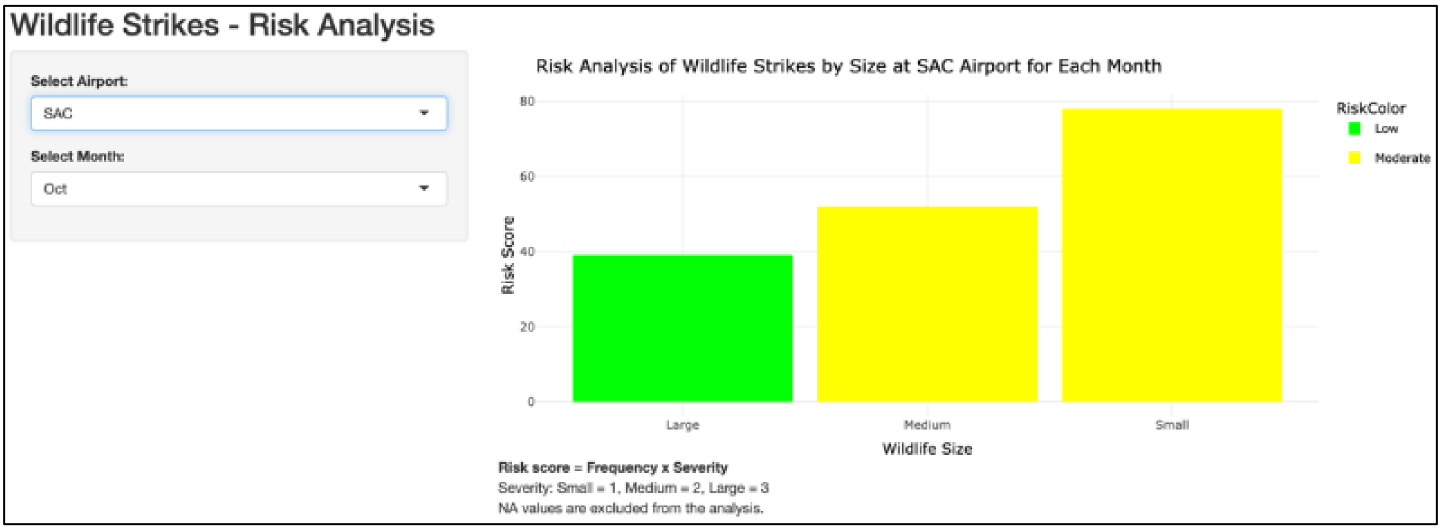

Fig. 21. Wildlife Risk Level – SAC in October

5. Conclusion

The completion of this study provides early wildlife alerts to stakeholders: airport operators, traffic controllers, and pilots. We apply Tableau and R for wildlife hazard data visualization to provide a quick reference to airport stakeholder in addition to providing an interactive and customizable risk decision-making tool using Shiny platform. The web-based system empowers airport stakeholders with the ability to promptly identify high-risk periods simply based on the coded report frequencies and wildlife sizes. When the new database is updated, the risk probability will be recalculated simultaneously supporting an accurate risk assessment. This approach not only facilitates a deeper understanding of the hazard report but also enhances the decision-making capabilities of airport operators. In summary, by leveraging advanced technologies to assess and determine risk levels, airport stakeholders not only can take a proactive approach in implementing strategic wildlife controls or measures, but also enhance overall airport safety and sustainability. While the authors use LAX and SAC airports to showcase the function of the proposed tool, researchers with an interest in the field can apply the codes to other airports by substituting their own wildlife hazard database. Utilizing interactive visualizations guarantees the effective communication of intricate data in a user-friendly manner, facilitating instant interpretation and enabling prompt airport wildlife preventive action.

This paper primarily serves as a demonstration of the potential capabilities of the risk matrix tool, laying the groundwork for future development into a fully operational solution. This study considers probability as the volume of operations and severity as the size of reported wildlife, forming the basic foundation of the risk assessment methodology used. Future iterations will incorporate additional factors such as geographical location, operational times, and wildlife migration patterns to provide a more comprehensive risk assessment framework. Understanding the impact of quiet hours, geographical features, and wildlife migration patterns is crucial for effective wildlife hazard management. Airports near natural flyways or breeding areas may experience higher wildlife activity during specific times of the year or day. The risk matrix tool is designed to be adaptable, allowing for integrating these critical factors in future updates to provide a more accurate and holistic risk assessment. The developers will develop and integrate these features, allowing stakeholders to select relevant variables without extensive coding. This ensures the tool remains user-friendly while accommodating wildlife hazards' complex and varied nature across different airports.

Future Study

This paper does not include meteorological information, quiet hours, geography, or airport wildlife movement patterns. Interested researchers or stakeholders can conduct a follow-up study. Specifically, integrating meteorological data could enhance predictive accuracy by accounting for weather-related wildlife behaviors. Investigating the impact of quiet hours on wildlife activity around airports could provide insights into optimal times for implementing control measures.

Further studies could also explore the influence of geographical features and airport wildlife movement patterns to refine risk assessments and improve the tool's adaptability across different airport environments. Future research should focus on incorporating machine learning algorithms to enhance predictive modeling capabilities, enabling more accurate and dynamic risk assessments.

During the development and implementation of the web-based system, several challenges were encountered. Data quality issues, such as inconsistent or incomplete wildlife strike reports, can affect the accuracy and reliability of the risk assessments. Integrating the tool with existing airport management systems posed technical challenges, requiring customized solutions for different airports. Ensuring that airport staff are adequately trained and comfortable using the new tool is critical for its success. The reliance on historical data may limit the tool's predictive accuracy in rapidly changing environments, highlighting the need for continuous data updates and model refinements. Validating the system's scalability and effectiveness across different airport settings remains an ongoing challenge, necessitating further research and testing.

CRediT Author Statement

Haoruo Fu: Data Visualization, Coding, Final Edit. **Chien-tsung Lu**: Topic, Literature Review, Contents, Data Visualization, Final Edit. **Ming Cheng**: Topic, Literature Review, Contents, Data Visualization, Final Edit. **Mengyi Wei**: Data Visualization, Coding, Final Edit.

Nomenclature

FAA	: Federal Aviation Administration
SMS	: Safety Management Systems
SRM	: Safety Risk Management
WHaM-RAT	: Wildlife Hazard Management Risk Assessment Tool
LAX	: Los Angeles International Airport
SAC	: Sacramento Airport
AGL	: Above Ground Level
R	: Risk level
P	: Probability (wildlife incident frequency)
S	: Severity (wildlife size)
Shiny	: An R-based platform for building interactive web applications
Tableau	: A data visualization software used for interactive reports and dashboards

References

14 CFR 139.337 Wildlife hazard management, n.d.. https://www.ecfr.gov/current/title-14/chapter-I/subchapter-G/part-139/subpart-D/section-139.337

Aircraft Accident Investigation Bureau of India (AAIB), 2014. Final investigation report on accident to SpiceJet Boeing B737-800 aircraft VT-SGK at Surat on 06.11.2014. Retrieved from https://www.skybrary.aero/sites/default/files/bookshelf/4127.pdf

Blackwell, B. F., DeVault, T. L., Fernández-Juricic, E., & Dolbeer, R. A. , 2009. Wildlife collisions with aircraft: A missing component of land-use planning for airports. Landscape and Urban Planning, 93(1), 1–9. https://doi.org/10.1016/j.landurbplan.2009.07.005

Colón, A. M. & Long, M. R., 2023. When can local bird detection radars best complement broad- scale early-warning forecasts of risk potential for bird–aircraft strikes as part of an integrated approach to strike mitigation? Ecology, 8. doi: 10.1111/ecog.06772

DeVault, T. L., Blackwell, B. F., Seamans, T. W., & Belant, J. L., 2016. Identification of Off Airport Interspecific Avian Hazards to Aircraft. The Journal of Wildlife Management 80(4):746–752. DOI: 10.1002/jwmg.1041

Dolbeer, R. A., 2013. The history of wildlife strikes and management at airports. U.S. Department of Agriculture: Animal and Plant Health Inspection Service. Retrieved from: https://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=2473&context=icwdm_usdanwrc

Dziak, D. et. al., 2022. Airport Wildlife Hazard Management System - A Sensor Fusion Approach. Elektronika ir Elektrotechnika, 28(3), 45–53.

Edwards, E., November 1972. Man and Machine - Systems for Safety. Outlook on Safety: Proceedings of the 13th Annual Technical Symposium. London: British Air Line Pilots Association, 21–36.

FAA. (2007). AC 150/5200-37 Introduction to safety management systems for airport operators. Retrieved from https://www.faa.gov/documentlibrary/media/advisory_circular/150-5200-37/150_5200_37.pdf (Accessed November 5, 2023)

FAA., August 2010. Order 5200.11 FAA airport (ARP) safety management. Retrieved from https://www.faa.gov/documentlibrary/media/order/order_5200_11_arp_sms.pdf (Accessed: October 28, 2023)

FAA., 2013. AC 150/5200-32B Reporting wildlife aircraft strikes. https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_150_5200-32B.pdf (Accessed: November 4, 2023)

FAA., 2017. Order 8040.4B. Safety risk management policy. Retrieved from https://www.faa.gov/documentLibrary/media/Order/FAA_Order_8040.4B.pdf (Accessed: November 4, 2023)

FAA., 2020. AC 150/5200-33C Hazardous wildlife attractants on or near airports. Retrieved from https://www.faa.gov/documentLibrary/media/Advisory_Circular/150-5200-33C.pdf (Accessed: November 19, 2023)

FAA., February 2021. Wildlife strikes to civil aviation – 1990 ~ 2019. Retrieved from file:///Users/chien-tsunglu/Downloads/Wildlife-Strike-Report-1990-2019.pdf (Accessed: November 13, 2023)

Federal Aviation Administration (FAA), n.d.. Report a strike. https://wildlife.faa.gov/add

Fu, H, Lu, c-t., & Ji, Z., September 2023. Risk Assessment Matrix of Operational Safety (RAMOS): Aviation Safety with a MATLAB® Design Toolkit, Journal of Aviation/Aerospace Education & Research. 32(2). DOI: https://doi.org/10.58940/2329-258X.1982

Heinrich, H. W., 1959. Industrial Accident Prevention: A Scientific Approach (4th ed.). New York: McGraw-Hill.

Kunkle, F., October 28, 2021. Plane Hits Deer. and so begins the annual rut, when lovesick animals collide with vehicles. The Washington Post. Retrieved December 8, 2022, from https://www.washingtonpost.com/news/tripping/wp/2016/10/25/plane-hits-deer-and-so-begins-the-annual-rut-when-lovesick-animals-collide-with-vehicles/

Lu, C-t., Schreckengast, S., & Jia, J., 2011. Safety risk management, assurance, and promotion: hazard control system for budget-constrained airports. Journal of Aviation Technology and Engineering, 1(1), 1-15. DOI: https://doi.org/10.5703/1288284314630

Mendonca, F. A. C., & Wallace, R., 2021. Utilizing UAS to support wildlife hazard management efforts by airport operators. Collegiate Aviation Review International, 39(2),238-248. Retrieved fromhttp://ojs.library.okstate.edu/osu/index.php/CARI/article/view/8385/7686

Misra, S., Toppo, I., & Mendonca, F., 2022. Assessment of aircraft damage due to bird strikes: a machine learning approach. International Journal of Sustainable Aviation, 8(2), 136-151. Retrieved from https://www.inderscienceonline.com/doi/abs/10.1504/IJSA.2022.122328

National Transportation Safety Board (NTSB)., October 2010. NTSB/AAR-10/03 Loss of Thrust in Both Engines After Encountering a Flock of Birds and Subsequent Ditching on the Hudson River. Retrieved from https://www.ntsb.gov/investigations/AccidentReports/Reports/AAR1003.pdf

Reason, J., 1990. Human Error. London, U.K.: Cambridge University Press.

Transportation Research Board (TRB)., 2012. Lesson learned from airport safety management systems pilot studies. Retrieved from https://nap.nationalacademies.org/download/22740

TRB., 2015. ACRP Report 145 - Applying an SMS approach to wildlife hazard management. Retrieved from file:///Users/chien-tsunglu/Downloads/22091.pdf

U.S. Department of Agriculture (USDA)., 2017, February. Wildlife Damage Management Technical Series. USDA APHIS | Wildlife Damage Management Technical Series. https://www.aphis.usda.gov/aphis/ourfocus/wildlifedamage/sa_reports/ct_wildlife+damage+management+technical+series

Wiegmann, D. A. & Shappell, S. A., 2017. A Human Error Approach to Aviation Accident Analysis: The Human Factors Analysis and Classification System. London: Taylor and Francis.

Wildlife Strikes - Risk Analysis., (2024). Shinyapps. Available at: https://hfu2014.shinyapps.io/ca_analysis/ (Accessed: 2024).

Appendix I Code of R Analysis

```r
##### California Wildlife Hazard Analysis #####

##### Notice #####
## This is just the analysis used in the paper. Most of the following code ##
## are just used for this analysis. ##
## For Shiny.io part, please refer to the second part of the code ##
## There will be some duplicates in this code, please check carefully ##

# Necessary packages
library(readxl)
library(gdata)
library(ggplot2)
library(dplyr)
library(lubridate)
library(leaflet)
library(tmap)
library(sf)
library(viridis)
library(cluster)
library(spdep)
library(gridExtra)
library(corrplot)

# Import Data We selected LAX and SAC data
# Modify your own file destination
LAX_Event <- read_excel("./LAX/LAX_Event_2002_2022.xlsx")
#LAX_Flight <- read_excel("./LAX/LAX_Flight_2002_2022.xls")
SAC_Event <- read_excel("./SAC/SAC_Event_2002_2022.xlsx")
#SAC_Flight <- read_excel("./SAC/SAC_Flight_2002_2022.xls")

##### Simply Descriptive Analysis #####
### SAC Airport Analysis
# Calculate the count of incidents per year for SAC
yearly_incidents_SAC <- SAC_Event %>%
  group_by(INCIDENT_YEAR) %>%
  summarise(Incidents = n()) %>%
  arrange(INCIDENT_YEAR)

# Create a bar plot for SAC
ggplot(yearly_incidents_SAC, aes(x = INCIDENT_YEAR, y = Incidents)) +
  geom_bar(stat = "identity", fill = "red") +
  geom_text(aes(label = Incidents), vjust = -0.3, size = 3.5) +
  labs(x = "Year", y = "Number of Incidents",
       title = "Number of Incidents per Year at SAC Airport") +
  theme_minimal()

### LAX Airport Analysis
# Calculate the count of incidents per year for LAX
yearly_incidents_LAX <- LAX_Event %>%
  group_by(INCIDENT_YEAR) %>%
  summarise(Incidents = n()) %>%
  arrange(INCIDENT_YEAR)

# Create a bar plot for LAX
ggplot(yearly_incidents_LAX, aes(x = INCIDENT_YEAR, y = Incidents)) +
  geom_bar(stat = "identity", fill = "deepskyblue") +
  geom_text(aes(label = Incidents), vjust = -0.3, size = 3.5) +
  labs(x = "Year", y = "Number of Incidents",
       title = "Number of Incidents per Year at LAX Airport") +
  theme_minimal()


# Combine these two for better comparison or visualization
yearly_incidents_SAC <- yearly_incidents_SAC %>%
  mutate(Airport = "SAC")

yearly_incidents_LAX <- yearly_incidents_LAX %>%
  mutate(Airport = "LAX")

# Combine the data
combined_data <- rbind(yearly_incidents_SAC, yearly_incidents_LAX)

# Create a grouped bar plot
ggplot(combined_data, aes(x = INCIDENT_YEAR, y = Incidents, fill = Airport)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  geom_text(aes(label = Incidents), vjust = -0.3, position = position_dodge(0.9), size = 3.5) +
  labs(x = "Year", y = "Number of Incidents",
       title = "Comparison of Incident Numbers per Year at SAC and LAX Airports") +
  theme_minimal() +
  scale_fill_manual(values = c("red", "deepskyblue"))

##### Per Month Section #####
# Calculate the count of incidents per month for SAC
monthly_incidents_SAC <- SAC_Event %>%
  group_by(INCIDENT_MONTH) %>%
  summarise(Incidents = n()) %>%
  arrange(INCIDENT_MONTH)

# Create a bar plot for SAC
ggplot(monthly_incidents_SAC, aes(x = INCIDENT_MONTH, y = Incidents)) +
  geom_bar(stat = "identity", fill = "red") +
  geom_text(aes(label = Incidents), vjust = -0.3, size = 3.5) +
  scale_x_continuous(breaks = 1:12, labels = month.abb) +
  labs(x = "Month", y = "Number of Incidents",
       title = "Number of Incidents per Month at SAC Airport") +
  theme_minimal()

# Same for for LAX
monthly_incidents_LAX <- LAX_Event %>%
  group_by(INCIDENT_MONTH) %>%
  summarise(Incidents = n()) %>%
  arrange(INCIDENT_MONTH)

# Create a bar plot for LAX
ggplot(monthly_incidents_LAX, aes(x = INCIDENT_MONTH, y = Incidents)) +
  geom_bar(stat = "identity", fill = "deepskyblue") +
  geom_text(aes(label = Incidents), vjust = -0.3, size = 3.5) +
  scale_x_continuous(breaks = 1:12, labels = month.abb) +
  labs(x = "Month", y = "Number of Incidents",
       title = "Number of Incidents per Month at LAX Airport") +
  theme_minimal()

#
monthly_incidents_SAC <- monthly_incidents_SAC %>%
  mutate(Airport = "SAC")

monthly_incidents_LAX <- monthly_incidents_LAX %>%
  mutate(Airport = "LAX")

# Combine the data
combined_monthly_data <- rbind(monthly_incidents_SAC, monthly_incidents_LAX)

# Create a grouped bar plot for comparison and visualization
ggplot(combined_monthly_data, aes(x = INCIDENT_MONTH, y = Incidents, fill = Airport)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  geom_text(aes(label = Incidents), vjust = -0.3, position = position_dodge(0.9), size = 3.5) +
  scale_x_continuous(breaks = 1:12, labels = month.abb) +
  labs(x = "Month", y = "Number of Incidents",
       title = "Comparison of Monthly Incident Numbers at SAC and LAX Airports") +
  theme_minimal() +
  scale_fill_manual(values = c("red", "deepskyblue"))

###### Hour Analysis #####
# Extract hour and clean NA for SAC ( The NAs need to be careful), some
# can use NAs and some may not.
SAC_Event$Hour <- as.integer(sub("^(\\d{2}):.*", "\\1", SAC_Event$TIME))
SAC_Event <- SAC_Event[!is.na(SAC_Event$Hour), ]

# Count incidents by hour for SAC
hourly_incidents_SAC <- SAC_Event %>%
  group_by(Hour) %>%
  summarise(Incidents = n()) %>%
  arrange(Hour)

# Create a bar plot for SAC
hourly_bar_chart_SAC <- ggplot(hourly_incidents_SAC, aes(x = Hour, y = Incidents)) +
  geom_bar(stat = "identity", fill = "red") +
  geom_text(aes(label = Incidents), vjust = -0.3, size = 3) +
  scale_x_continuous(breaks = 0:23, labels = sprintf("%02d:00", 0:23)) +
  labs(x = "Hour of the Day", y = "Number of Incidents", title = "Number of Incidents by Hour
of the Day at SAC Airport") +
  theme_minimal()
hourly_bar_chart_SAC

# Extract hour and clean NA for LAX (same as the SAC)
LAX_Event$Hour <- as.integer(sub("^(\\d{2}):.*", "\\1", LAX_Event$TIME))
LAX_Event <- LAX_Event[!is.na(LAX_Event$Hour), ]

# Count incidents by hour for LAX
hourly_incidents_LAX <- LAX_Event %>%
  group_by(Hour) %>%
  summarise(Incidents = n()) %>%
  arrange(Hour)

# Create a bar plot for LAX
hourly_bar_chart_LAX <- ggplot(hourly_incidents_LAX, aes(x = Hour, y = Incidents)) +
  geom_bar(stat = "identity", fill = "deepskyblue") +
  geom_text(aes(label = Incidents), vjust = -0.3, size = 3) +
  scale_x_continuous(breaks = 0:23, labels = sprintf("%02d:00", 0:23)) +
  labs(x = "Hour of the Day", y = "Number of Incidents", title = "Number of Incidents by Hour
of the Day at LAX Airport") +
  theme_minimal()
hourly_bar_chart_LAX

# Add an airport column to each dataset
hourly_incidents_SAC <- hourly_incidents_SAC %>%
  mutate(Airport = "SAC")

hourly_incidents_LAX <- hourly_incidents_LAX %>%
  mutate(Airport = "LAX")

# Combine the data
combined_hourly_data <- rbind(hourly_incidents_SAC, hourly_incidents_LAX)

# Create a grouped bar plot for comparison and visualization
combined_hourly_chart <- ggplot(combined_hourly_data, aes(x = Hour, y = Incidents, fill =
Airport)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  geom_text(aes(label = Incidents), vjust = -0.3, position = position_dodge(0.9), size = 3) +
  scale_x_continuous(breaks = 0:23, labels = sprintf("%02d:00", 0:23)) +
  labs(x = "Hour of the Day", y = "Number of Incidents",
       title = "Comparison of Hourly Incident Numbers at SAC and LAX Airports") +
  theme_minimal() +
  scale_fill_manual(values = c("red", "deepskyblue"))

# Print the combined chart
combined_hourly_chart

##### Time Section Analysis #####
# Create Function to categorize time into sections
# So for this we splitted them into four time sections
# Midnight 0000-0559 Morning 6000-1159 Afternoon 1200-1759 Evening 1800-2359
categorize_time <- function(data) {
  data$TimeObj <- as.POSIXct(data$TIME, format = "%H:%M", tz = "UTC")
  data$TimeOfDay <- cut(data$TimeObj,
                        breaks = c(as.POSIXct('00:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('06:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('12:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('18:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('23:59', format='%H:%M', tz='UTC')),
                        labels = c(‘Midnight’, ‘Morning’, ‘Afternoon’, ‘Evening’),
                        include.lowest = TRUE)
  data <- data[!is.na(data$TimeOfDay), ]
  return(data)
}

# Apply the function to LAX and SAC datasets
LAX_Event <- categorize_time(LAX_Event)
SAC_Event <- categorize_time(SAC_Event)

# Function to create time section analysis plots
create_time_section_plots <- function(data, airport_name) {
  # Count the number of incidents in each time section
  time_section_incidents <- data %>%
    group_by(TimeOfDay) %>%
    summarise(Incidents = n())

  # Create a bar chart
  bar_chart <- ggplot(time_section_incidents, aes(x = TimeOfDay, y = Incidents, fill =
TimeOfDay)) +
    geom_bar(stat = "identity") +
    geom_text(aes(label = Incidents), vjust = -0.3, size = 5) +
    labs(x = "Time of Day", y = "Number of Incidents", title = paste("Number of Incidents by
Time of Day at", airport_name, "Airport")) +
    theme_minimal() +
    scale_fill_brewer(palette="Pastel1")

  # Calculate the percentage for the pie chart labels
  time_section_incidents$Percentage <- (time_section_incidents$Incidents /
sum(time_section_incidents$Incidents)) * 100

  # Pie chart with numbers and percentages
  pie_chart <- ggplot(time_section_incidents, aes(x = "", y = Incidents, fill = TimeOfDay)) +
    geom_bar(width = 1, stat = "identity") +
    coord_polar("y", start = 0) +
```

```
    geom_text(aes(label = paste(Incidents, " (", round(Percentage, 1), "%)", sep = "")),
              position = position_stack(vjust = 0.5)) +
    labs(x = "", y = "", title = paste("Incident Distribution by Time of Day at", airport_name,
"Airport")) +
    theme_void() +
    scale_fill_brewer(palette="Pastel1")

  # Print the bar chart and the pie chart
  print(bar_chart)
  print(pie_chart)
}

# Apply the function to LAX and SAC
create_time_section_plots(LAX_Event, "LAX")
create_time_section_plots(SAC_Event, "SAC")

# Comparison we made plot place in the same chart for easier comparison
# There are a lot of duplicates down, you can modify them.
# Function to Create Time Section Analysis Plots
create_time_section_plots <- function(data, airport_name) {
  # Count the number of incidents in each time section
  time_section_incidents <- data %>%
    group_by(TimeOfDay) %>%
    summarise(Incidents = n())

  # Create a bar chart
  bar_chart <- ggplot(time_section_incidents, aes(x = TimeOfDay, y = Incidents, fill =
TimeOfDay)) +
    geom_bar(stat = "identity") +
    geom_text(aes(label = Incidents), vjust = -0.3, size = 5) +
    labs(x = "Time of Day", y = "Number of Incidents", title = paste("Number of Incidents by
Time of Day at", airport_name, "Airport")) +
    theme_minimal() +
    scale_fill_brewer(palette="Pastel1")

  # Calculate the percentage for the pie chart labels
  time_section_incidents$Percentage <- (time_section_incidents$Incidents /
sum(time_section_incidents$Incidents)) * 100

  # Pie chart with numbers and percentages
  pie_chart <- ggplot(time_section_incidents, aes(x = "", y = Incidents, fill = TimeOfDay)) +
    geom_bar(width = 1, stat = "identity") +
    coord_polar("y", start = 0) +
    geom_text(aes(label = paste(Incidents, " (", round(Percentage, 1), "%)", sep = "")),
              position = position_stack(vjust = 0.5)) +
    labs(x = "", y = "", title = paste("Incident Distribution by Time of Day at", airport_name,
"Airport")) +
    theme_void() +
    scale_fill_brewer(palette="Pastel1")

  # Return the plots
  return(list(bar_chart = bar_chart, pie_chart = pie_chart))
}

# Apply the categorize_time function to LAX and SAC datasets
LAX_Event <- categorize_time(LAX_Event)
SAC_Event <- categorize_time(SAC_Event)

# Generate the plots for each airport
plots_LAX <- create_time_section_plots(LAX_Event, "LAX")
plots_SAC <- create_time_section_plots(SAC_Event, "SAC")

# Arrange the plots in a 2x2 grid
combined_plot <- grid.arrange(
  plots_SAC$bar_chart, plots_LAX$bar_chart,
  plots_SAC$pie_chart, plots_LAX$pie_chart,
  ncol = 2
)

##### Size Distribution #####
## THere are small medium and large in the data
## THere are also species in the data. you can do them in either way
## We used NA in this part
# Function to process and plot data
process_and_plot <- function(data, airport_name) {
  # Replace NA or empty entries with “Not Available”
  data$SIZE <- as.character(data$SIZE)
  data$SIZE[is.na(data$SIZE) | data$SIZE == ""] <- "Not Available"

  # Convert back to factor with all levels
  data$SIZE <- factor(data$SIZE, levels = c(“Small”, “Medium”, “Large”, “Not Available”))

  # Count the number of incidents by wildlife size
  size_distribution <- data %>%
    group_by(SIZE) %>%
    summarise(Incidents = n())

  # Bar chart
  size_chart <- ggplot(size_distribution, aes(x = SIZE, y = Incidents, fill = SIZE)) +
    geom_bar(stat = "identity") +
    geom_text(aes(label = Incidents), vjust = -0.3, size = 5) +
    labs(x = "Wildlife Size Category", y = "Number of Incidents",
         title = paste("Number of Wildlife Incidents by Size Category at", airport_name)) +
    theme_minimal() +
    scale_fill_brewer(palette="Pastel1")

  # Percentage for pie chart labels
  size_distribution$Percentage <- (size_distribution$Incidents /
sum(size_distribution$Incidents)) * 100

  # Pie chart
  pie_chart <- ggplot(size_distribution, aes(x = "", y = Incidents, fill = SIZE)) +
    geom_bar(width = 1, stat = "identity") +
    coord_polar("y", start = 0) +
    geom_text(aes(label = paste(Incidents, " (", round(Percentage, 1), "%)", sep = "")),
              position = position_stack(vjust = 0.5)) +
    labs(x = "", y = "",
         title = paste("Wildlife Size Category Distribution at", airport_name)) +
    theme_void() +
    scale_fill_brewer(palette="Pastel1")

  # Print the charts
  list(BarChart = size_chart, PieChart = pie_chart)
}

# Process and plot for LAX
lax_charts <- process_and_plot(LAX_Event, "LAX")
lax_charts$BarChart
lax_charts$PieChart

# Process and plot for SAC
sac_charts <- process_and_plot(SAC_Event, "SAC")
sac_charts$BarChart
sac_charts$PieChart

# Generate the charts for LAX and SAC
lax_charts <- process_and_plot(LAX_Event, "LAX")
sac_charts <- process_and_plot(SAC_Event, "SAC")

# Arrange the charts into a 2x2 grid
combined_chart <- grid.arrange(
  sac_charts$BarChart, lax_charts$BarChart,
  sac_charts$PieChart, lax_charts$PieChart,
  ncol = 2, nrow = 2
)

# Print the combined chart
combined_chart

# Percentage
# Function to create pie chart for a given dataset
create_pie_chart <- function(data, airport_name) {
  # Replace NA or empty entries with “Not Available”
  data$SIZE <- as.character(data$SIZE) # Convert factor to character if it’s not already
  data$SIZE[is.na(data$SIZE) | data$SIZE == ""] <- "Not Available"
  data$SIZE <- factor(data$SIZE, levels = c(“Small”, “Medium”, “Large”, “Not Available”))

  # Count the number of incidents by wildlife size
  size_distribution <- data %>%
    group_by(SIZE) %>%
    summarise(Incidents = n())

  # Calculate the percentage for the pie chart labels
  size_distribution$Percentage <- (size_distribution$Incidents /
sum(size_distribution$Incidents)) * 100

  # Pie chart with numbers and percentages
  pie_chart <- ggplot(size_distribution, aes(x = "", y = Incidents, fill = SIZE)) +
    geom_bar(width = 1, stat = "identity") +
    coord_polar("y", start = 0) +
    geom_text(aes(label = paste(Incidents, " (", round(Percentage, 1), "%)", sep = "")),
              position = position_stack(vjust = 0.5)) +
    labs(x = "", y = "",
         title = paste("Wildlife Size Category Distribution at", airport_name)) +
    theme_void() +
    scale_fill_brewer(palette="Pastel1")

  return(pie_chart)
}

# Create pie chart for LAX
lax_pie_chart <- create_pie_chart(LAX_Event, "LAX")

# Create pie chart for SAC
sac_pie_chart <- create_pie_chart(SAC_Event, "SAC")

# Print the pie charts
lax_pie_chart
sac_pie_chart

##### Section 02 Event Categories #####
# Load required libraries
library(ggplot2)
library(dplyr)
library(gridExtra)

# In case the time slot is missing we did it again here.
# Function to categorize time into sections
categorize_time <- function(data) {
  data$TimeObj <- as.POSIXct(data$TIME, format = "%H:%M", tz = "UTC")
  data$TimeOfDay <- cut(data$TimeObj,
                        breaks = c(as.POSIXct('00:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('06:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('12:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('18:00', format='%H:%M', tz='UTC'),
                                   as.POSIXct('23:59', format='%H:%M', tz='UTC')),
                        labels = c(‘Midnight’, ‘Morning’, ‘Afternoon’, ‘Evening’),
                        include.lowest = TRUE)
  data <- data[!is.na(data$TimeOfDay), ]
  return(data)
}

# Function to create time and size distribution plots
create_time_size_plots <- function(data, airport_name) {
  # Count the number of incidents by wildlife size for each time of day
  size_time_distribution <- data %>%
    group_by(TimeOfDay, SIZE) %>%
    summarise(Incidents = n(), .groups = 'drop') %>%
    mutate(Percentage = (Incidents / sum(Incidents)) * 100)

  # Bar chart with size distribution for each time of day
  bar_chart_time_size <- ggplot(size_time_distribution, aes(x = SIZE, y = Incidents, fill =
SIZE)) +
    geom_bar(stat = "identity") +
    geom_text(aes(label = Incidents), vjust = -0.3, size = 3) +
    facet_wrap(~TimeOfDay, scales = "free_y") +
    labs(x = "Wildlife Size Category", y = "Number of Incidents",
         title = paste("Wildlife Size Distribution for Each Time of Day at", airport_name)) +
    theme_minimal() +
    scale_fill_brewer(palette="Pastel1")

  # Pie charts for each time of day
  pie_charts_time_size <- lapply(unique(size_time_distribution$TimeOfDay),
function(time_section) {
    data_section <- size_time_distribution[size_time_distribution$TimeOfDay == time_section, ]
    ggplot(data_section, aes(x = "", y = Incidents, fill = SIZE)) +
      geom_bar(width = 1, stat = "identity") +
      coord_polar("y", start = 0) +
      geom_text(aes(label = paste(Incidents, " (", round(Percentage, 1), "%)", sep = "")),
                position = position_stack(vjust = 0.5)) +
      labs(title = paste("Size Distribution at", airport_name, "-", time_section), x = "", y =
"") +
      theme_void() +
      scale_fill_brewer(palette="Pastel1")
  })

  # Print the bar chart and arrange the individual pie charts
  print(bar_chart_time_size)
  do.call(grid.arrange, pie_charts_time_size)
}

# Apply the function to LAX and SAC datasets
LAX_Event <- categorize_time(LAX_Event)
SAC_Event <- categorize_time(SAC_Event)

###### Total number of incidents per month for LAX #####
## This is to provide operator with the understand of the distribution of
```

```
## the incident every month
total_incidents_per_month_lax <- LAX_Event %>%
  group_by(INCIDENT_MONTH) %>%
  summarise(TotalIncidents = n())

# Function to calculate and plot time of day incidents
plot_time_of_day_incidents <- function(data, time_of_day, color, label) {
  incidents_per_month <- data %>%
    filter(TimeOfDay == time_of_day) %>%
    group_by(INCIDENT_MONTH) %>%
    summarise(Incidents = n())

  # Merge with total incidents to calculate the percentage
  percentage_incidents <- merge(total_incidents_per_month_lax, incidents_per_month, by =
"INCIDENT_MONTH", all = TRUE)
  percentage_incidents$Incidents[is.na(percentage_incidents$Incidents)] <- 0
  percentage_incidents$Percentage <- (percentage_incidents$Incidents /
percentage_incidents$TotalIncidents)

  # Plot the percentages by month as a line plot
  percentage_plot <- ggplot(percentage_incidents, aes(x = INCIDENT_MONTH, y = Percentage)) +
    geom_line(group=1, colour=color) +
    geom_point(colour=color) +
    scale_x_continuous(breaks = 1:12, labels = month.abb) +
    labs(x = “Month”, y = “Percentage”, title = paste(“Percentage of Incidents in the”, label,
“by Month at LAX”)) +
    theme_minimal()

  return(percentage_plot)
}

# Plot for each time of day for LAX
midnight_plot_lax <- plot_time_of_day_incidents(LAX_Event, ‘Midnight’, ‘blue’, ‘Midnight’)
morning_plot_lax <- plot_time_of_day_incidents(LAX_Event, ‘Morning’, ‘green’, ‘Morning’)
afternoon_plot_lax <- plot_time_of_day_incidents(LAX_Event, ‘Afternoon’, ‘orange’, ‘Afternoon’)
evening_plot_lax <- plot_time_of_day_incidents(LAX_Event, ‘Evening’, ‘purple’, ‘Evening’)

# Print the plots
midnight_plot_lax
morning_plot_lax
afternoon_plot_lax
evening_plot_lax

# Function to calculate percentages for a given time of day for LAX
calculate_percentages_lax <- function(data, time_of_day, color) {
  incidents_per_month <- data %>%
    filter(TimeOfDay == time_of_day) %>%
    group_by(INCIDENT_MONTH) %>%
    summarise(Count = n()) %>%
    merge(total_incidents_per_month_lax, by = "INCIDENT_MONTH", all = TRUE) %>%
    mutate(Percentage = Count / TotalIncidents,
           TimeOfDay = time_of_day,
           Color = color)

  # Replace NA with 0
  incidents_per_month$Count[is.na(incidents_per_month$Count)] <- 0
  incidents_per_month$Percentage[is.na(incidents_per_month$Percentage)] <- 0

  return(incidents_per_month)
}

# Calculate percentages for each time of day for LAX
midnight_data_lax <- calculate_percentages_lax(LAX_Event, "Midnight", "blue")
morning_data_lax <- calculate_percentages_lax(LAX_Event, "Morning", "green")
afternoon_data_lax <- calculate_percentages_lax(LAX_Event, "Afternoon", "orange")
evening_data_lax <- calculate_percentages_lax(LAX_Event, "Evening", "purple")

# Combine all data into one dataframe
combined_data_lax <- rbind(midnight_data_lax, morning_data_lax, afternoon_data_lax,
evening_data_lax)

# Create one combined line plot for LAX
combined_line_plot_lax <- ggplot(combined_data_lax, aes(x = INCIDENT_MONTH, y = Percentage, group
= TimeOfDay, color = TimeOfDay)) +
  geom_line() +
  geom_point() +
  geom_text(aes(label = round(Percentage, 2)), vjust = -1, size = 3) +
  scale_x_continuous(breaks = 1:12, labels = month.abb) +
  labs(x = "Month", y = "Percentage of Incidents",
       title = "Combined Percentage of Incidents by Time of Day and Month at LAX") +
  theme_minimal() +
  scale_color_manual(values = c("Midnight" = "blue", "Morning" = "green", "Afternoon" = "orange",
"Evening" = "purple"))

# Print the combined line plot for LAX
combined_line_plot_lax

##### Total number of incidents per month for SAC  #####
## Basically it is the same as LAX
# Total number of incidents per month for SAC
total_incidents_per_month_sac <- SAC_Event %>%
  group_by(INCIDENT_MONTH) %>%
  summarise(TotalIncidents = n())

# Function to calculate percentages for a given time of day for SAC
calculate_percentages_sac <- function(data, time_of_day, color) {
  incidents_per_month <- data %>%
    filter(TimeOfDay == time_of_day) %>%
    group_by(INCIDENT_MONTH) %>%
    summarise(Count = n()) %>%
    merge(total_incidents_per_month_sac, by = "INCIDENT_MONTH", all = TRUE) %>%
    mutate(Percentage = Count / TotalIncidents,
           TimeOfDay = time_of_day,
           Color = color)

  # Replace NA with 0
  incidents_per_month$Count[is.na(incidents_per_month$Count)] <- 0
  incidents_per_month$Percentage[is.na(incidents_per_month$Percentage)] <- 0

  return(incidents_per_month)
}

# Calculate percentages for each time of day for SAC
midnight_data_sac <- calculate_percentages_sac(SAC_Event, "Midnight", "blue")
morning_data_sac <- calculate_percentages_sac(SAC_Event, "Morning", "green")
afternoon_data_sac <- calculate_percentages_sac(SAC_Event, "Afternoon", "orange")
evening_data_sac <- calculate_percentages_sac(SAC_Event, "Evening", "purple")

# Combine all data into one dataframe
combined_data_sac <- rbind(midnight_data_sac, morning_data_sac, afternoon_data_sac,
evening_data_sac)

# Create one combined line plot for SAC
combined_line_plot_sac <- ggplot(combined_data_sac, aes(x = INCIDENT_MONTH, y = Percentage, group
= TimeOfDay, color = TimeOfDay)) +
  geom_line() +
  geom_point() +
  geom_text(aes(label = round(Percentage, 2)), vjust = -1, size = 3) +
  scale_x_continuous(breaks = 1:12, labels = month.abb) +
  labs(x = "Month", y = "Percentage of Incidents",
       title = "Combined Percentage of Incidents by Time of Day and Month at SAC") +
  theme_minimal() +
  scale_color_manual(values = c("Midnight" = "blue", "Morning" = "green", "Afternoon" = "orange",
"Evening" = "purple"))

# Print the combined line plot for SAC
combined_line_plot_sac
```

Appendix II Code of Shiny.io Website

```
# GitHub: hfu2014
# This Code focus on LAX and SAC.

# Packages
library(shiny)
library(ggplot2)
library(dplyr)
library(lubridate)
library(plotly)

# UI Set up
ui <- fluidPage(
  titlePanel("Wildlife Strikes - Risk Analysis"),
  sidebarLayout(
    sidebarPanel(
      selectInput("airportInput", "Select Airport:", choices = c("SAC", "LAX")),
      selectInput("monthInput", "Select Month:", choices = setNames(1:12, month.abb))
    ),
    mainPanel(
      plotlyOutput("timeOfDayPlot"),
      HTML("<strong>Risk score = Frequency x Severity</strong><br/>
            Severity: Small = 1, Medium = 2, Large = 3<br/>
            NA values are excluded from the analysis.")
    )
  )
)

# Server Set up
server <- function(input, output, session) {

  # Reactive expression for the data filtered by the selected airport and month
  # Same as the paper we did SAC and LAX
  # Can also be used in other airport
  filtered_data <- reactive({
    airport_data <- switch(input$airportInput,
                           "SAC" = SAC_Event,
                           "LAX" = LAX_Event)

    # Clean out Not Available for sizes
    processed_data <- airport_data %>%
      filter(!is.na(SIZE), SIZE %in% c(‘Small’, ‘Medium’, ‘Large’),
             INCIDENT_MONTH == as.integer(input$monthInput))

    processed_data
  })


  # Generate the bar chart based on the filtered data
  output$timeOfDayPlot <- renderPlotly({
    data <- filtered_data()

    if (nrow(data) == 0) {
      return()
    }

    # Calculate the risk score and determine the risk color
    size_risk <- data %>%
      group_by(SIZE) %>%
      summarise(Frequency = n(), .groups = 'drop') %>%
      mutate(
        Score = case_when(
          SIZE == 'Small' ~ 1,
          SIZE == 'Medium' ~ 2,
          SIZE == 'Large' ~ 3
        ),
        RiskScore = Frequency * Score
      ) %>%
      arrange(desc(RiskScore))

    # Add the risk color outside of the mutate function
    size_risk$RiskColor <- with(size_risk, case_when(
      RiskScore <= 50 ~ ‘Low’,
      RiskScore > 50 & RiskScore <= 100 ~ 'Moderate',
      RiskScore > 100 ~ 'High'
    ))

    # Plot the data with the correct colors for the risk levels
    p <- ggplot(size_risk, aes(x = SIZE, y = RiskScore, fill = RiskColor, text = paste("Frequency:
", Frequency, "\nSeverity: ", Score, "\nRisk Score: ", RiskScore))) +
      geom_bar(stat = "identity") +
      scale_fill_manual(values = c('Low' = 'green', 'Moderate' = 'yellow', 'High' = 'red')) +
      labs(title = paste("Risk Analysis of Wildlife Strikes by Size at", input$airportInput,
"Airport for Each Month"),
           x = "Wildlife Size", y = "Risk Score") +
      theme_minimal()

    ggplotly(p, tooltip = "text")  # Enable tooltips
  })
}

# Run the Shiny app
shinyApp(ui = ui, server = server)


### Notes: This is just three levels of risk matrix, total flight is not used.
### Please follow us for the update.
```