BIRD STRIKE RISK ASSESSMENT AT COMMERCIAL AIRPORTS: SUB-MODEL DEVELOPMENT ACCOUNTING FOR STRIKE OCCURRENCE AND SEVERITY WITH STRIKE CONTRIBUTORY FACTORS

BY

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THESIS

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ABSTRACT

The collisions between birds and airplanes, or bird strikes, pose a substantial safety and financial threat to the public through issues such as delays, airplane damage, passenger injuries or deaths, and environmental impacts. Current records indicate that an average of 19 bird strikes are reported each day in the United States, and the number has been increasing very quickly over recent years. The reported bird strikes have resulted in a financial loss of more than $600 million for commercial aviation in the United States and $1.2-1.5 billion worldwide. Despite the number and severity, quantifications of bird strike contributory factors have been quite limited because of the absence of data, especially bird movement data on airfields. The goal of this study is to provide additional insight into this important problem by combining a number of databases, including the newly available bird movement data collected by the avian radar, the FAA wildlife strike database, airport operations, airplane characteristics and meteorological data. Statistical models were developed to quantitatively evaluate the factors that contribute to bird strike occurrence and severity.

The study of bird strike occurrence is composed of two sub-studies. One sub-study investigated the impacts of bird and airplane movement on bird strike occurrence. This study was carried out at Seattle Tacoma International Airport. Logistic regression was applied and the results showed that bird strike occurrence was positively related to both bird density and airplane movement frequency. The other sub-study analyzed the effects of meteorological variables (e.g., temperature) on bird strike occurrence also with logistic regression. Ten years of meteorological data collected from six U.S. major airports was used and the results indicated that temperature and precipitation were major factors that have significant effects on bird strike occurrence at

most of these airports, while other factors including wind speed, visibility and pressure, only have effects at certain airports.

The study of bird strike severity evaluated the effects of a set of variables, such as airplane mass, engine type, number of engines, altitude, bird size, and strike position of an airplane. Multinomial regression model was used to quantitatively analyze the impacts that such variables pose on three severity categories: no damage, minor damage and serious damage. Based on the data collected from commercial airports in the United States, the results indicated that small airplanes, single engine, fast flight speed, takeoff, large and flocking birds, strikes occurring at engine, wing, tail and light increased the propensity toward both serious and minor damage. Variables such as landing, warned status, and strikes occurring at nose, propeller and fuselage increased the chance of no damage.

The overall study provides a series of empirical and methodological assessments to examine the effects of bird strike contributory factors on strike occurrence and severity. Logistic and multinomial regression models were applied respectively and were estimated with full information maximum likelihood to yield statistically efficient results. The findings provide quantitative evidence demonstrating factors that are relevant, and the significance of their impacts. The results not only support potential changes in airport bird hazard management and airplane operations, but also suggest improvements in engine and airframe design for safety considerations. The study also highlights the importance of managing accurate bird strike reports and applying new statistical approaches in the future as more data becomes available.

To my family

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CHAPTER 1
INTRODUCTION

1.1 Bird Strike Hazards

A bird-aircraft/airplane collision (hereafter "bird strike") is defined as "any contact between a moving aircraft and a bird or a group of birds" (Blokpoel, 1976). For operational convenience, the Bird Strike Committee Canada refined the definition subsequently as: "a bird strike is deemed to have occurred whenever: (1) a pilot reports a bird strike; (2) aircraft maintenance personnel identify damage to an aircraft as having been caused by a bird strike; (3) personnel on the ground report seeing an aircraft strike one or more birds; and (4) bird remains, whether in whole or in part, are found on an air side pavement area or within 200 feet of a runway, unless another reason for the bird's death is identified" (Transport Canada, 1997; Meeking, 1998).

Bird strike has been a major concern since the early age of aviation. It poses a substantial safety and financial threat to the public. For example, bird strikes can result in costly delays, airplane damage, and passenger injuries or deaths, and become environmental impacts. From 1985 to 2001, the United States Air Force (USAF) lost 20 aircraft and 32 people because of bird strikes (Allan, 2003). Worldwide, reported bird strikes resulted in the loss of 88 civilian aircraft and 243 human lives between 1912 and 2004. A financial estimation, which was made in 2000, showed that bird strikes took the U.S. commercial aviation more than $600 million each year in direct and indirect loss (Richardson, 2009). They also resulted in a $33 million annual loss for the USAF (Allan, 2002). Another cost evaluation made in 1997 indicated that the total direct and indirect annual cost in Canada was between $248 million and $613 million (Meeking, 1998). In

Europe, before 2000, the United Kingdom Royal Air Force (RAF) spent about $23.3 million annually in bird strike damage excluding the cost of aircraft loss (Allan, 2006). Worldwide, the statistical data indicated that the world's commercial airlines suffered a conservatively loss of $1.2~ $1.5 billion every year as a result of damage and delays caused by bird strikes (Allan, 2002; 2006).

The number of reported bird strikes has increased substantially in the past decades. For example, the annual bird strikes for the U.S. commercial airlines, which was reported to Federal Aviation Administration (FAA), increased from 2000 in 1990 to about 7000 in 2010 (FAA wildlife strike database, 2011). The increasing incidence of reported bird strikes can be explained by the growing population of hazardous bird species, increasing air traffic, and improved awareness of bird strike reporting. In the past, it is estimated that only 20% of the actual strikes across the United States were reported, while currently the estimated reporting rate has increased to about 33%~39% because of the new convenient web-based reporting system (FAA report, 2009).

Wildlife hazard management is a FAA required activity that airports must undertake. The goal of bird hazard management at airports is to decrease bird strike probability and reduce monetary damages when a strike does occur. To achieve this goal, airport personnel are responsible for understanding the serious effect of bird strikes and acting proactively to prevent a triggering event. The prearranged action relies on the identification of critical factors that contribute to a collision, and their impacts. Therefore, investigating effects of these contributory factors is an essential and important task.

1.2 Bird Strike Contributory Factors

A set of factors, including bird abundance/density, bird size, altitude, airplane mass, airplane flight phase, engine type and struck position of an airplane are known to affect the occurrence and severity of a bird strike. Besides, time of the day, seasonality, weather and land use, which are associated with bird activities, may also have impacts on bird strikes.

1.2.1 Bird abundance and bird size

Bird strike occurrence is affected by the number of birds, or bird abundance, on airfield (Meeking, 1998). A large number of birds tend to increase the likelihood of a bird strike, because under such a circumstance, there is a higher chance of an airplane hitting one or more birds. A study from Melbourne airport showed that from 1986 to 2000, the greatest number of bird strikes was reported between April and May, when the largest number of birds were observed on the airfield (Steele, 2001).

The severity/consequence of a bird strike is associated with the impact force generated from the collision. If assumed that a bird is "butter soft" and stationary, and an airplane is inflexible and perpendicular to the bird, the impact force ($F = ma = m_{bird} \frac{\Delta v_{aircraft}}{\Delta t}$) depends on bird body mass m_{bird} and airplane speed $v_{aircraft}$. For example, when a small bird hits the front end of a turbine engine, it may not cause severe damage. However, a large bird may cause serious issues since the strike could deform or break the blades (Blokpoel, 1976). Table 1 and Table 2 summarize the results of a statistical analysis of bird strike damage with respect to different bird size and flocking size based on FAA wildlife database for commercial airlines. The results indicate that the ratio of serious damage caused by large and flocking birds was higher than that caused by small and solitary birds. The results are consistent with what was indicated in previous studies that large birds were more hazardous than small ones when creating a threat to a moving airplane (Dolbeer et al., 2000; Zakrajsek and Bissonette, 2005).

Table 1 Frequency of reported bird strikes by damage levels and bird size (FAA wildlife strike database, 2011)

Damage	Size of bird as reported by pilot in a relative scale		
Percentage	Large	Medium	Small
None	0.47	0.86	0.95
Minor	0.35	0.11	0.04
Serious	0.18	0.03	0.01
Total Number	5847	31772	31123

Table 2 Frequency of reported bird strikes by damage levels and number of birds involved (FAA wildlife strike database, 2011)

Damage	Number of birds/strike			
Percentage	Single (1)	Small Flock (2-10)	Medium Flock (10-100)	Large Flock (>100)
None	0.87	0.81	0.69	0.51
Minor	0.10	0.13	0.17	0.23
Serious	0.03	0.06	0.14	0.26
Total Number	2167	12322	762	31

1.2.2 Altitude and airplane flight phase

The FAA wildlife strike database shows that reported bird strikes frequently occurred in the vicinity of airports, at low altitudes. For example, 92% of reported bird strikes of the U.S. commercial airlines occurred below 3000 feet (914.4 meters) and 80% of them occurred below 1000 feet (304.6 meters) relative to ground level (FAA wildlife strike database, 2011). The reason might be that the majority of birds fly no higher than 3000 feet. Bellrose (1971) argued that most birds flew below 1000 feet. In terms of strike severity, the number of bird strikes that resulted in substantial damage varies with altitude. Dolbeer (2006) studied the distribution of reported bird strikes with respect to altitude using FAA wildlife strike database of commercial airlines. He reported that the proportion of bird strikes between altitude 501 and 3500 feet that caused substantial damage (6.0%) is higher than that reported below 500 feet (3.6%). The possible reasons are: (1) airplanes are experiencing climb or approach with a relative high speed when they are above 500 feet; and (2) migratory birds, which could easily cause substantial damage to the airplane, commonly fly above 500 feet.

Bird strikes are usually reported at airplane landing and take-off. The FAA wildlife strike database for commercial airlines in the United States showed that about 36% of reported bird strikes occurred at take-off and climb and about 58% of strikes were reported at approach and landing roll. In terms of damage, 6.1% and 10.0% of take-off and climb strikes caused substantial or minor damage, while 2.3% and 8.8% of approach and landing roll strikes caused substantial or minor damage, respectively (FAA wildlife strike database, 2011). These statistics indicate that takeoff and climb are more critical than other flight phases, because during these two flight phases, airplane engines are operating at full power, weight is high, speed is high, altitude is low, and options for safe landing are limited (Herricks and Schaeffer 2002).

1.2.3 Airplane mass

The most vulnerable airplanes are those weighting between 27001-272000kg. These airplanes involved about 66.88% of all reported bird strikes in the United States from 1990 to 2010 (FAA wildlife database, 2011). The reason might be the most commonly used commercial airplanes are weight within this range. The frequent take-off and landing cycles of these airplanes increase their risk of hitting birds. Regarding strike severity, smaller airplanes are more likely to experience serious damage. In particular, 26.7% (1384/5193) of reported bird strikes with airplanes weighting less than 2250kg caused minor damage, and 10.6% of which resulted in serious damage, whereas the ratios of damaging strikes with larger and heavier airplanes were much less (FAA wildlife strike database, 2011).

1.2.4 Engine type

Generally, any type of airplane engine can be destroyed when it is struck by birds. In modern aviation, turbine engines are particularly vulnerable because they depend on the passage of large volumes of air through the engine mechanism. The statistical data from the U.S. commercial airlines showed that a large percentage (81.62%) of bird strikes were with airplanes powered by turbofan engine, which is the most commonly used engine in modern aviation. Regarding strike severity, airplane powered by reciprocating engine, turbojet and turboshaft engine are more likely to experience serious damage than those powered by other types of engine. The ratios of serious damaging strikes that were related to the three types of engine were 10.2% (578/5679), 13.6% (32/235) and 11.6% (78/671), respectively.

1.2.5 Struck position of an airplane

Engine related strikes (struck engine) can easily cause serious damage. When birds strike an engine or engines of an airplane, they can cause the airplane to experience asymmetric thrust or totally lose power, resulting in a disastrous consequence. For example, the U.S. Airways Flight 1549 was forced to land on the Hudson River on January 15, 2009 after both engines were struck by Canada geese. The statistical data from the FAA wildlife strike database also showed that about 17.1% (2084/12208) of engine involved strikes resulted in serious damage, which was 15.7% higher than strikes without engine involved.

Airframe components related strikes (struck airframe) may result in a dent in the skin, torn and crumpled metal or an actual hole. For example, when birds strike the windshield, they may cause shattering of the windshield or complete penetration into the cockpit causing pilot injury or death (Blokpoel, 1976). Bird strike reports showed that about 23% of wing related strikes caused damage with high repair costs (FAA wildlife strike database, 2011). Bird strikes with other parts of the airframe, such as landing gear, lights, radio antennas and pitot tubes, were reported but the damage costs were lower.

1.2.6 Time of the day and seasonality

Usually, more bird strikes are reported at daytime. Dolbeer (2006) found that there were about 2.5 times more strikes reported at daytime than at night. The reason might be that there are more bird activity and airplane movement at daytime than at night. When estimating the number of strikes per airplane movement, about 1.8 times more strikes occurred at night than in the day (Dolbeer, 2006). Most of these night strikes were reported above 500 feet, and they were probably caused by bird migration (Dolbeer, 2006).

Reported bird strikes vary with season. Figure 1 shows the number of reported bird strikes by month in the United States from 1990 to 2010. The maximum number was reported between August and October. Dolbeer (2006) found that bird strikes reported between July and October mostly occurred below 500 feet. This finding supports a hypothesis that these strikes were caused by birds that were recently fledged. A relatively high number of strikes were reported between April and June. These strikes were probably related to spring migration. In contrast, fewer bird strikes were reported in winter months, including January, February and December, during which a majority of birds have migrated and overall activity levels are low.

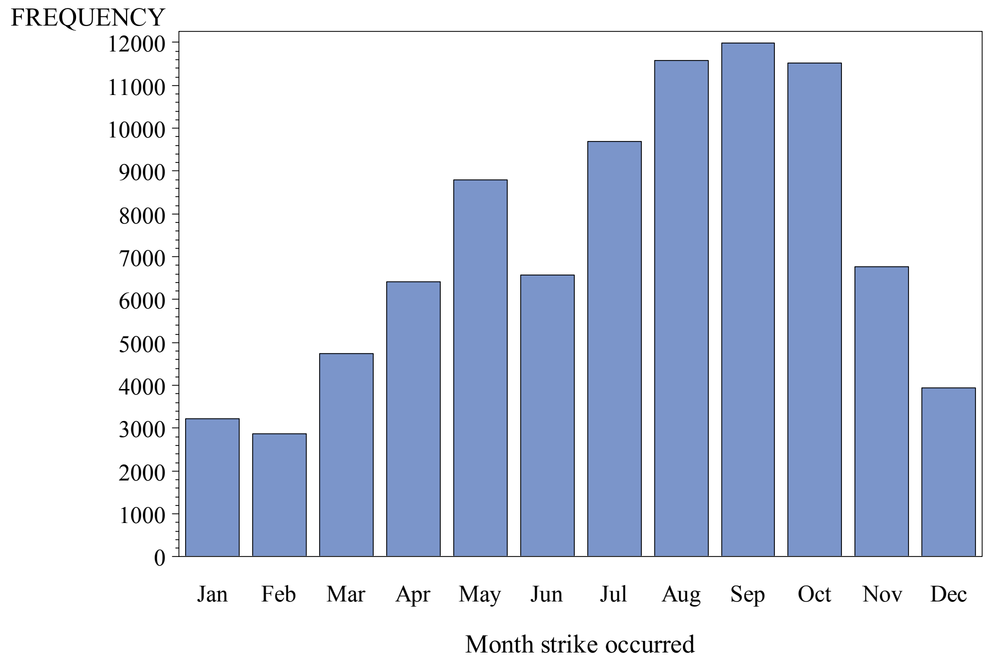

Figure 1 Monthly reported bird strikes at U.S. commercial airports (1990-2010).

1.2.7 Weather

Weather poses both direct and indirect impacts on bird activity. Studies have shown the direct effect of wind speed and direction on bird flight patterns (Tucker and Schmidt-Koenig 1971, Schnell and Hellack 1979, Gudmundsson et al. 1992, Spear and Ainley 1997). Birds usually fly with the wind. When flying against the wind, ground speed is reduced (Schnell 1974, Blokpoel 1976). Rainfall may result in standing water on airfield, creating attractants for birds. Standing water has been recognized as an important factor in previous studies (Gabrey and Dolbeer 1996, Manktelow 2000, Steel 2001). Temperature may affect bird activity because of its impacts on bird metabolism (energy intake and consumption) (Bowen 1933, McNab 1966, Canterbury 2002). Poor visibility is commonly assumed to increase the chance of bird strikes because it may lower the capability of birds to detect the approaching airplane. However, Manktelow (2000) found that more bird strikes occurred under good visibility conditions. She suggested that fewer airplane movements under poor visibilities may explain this inconsistency.

Visibility can also affect the outcome of a bird strike, because poor visibility is associated with adverse weather, complicating an already dangerous situation.

1.2.8 Land use and airport settings

Birds are attracted to airports because of the absence of predators, and the presence of vegetation and open space (Brown et al., 2001). It is important to understand the effects of some airport attractants such as food, shelter, and water, on bird behavior to better manage bird hazards at airports. For many bird species, two important attractants are vegetation and open, standing water. Vegetation provides food and cover for birds. Ponds offer clear site lines and safety from land-based predators. Water bodies clearly attract waterfowl including Canada geese and Mallard ducks, (Brown and Dinsmore 1986). In addition, waste-transfer stations and waste landfills in the vicinity of an airfield are known to attract birds. Putrescible waste landfills, food waste hog farms, wildlife refuges and waterfowl feeding stations near airports have been identified as high risk land uses that can attract a large number of hazardous birds (Sowden et al., 2007). Removing or mitigating these attractants can reduce bird strike hazard. However, some land use is constrained by airport design requirements and operational regulations. For example, land uses at airports are required to maintain safety zones and open areas not to obstruct the flight of an airplane. Security and operational considerations may limit maintenance and lead to attractant (Blokpoel 1976). Although land use is an important factor in bird strikes, this factor was not considered in this study because accurate information on strike location is not available. It is difficult to relate the number of bird strikes to certain land use types.

1.3 Objectives of This Research

Bird strikes continue to be a public concern. Despite the number and severity of reported bird strikes, quantification of strike contributory factors has been quite limited. The purpose of this study is to provide additional insight into this important problem, quantitatively evaluating the factors that are related to bird strikes. To achieve this goal, the following sub-studies were conducted:

- Bird strike occurrence study: investigate the impacts of bird and airplane movement on bird strike occurrence using newly available bird movement data collected by the avian radar at Seattle Tacoma International Airport; and analyze the effects of meteorological factors (e.g., temperature) on bird strike occurrence using statistical models.
- Bird strike severity study: evaluate the effects of a set of factors, such as airplane mass, engine type, number of engines, altitude, bird size, cloud cover, and visibility, on different bird strike severity levels (e.g. minor damage or serious damage) by developing statistical models.

To accomplish these studies, the following primary data sets were collected and organized at research airports:

- Detailed bird movement data collected using avian radar.
- FAA wildlife strike database.
- Airport operation data (e.g., airplane movement).
- Meteorological data, including daily averages of temperature, precipitation, wind speed, visibility and pressure.

The remainder of the thesis is organized as follows. Chapters 2 focuses on investigation of bird strike occurrence and related factors. It includes: (1) evaluation of effects of bird density and airplane movement frequency (Section 2.1); and (2) evaluation of effects of weather (Section 2.2). Chapter 3 assesses impact of selected factors, such as bird size, airplane mass, engine type and time of day, on bird strike severity. Chapter 4 summarizes the study findings and future work.

CHAPTER 2

BIRD STRIKE OCCURRENCE

For a given time period and a given runway, bird strike occurrence can be assessed in terms of strike probability, strike frequency, and strike status. Strike probability is defined as the number of strikes divided by the number of airplane movements under similar circumstances, which may refer to the similar time period, location, airplane type, and weather. Currently, developing a statistical model to evaluate and predict bird strike probability is challenging, because detailed information on variables describing the circumstance of each airplane movement is missing. Strike frequency is defined by the number of bird strikes for a given time period and a given runway. In general practice, frequency is modeled using count data models, such as Poisson and Negative binomial regression, and their extensions (e.g. Zero-inflated Poisson regression and Zero-inflated Negative binomial regression) (Milton and Mannering, 1998). These models have been used to model vehicle accidents for decades (El-Basyouny and Sayed, 2006; Lord and Bonneson, 2005). However, such models may not be effective to model bird strike frequency and further build the relationship between strike frequency and its explanatory variables of interest. First of all, bird strikes are characterized as rare events. Data characterized by a small sample size and low sample mean (the small average count number over a short time period) can cause estimation problems in traditional count-frequency models (Lord and Bonneson, 2005; Lee and Mannering, 2002). When modeling vehicle accident frequency, researchers usually use long-term (e.g., a month or a year) count-data and modify model structure to account for this issue (Lee and Mannering, 2002; Geedipally and Lord, 2010). That being said, the aggregation of data over time periods may lead to a biased estimation, because the change of explanatory variables with time is ignored (Washington, et al., 2010). In bird strike frequency analysis, the explanatory variables include bird density and airplane movement frequency, both of which change significantly with time. Hence, using the long-term count method may result in information loss and introduce errors in model estimation. Therefore, modeling strike frequency is not an appropriate approach for analyzing bird strike occurrence.

Bird strike status is a binary outcome, which is defined for a given runway and time period as: if there are one or more bird strikes reported, the bird strike status is defined as “1”; and if there are no bird strikes reported, the status is defined as “0”. The status does not relate to the real quantity of bird strikes. Therefore, analyzing bird strike status would not be affected by issues caused by small sample mean. Hence the analysis can be conducted with a shorter time interval (e.g., an hour or a day depending on reported bird strike records) compared with that used in vehicle accident frequency modeling. Even though the fluctuation of bird density and airplane movement frequency within the small time interval, such as an hour or a day, is not considered, the information loss during the analysis is much less than that with a time interval of a month or a year. Therefore, modeling strike status is a better and more applicable way, compared to modeling strike probability and frequency.

The study of bird strike occurrence focuses on bird strike status. It was carried out with two separate investigations. One investigation analyzes the effects of bird density and airplane movement frequency at Seattle Tacoma International Airport. The other one examines the effects of meteorological variables using data from six major US airports. The two investigations cannot be combined because bird density data is only available in airports with avian radar systems which are limited. An integrated model, which can study all contributory factors simultaneously, is expected to be developed in the future once more data becomes available.

2.1 Study of Bird Density and Airplane Movement

Recently, with the introduction of avian radar technology, it is possible to obtain detailed information on bird movement and dynamics to improve the identification of bird strike hazards. The study purpose of this section is to examine effects of bird density developed from an avian radar and airplane movement frequency data provided by the airport on bird strike status. This study uses new data on bird movement available from avian radars at Seattle Tacoma International Airport (SEA). The analysis also includes data on airplane movement frequency and bird strike records from SEA to account for multiple causal factors during the model development.

2.1.1 Methodology

This study used logistic regression to build the relationship between bird strike status and its explanatory variables, which include bird density and airplane movement frequency for a given time period. Logistic regression is a statistical method used to analyze data in which there are one or more independent variables that determine a binary outcome (Hosmer and Lemeshow, 2000). Formally, the model is given by equation (1) and (2) (Agresti, 1996).

$$\text{Logit}(p_i)=\ln\frac{p_i}{1-p_i}=(X\beta')_i=\beta_{0i}+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_k x_{ki} \tag{1}$$

$$p_i=\frac{1}{1+e^{(-(\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_i x_{ki}))}} \tag{2}$$

Where, p_i is the probability to have bird strikes during time period i; X_i is a vector of k variables observed in time period i, such as bird density and airplane movement frequency, which affect the occurrence of bird strikes; β is a vector of k unknown regression coefficients, which can be estimated by standard maximum likelihood methods (Agresti, 1996).

With logistic regression, the following assumptions were made: (1) The bird strike occurrence for a given runway and time period can be represented by binary outcomes ("1" =Strike occurred and "0"=No strikes); (2) the relationship between log odds ($\log \frac{p}{1-p}$) and independent variables is linear; and (3) the explanatory variables are not highly correlated, otherwise, a variable reduction procedure or factor analysis needs to be considered.

2.1.2 Data

The data used in this study was collected from SEA, Seattle, WA. There are three runways at SEA: 34R/16L, 34C/16C and 34L/16R (Figure 2)

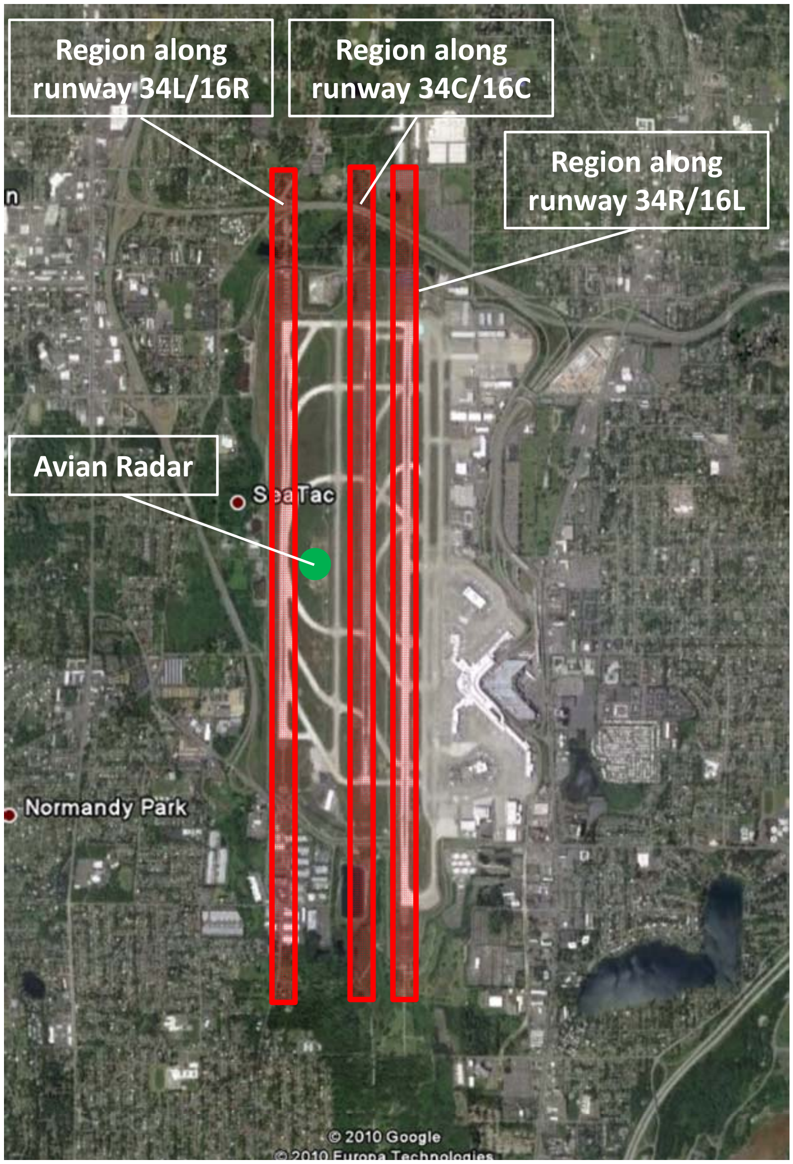

Figure 2 Locations of runway, AR-1 radar and three defined regions at SEA.

The analysis was conducted for each of the three runways. Two variables were selected: bird density and airplane movement frequency. Bird density was computed using data that was collected by an Accipiter Radar Technologies, Inc (ARTI) avian radar system (AR-1). The AR-1 is located in the midfield of SEA airport between Runways 16C/34C and 16R/34L (Figure 2). It is a 25 kW, X-band marine radar operating at 9.4 GHz with a wavelength of 3 cm. The data from ARTI systems was processed by a Digital Radar Processor (DRP). The primary logic and algorithms of the DRP are used to classify radar returns of interest as plots and correlate them into tracks. A track is created and assigned an ID number when three detections, or plots, meet criteria for a track. Radar data used in this study was pre-processed to exclude extraneous targets or non-bird targets. Bird tracks were isolated and organized for analysis. The techniques used in data pre-process step involved visual observations, use of masking capabilities in the DRP, and the application of target classification algorithms using Matlab®. Since it is very difficult to obtain the real number of birds from the radar data, bird track density was used to represent bird density. Bird track density was defined by the number of bird tracks detected in a given region and time period. Three 150m by 8000m rectangular regions were defined along the three runways (Figure 2). Tracks were accumulated for one day (24 hours) to determine region track density.

Bird tracks detected from May 1st to October 31st in 2009 and 2010 at SEA were used. These tracks were exacted from the original radar data and organized over time and region to compute track density (Table 3). Track density was calculated with the following assumptions: (1) only birds within the three defined regions could affect the occurrence of bird strikes and are thus considered; (2) Birds of different species could be treated as unit avian targets when computing bird density, and differences in bird size and flight behavior could be ignored; and (3) bird density can be represented by track density. Because rainfall negatively affects avian radar performance, radar data collected on rainy dates was excluded. The airplane movement information was provided by SEA. The movement frequency of commercial airplanes over the same time period for each of the runways was calculated and organized in Table 3. The dependent variable, bird strike status, for the same time period and runway was coded based on SEA bird strike reports from FAA Wildlife Strike Database. There were 210 records that were applied for runway 34C/16C and 34L/16R, and 122 records used for runway 34R/16L.

Table 3 Variables used in bird strike status analysis

Region Location	Variable	Daily Mean	Maximum	Minimum	Standard deviation
34R/16L	Track density (number of tracks by region)	3313	6023	806	1197
	Airplane movement frequency (takeoffs and landings)	284	550	0	154
34C/16C	Track density (number of tracks by region)	6555	9996	1699	2005
	Airplane movement frequency (takeoffs and landings)	189	502	0	143
34L/16R	Track density (number of tracks by region)	9187	14045	3838	2432
	Airplane movement frequency (takeoffs and landings)	232	765	2	170

2.1.3 Estimation results and discussion

The models were estimated using R version 2.13.0 (R Development Core Team, 2011). The estimation results of the logistic regression indicated a significant positive relationship between reported bird strike status and the two explanatory variables (track density and airplane movement frequency) at SEA for all three runways ($P < 0.05$) (Table 4).

Table 4 Logistic regression estimation results of bird strike status

Runway	Variable	Estimated coefficients	T test	P Value
34R/16L	Intercept	-6.3024	-4.232	<0.001
	Track density (number of tracks by region)	0.0006	2.249	0.025
	Airplane movement frequency (takeoffs and landings)	0.0065	2.776	0.005
34C/16C	Intercept	-8.775	-3.578	<0.001
	Track density (number of tracks by region)	0.0007	2.711	0.007
	Airplane movement frequency (takeoffs and landings)	0.0074	2.876	0.004

Table 4 (cont.)

Runway	Variable	Estimated coefficients	T test	P Value
34L/16R	Intercept	-10.98	-4.201	<0.001
	Track density (number of tracks by region)	0.0007	3.258	<0.001
	Airplane movement frequency (takeoffs and landings)	0.0070	4.953	<0.001

The estimation results confirmed the empirical assumption that large bird density and high airplane movement frequency increased the chance of bird strikes. The coefficients associated with the two variables could help predict bird strike status for a given non-rainfall day between May and October at SEA. However, the false positive (the actual strike status is “0” while the predicted status becomes “1”) and false negative (the actual strike status is “1” while the predicted status becomes “0”) may make the model less promising in prediction.

There are several reasons that could cause such inconsistencies. First of all, bird strikes are instantaneous events. Data from smaller time intervals could better characterize the relationship between strike status and the two variables. However, because of the sparse bird strike records, the logistic regression model was fitted using daily track density and daily airplane movement frequency. Daily data could depict daily variations of the two variables, indicating differences between strike dates and non-strike dates, but it ignores variable variations within a day. The second reason is the under reporting issue associated with the bird strike database. A large portion of actual bird strikes, particularly those resulting in no obvious damage, are not reported because of the unawareness of pilots or the inconvenient process of reporting a strike (Linnell, 1999). Hence, days with strikes (strike status= “1”) may be categorized as no strike days (strike status= “0”).

Finally, radar data issues bring in uncertainties to the model. Lack of elevation information is one of the issues. Because of that, all bird tracks within the defined regions were counted to compute track density. But in the ideal case, only birds at the same altitude as the airplanes could pose causal effects. The issue could be solved once more advanced radar is deployed. In addition, bird tracks were extracted from the original radar data which included different kinds of data noise (e.g., multi-path tracks, vehicle tracks, insect tracks and even tracks caused by particulates caught in the wind). Mathematical techniques such as data clustering and filtering have been used to reduce such data noise. The consistency between actual bird numbers and bird tracks also needs to be further verified with field observations in the future.

2.2 Study of Meteorological Variables

Previous studies have noted the fact that weather has impacts on bird strike occurrence (Linnell et al. 1996, Steel 2001, Zakrajsek, 2002). For example, Gabrey and Dolbeer (1996) found the presence of standing water from rainfall increased the bird strike rate at Chicago O'Hare International Airport. Manktelow (2000) showed that temperature and rainfall have positive effects on bird strike occurrence. However, quantitative analyses of such relationships using statistical models are limited. The purpose of this section is to develop statistical models to examine the effect of a set of meteorological variables on bird strike status. As addressed previously, bird strike status was defined as follows: if there are one or more bird strikes reported, the bird strike status is defined as "1"; otherwise, the status is defined as "0". The meteorological variables selected in this study include temperature, precipitation, wind speed, visibility, and barometric pressure. Correlations between different variables were tested, and only variables with low correlations were selected to avoid multicollinearity in regression analysis (Farrar and Glauber, 1967).

2.2.1 Data

Six commercial airports were selected as study sites (Figure 3), including John F. Kennedy International Airport (JFK), Detroit Metropolitan Wayne County Airport (DTW), Chicago O'Hare International Airport (ORD), Dallas Fort Worth International Airport (DFW), Los Angeles International Airport (LAX), and Seattle-Tacoma International Airport (SEA).

The bird strike reports for each airport were obtained from FAA wildlife strike database. Reports without known dates were excluded. The meteorological data was collected from Weather Underground (WU), which provides daily average of selected variables. Dates with missing meteorological data were excluded. Both bird strike reports and meteorological data used were from 2000 to 2009. A summary of the bird strike reports was presented in Table 5.

Table 5 Bird strike reports at the six airports (FAA wildlife strike database, 2011)

Airport	Available data	Bird strikes	Airport	Available data	Bird strikes
DTW	2000-Aug 2009	257	SEA	2000-Nov 2008	177
ORD	2000-Aug 2008	233	DFW	2000-Nov 2008	578
JFK	2000-Oct 2008	331	LAX	2000-Nov 2008	192

Figure 3 Locations of the six selected airports.

2.2.2 Methodology

The relationship between bird strike status and selected meteorological variables were examined using Logistic regression, which was introduced in Section 2.1.2. Since bird strikes do not occure under a specific weather variable but under a combination of several variables, the regression analysis involves multiple meteological variables. Multicolinearity may occure when two or more variables are highly correlated. This statistical phonomenon may affect the accuacy of parameter estimations. Thus, it is necessary to test variable correlations before model development. The correlations between variables in each of the six airports were examined using Pearson's correlation equation (Rodgers and Nicewander, 1988), and the maximum correlation coefficients of the six airports were summarized in Table 5. The results indicated weak correlations between most of these variables ($|\rho_{\max}| < 0.5$) except temperature-versus-pressure in

DFW ($|\rho_{DFW}|=|\rho_{\max}|=0.573$). Therefore, variables, including temperature, precipitation, wind speed, visibility, and barometric pressure were selected in the logistic regression analysis for all airports except DFW. Barometric pressure was excluded in models developed for DFW to avoid multicolinearity.

Table 6 The maximum absolute correlation coefficients among the 6 airports

		Temperature	Rainfall	Windspeed	Visibility	Pressure
Temperature	$\|\rho_{\max}\|$	1	0.183	0.348	0.225	0.573
	Sig. (2-tailed)		≤ 0.001	≤ 0.001	≤ 0.001	≤ 0.001
Rainfall	$\|\rho_{\max}\|$	0.183	1	0.25	0.461	0.350
	Sig. (2-tailed)	≤ 0.001		≤ 0.001	≤ 0.001	≤ 0.001
Wind speed	$\|\rho_{\max}\|$	0.036	0.25	1	0.2	0.368
	Sig. (2-tailed)	≤ 0.001	≤ 0.001		≤ 0.001	≤ 0.001
Visibility	$\|\rho_{\max}\|$	0.225	0.461	0.2	1	0.298
	Sig. (2-tailed)	≤ 0.001	≤ 0.001	≤ 0.001		≤ 0.001
Pressure	$\|\rho_{\max}\|$	0.573	0.35	0.368	0.298	1
	Sig. (2-tailed)	≤ 0.001	≤ 0.001	≤ 0.001	≤ 0.001	

The daily average value was applied to all the variables except precipitation. Previous study indicated that bird strikes usually occur after rainfall dates (Gabrey and Dolbeer 1996). To evaluate such residual effect, all dates were grouped into 7 classes, based on the number of days since the last rainfall had occurred. For example, dates with a specified amount (e.g., ⩾1.27 cm) of rain were classified as day 0, and consecutive, subsequent days in which there is no rainfall or the rainfall is less than the specified amount were classified as day 1, day 2, et al. Dates that were more than 6 days since the last rainfall were all classified as day 6. The residual effect of precipitation was studies three times, with three levels of rainfall, including ⩾1.27 cm, ⩾0.76

cm, and ⩾0.25 cm. A regression model was developed for each airport, season and precipitation level. Because of the snow and frozen water, precipitation was excluded from models developed in winter in airport ORD, JFK and DTW. Therefore, 12 regression models were developed for SEA, LAX and DFW, and 10 models were developed for ORD, JFK and DTW, resulting in 66 models in total. The model estimations were carried out using R version 2.13.0 (R Development Core Team, 2011). The significance level of parameter estimation is 0.05.

2.2.3 Estimation Results

The regression models were summarized by airport, in Table 7, 8, 9, 10, 11, and 12. No valid models were developed in summer of LAX with precipitation level ⩾1.27 cm, and ⩾0.76 cm, because all the dates have rainfall lower than these levels.

Temperature was demonstrated to be an important factor. In autumn, it showed positive effects at all the six airports except SEA. Its effect at SEA was positive but not significant. In winter, temperature posed positive effects at JFK and DTW, and positive but insignificant effect at the rest airports. In spring, temperature only showed positive effects at JFK. In summer, temperature posed negative effects at LAX. Its negative effects at DFW were not significant.

Precipitation was another key factor. When precipitation level was ⩾1.27 cm, 3 days after the rain increased the chance of bird strikes in spring and summer at ORD, in winter at LAX, and in spring at JFK. When precipitation level was ⩾0.76 cm, 1 day after the rain posed positive effects on reported bird strike status in spring and summer at ORD, and in winter at LAX and DFW; and 3 days after the rain showed positive effects in spring and summer at ORD, in winter at LAX, and in spring at JFK. When precipitation level was ⩾0.25 cm, 1 day after the rainfall showed positive effects in spring at JFK and DTW, and negative effects in autumn of ORD.

For other factors, wind speed was negatively related to the occurrence of reported bird strike status in autumn at LAX and in winter at JFK. Better visibility increased the chance of bird strike in winter at ORD and in autumn at JFK. Pressure posed positive effects in autumn at SEA.

Table 7 Variable estimations of logistic regression models developed for SEA

SEA_Spring								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-47.600	0.082	Intercept	-41.364	0.137	Intercept	-35.856	0.199
Temperature	0.019	0.615	Temperature	0.026	0.493	Temperature	0.031	0.407
Wind speed	-0.002	0.975	Wind speed	0.015	0.801	Wind speed	0.044	0.461
Visibility	-0.062	0.548	Visibility	-0.094	0.353	Visibility	-0.093	0.346
Pressure	1.475	0.103	Pressure	1.235	0.178	Pressure	1.038	0.259
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	-0.036	0.971	Day 1	0.866	0.294	Day 1	-0.511	0.545
Day 2	0.016	0.988	Day 2	0.359	0.716	Day 2	0.945	0.160
Day 3	-16.610	0.992	Day 3	-15.759	0.991	Day 3	-0.491	0.661
Day 4	-16.600	0.993	Day 4	-0.154	0.899	Day 4	0.845	0.271
Day 5	-16.700	0.993	Day 5	-15.800	0.992	Day 5	0.220	0.845
Day 6	-0.479	0.519	Day 6	0.475	0.506	Day 6	0.659	0.277
SEA_Summer								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	7.685	0.831	Intercept	4.880	0.892	Intercept	-3.914	0.915
Temperature	0.005	0.842	Temperature	0.001	0.962	Temperature	0.002	0.925
Wind speed	-0.016	0.755	Wind speed	-0.017	0.727	Wind speed	-0.020	0.681
Visibility	-0.086	0.469	Visibility	-0.081	0.491	Visibility	-0.067	0.574
Pressure	-0.309	0.797	Pressure	-0.218	0.856	Pressure	0.075	0.951
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	-15.340	0.988	Day 1	-0.781	0.518	Day 1	-0.475	0.517
Day 2	1.047	0.332	Day 2	0.481	0.597	Day 2	0.191	0.768
Day 3	-15.320	0.989	Day 3	0.105	0.917	Day 3	-0.625	0.471
Day 4	1.924	0.065	Day 4	1.413	0.101	Day 4	0.671	0.289
Day 5	-15.310	0.989	Day 5	-14.033	0.979	Day 5	-0.069	0.927
Day 6	-0.200	0.813	Day 6	0.115	0.867	Day 6	-0.125	0.792

Table 7 (cont.)

SEA_Autumn								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-40.528	0.051	Intercept	-42.335	0.047	Intercept	-48.734	0.029
Temperature	0.024	0.197	Temperature	0.024	0.193	Temperature	0.028	0.146
Wind speed	0.003	0.940	Wind speed	-0.004	0.914	Wind speed	-0.013	0.724
Visibility	0.057	0.443	Visibility	0.065	0.394	Visibility	0.065	0.413
Pressure	1.196	0.082	Pressure	1.267	0.071	Pressure	1.481	0.044
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.791	0.292	Day 1	0.179	0.747	Day 1	0.126	0.769
Day 2	0.927	0.228	Day 2	0.231	0.702	Day 2	-0.285	0.590
Day 3	-0.921	0.441	Day 3	-0.895	0.294	Day 3	-0.362	0.540
Day 4	-0.110	0.910	Day 4	-0.324	0.665	Day 4	-1.782	0.096
Day 5	-0.071	0.942	Day 5	-0.192	0.795	Day 5	-0.854	0.286
Day 6	0.202	0.760	Day 6	-0.251	0.597	Day 6	-0.576	0.191
SEA_Winter								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-47.620	0.082	Intercept	-41.364	0.137	Intercept	-35.856	0.199
Temperature	0.019	0.615	Temperature	0.026	0.493	Temperature	0.031	0.407
Wind speed	-0.002	0.975	Wind speed	0.015	0.801	Wind speed	0.044	0.461
Visibility	-0.062	0.548	Visibility	-0.094	0.353	Visibility	-0.093	0.346
Pressure	1.475	0.103	Pressure	1.235	0.178	Pressure	1.038	0.259
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	-0.036	0.971	Day 1	0.866	0.294	Day 1	-0.511	0.545
Day 2	0.016	0.988	Day 2	0.359	0.716	Day 2	0.945	0.160
Day 3	-16.610	0.992	Day 3	-15.759	0.991	Day 3	-0.491	0.661
Day 4	-16.600	0.993	Day 4	-0.154	0.899	Day 4	0.845	0.271
Day 5	-16.700	0.993	Day 5	-15.800	0.992	Day 5	0.220	0.845
Day 6	-0.479	0.519	Day 6	0.475	0.506	Day 6	0.659	0.277

Table 8 Variable estimations of logistic regression models developed for LAX

LAX_Spring								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	31.670	0.974	Intercept	44.256	0.277	Intercept	41.346	0.306
Temperature	-0.005	0.839	Temperature	-0.002	0.922	Temperature	0.002	0.934
Wind speed	-0.004	0.911	Wind speed	-0.004	0.916	Wind speed	-0.020	0.602
Visibility	-0.002	0.967	Visibility	0.002	0.971	Visibility	0.013	0.786
Pressure	-1.599	0.228	Pressure	-1.523	0.256	Pressure	-1.416	0.288
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	15.000	0.988	Day 1	-0.551	0.677	Day 1	-0.774	0.321
Day 2	16.040	0.987	Day 2	0.798	0.454	Day 2	-0.400	0.585
Day 3	15.960	0.987	Day 3	0.714	0.501	Day 3	-0.679	0.390
Day 4	0.146	1.000	Day 4	-14.962	0.984	Day 4	-1.790	0.115
Day 5	0.126	1.000	Day 5	-14.969	0.984	Day 5	-1.040	0.242
Day 6	14.860	0.988	Day 6	-0.199	0.806	Day 6	-0.783	0.103
LAX_Summer								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-	-	Intercept	-	-	Intercept	-29.972	0.494
Temperature	-	-	Temperature	-	-	Temperature	-0.065	0.020
Wind speed	-	-	Wind speed	-	-	Wind speed	-0.026	0.479
Visibility	-	-	Visibility	-	-	Visibility	0.014	0.755
Pressure	-	-	Pressure	-	-	Pressure	1.186	0.413
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	-	-	Day 1	-	-	Day 1	-16.143	0.984
Day 2	-	-	Day 2	-	-	Day 2	-1.231	0.489
Day 3	-	-	Day 3	-	-	Day 3	-16.266	0.984
Day 4	-	-	Day 4	-	-	Day 4	-0.002	0.999
Day 5	-	-	Day 5	-	-	Day 5	-1.369	0.441
Day 6	-	-	Day 6	-	-	Day 6	-2.197	0.086

Table 8 (cont.)

LAX_Autumn								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	20.615	0.492	Intercept	23.865	0.427	Intercept	28.624	0.346
Temperature	0.055	0.003	Temperature	0.050	0.005	Temperature	0.045	0.014
Wind speed	-0.085	0.049	Wind speed	-0.084	0.050	Wind speed	-0.079	0.073
Visibility	0.081	0.060	Visibility	0.084	0.050	Visibility	0.077	0.072
Pressure	-0.852	0.389	Pressure	-0.971	0.326	Pressure	-1.140	0.254
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	-1.260	0.301	Day 1	-0.378	0.697	Day 1	0.594	0.405
Day 2	-0.672	0.504	Day 2	-0.437	0.655	Day 2	0.652	0.368
Day 3	-0.237	0.798	Day 3	-0.014	0.988	Day 3	1.157	0.090
Day 4	-15.223	0.979	Day 4	-1.137	0.345	Day 4	-0.297	0.742
Day 5	0.198	0.821	Day 5	0.502	0.550	Day 5	-0.225	0.803
Day 6	-0.540	0.416	Day 6	0.061	0.924	Day 6	0.749	0.169
LAX_Winter								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	47.102	0.168	Intercept	47.631	0.161	Intercept	60.190	0.082
Temperature	-0.006	0.811	Temperature	-0.003	0.902	Temperature	-0.004	0.867
Wind speed	-0.009	0.832	Wind speed	0.002	0.954	Wind speed	0.000	0.998
Visibility	0.051	0.361	Visibility	0.033	0.557	Visibility	0.033	0.562
Pressure	-1.676	0.139	Pressure	-1.710	0.129	Pressure	-2.095	0.068
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	1.444	0.095	Day 1	2.294	0.006	Day 1	0.885	0.084
Day 2	1.345	0.149	Day 2	1.940	0.030	Day 2	1.194	0.024
Day 3	2.368	0.006	Day 3	2.036	0.023	Day 3	0.833	0.165
Day 4	1.643	0.082	Day 4	2.163	0.016	Day 4	1.456	0.009
Day 5	0.829	0.437	Day 5	1.880	0.043	Day 5	1.215	0.037
Day 6	1.009	0.191	Day 6	1.444	0.058	Day 6	0.408	0.346

Table 9 Variable estimations of logistic regression models developed for DFW

DFW_Spring								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	16.046	0.381	Intercept	17.274	0.347	Intercept	14.641	0.426
Temperature	0.010	0.289	Temperature	0.009	0.312	Temperature	0.010	0.279
Wind speed	-0.013	0.453	Wind speed	-0.012	0.462	Wind speed	-0.012	0.462
Visibility	0.012	0.879	Visibility	0.010	0.897	Visibility	-0.042	0.583
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.080	0.826	Day 1	-0.032	0.921	Day 1	0.200	0.464
Day 2	0.050	0.895	Day 2	0.086	0.804	Day 2	0.243	0.410
Day 3	-0.476	0.233	Day 3	-0.625	0.096	Day 3	-0.252	0.439
Day 4	-0.083	0.833	Day 4	0.124	0.732	Day 4	0.447	0.157
Day 5	0.083	0.835	Day 5	0.130	0.733	Day 5	0.235	0.480
Day 6	-0.374	0.194	Day 6	-0.386	0.144	Day 6	-0.040	0.864
DFW_Summer								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-0.426	0.987	Intercept	1.598	0.953	Intercept	-1.435	0.958
Temperature	-0.012	0.427	Temperature	-0.014	0.396	Temperature	-0.009	0.599
Wind speed	0.020	0.357	Wind speed	0.018	0.417	Wind speed	0.021	0.330
Visibility	0.093	0.403	Visibility	0.123	0.273	Visibility	0.106	0.316
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.199	0.656	Day 1	0.196	0.625	Day 1	0.331	0.288
Day 2	0.462	0.340	Day 2	-0.148	0.730	Day 2	0.190	0.567
Day 3	-0.133	0.786	Day 3	-0.131	0.758	Day 3	-0.028	0.935
Day 4	0.576	0.238	Day 4	0.221	0.612	Day 4	-0.017	0.963
Day 5	0.352	0.488	Day 5	0.188	0.679	Day 5	-0.487	0.208
Day 6	0.051	0.891	Day 6	-0.086	0.803	Day 6	-0.082	0.754

Table 9 (cont.)

DFW_Autumn								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-15.555	0.281	Intercept	-13.608	0.343	Intercept	-16.271	0.256
Temperature	0.025	0.0001	Temperature	0.024	0.0001	Temperature	0.026	0.0001
Wind speed	-0.016	0.369	Wind speed	-0.017	0.314	Wind speed	-0.016	0.362
Visibility	0.053	0.278	Visibility	0.071	0.164	Visibility	0.103	0.056
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.509	0.218	Day 1	-0.189	0.611	Day 1	-0.102	0.728
Day 2	0.266	0.528	Day 2	-0.214	0.576	Day 2	-0.333	0.304
Day 3	0.358	0.401	Day 3	0.330	0.391	Day 3	0.214	0.524
Day 4	0.827	0.063	Day 4	0.287	0.468	Day 4	-0.349	0.323
Day 5	-0.410	0.378	Day 5	-0.929	0.035	Day 5	-0.965	0.013
Day 6	-0.314	0.322	Day 6	-0.484	0.090	Day 6	-0.662	0.007
DFW_Winter								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-5.889	0.731	Intercept	-9.694	0.577	Intercept	-6.490	0.710
Temperature	0.017	0.118	Temperature	0.020	0.075	Temperature	0.018	0.113
Wind speed	0.012	0.553	Wind speed	0.015	0.480	Wind speed	0.012	0.578
Visibility	0.009	0.878	Visibility	-0.009	0.877	Visibility	0.017	0.779
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.453	0.419	Day 1	1.088	0.021	Day 1	0.265	0.474
Day 2	0.634	0.264	Day 2	0.783	0.120	Day 2	0.026	0.950
Day 3	-0.144	0.823	Day 3	0.186	0.741	Day 3	0.065	0.876
Day 4	-0.334	0.628	Day 4	0.060	0.919	Day 4	-0.274	0.557
Day 5	0.318	0.610	Day 5	0.499	0.365	Day 5	-0.044	0.924
Day 6	0.164	0.708	Day 6	0.395	0.329	Day 6	0.006	0.984

Table 10 Variable estimations of logistic regression models developed for ORD

ORD_Spring								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	10.143	0.573	Intercept	10.035	0.582	Intercept	19.486	0.303
Temperature	-0.006	0.607	Temperature	-0.007	0.578	Temperature	-0.010	0.382
Wind speed	-0.013	0.594	Wind speed	-0.014	0.552	Wind speed	-0.010	0.657
Visibility	-0.078	0.188	Visibility	-0.098	0.101	Visibility	-0.109	0.065
Pressure	-0.304	0.607	Pressure	-0.298	0.619	Pressure	-0.599	0.334
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.507	0.168	Day 1	0.801	0.009	Day 1	0.338	0.145
Day 2	0.348	0.362	Day 2	0.233	0.475	Day 2	0.497	0.055
Day 3	0.952	0.020	Day 3	0.745	0.031	Day 3	0.403	0.153
Day 4	0.424	0.293	Day 4	0.564	0.107	Day 4	0.522	0.084
Day 5	0.115	0.780	Day 5	0.244	0.503	Day 5	-0.109	0.738
Day 6	0.051	0.858	Day 6	0.257	0.296	Day 6	0.302	0.161
ORD_Summer								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	10.143	0.573	Intercept	10.035	0.582	Intercept	19.486	0.303
Temperature	-0.006	0.607	Temperature	-0.007	0.578	Temperature	-0.010	0.382
Wind speed	-0.013	0.594	Wind speed	-0.014	0.552	Wind speed	-0.010	0.657
Visibility	-0.078	0.188	Visibility	-0.098	0.101	Visibility	-0.109	0.065
Pressure	-0.304	0.607	Pressure	-0.298	0.619	Pressure	-0.599	0.334
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.507	0.168	Day 1	0.801	0.009	Day 1	0.338	0.145
Day 2	0.348	0.362	Day 2	0.233	0.475	Day 2	0.497	0.055
Day 3	0.952	0.020	Day 3	0.745	0.031	Day 3	0.403	0.153
Day 4	0.424	0.293	Day 4	0.564	0.107	Day 4	0.522	0.084
Day 5	0.115	0.780	Day 5	0.244	0.503	Day 5	-0.109	0.738
Day 6	0.051	0.858	Day 6	0.257	0.296	Day 6	0.302	0.161

Table 10 (cont.)

ORD_Autumn								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	17.841	0.157	Intercept	18.918	0.137	Intercept	23.762	0.066
Temperature	0.035	0.0001	Temperature	0.035	0.0001	Temperature	0.036	0.0001
Wind speed	-0.003	0.876	Wind speed	-0.006	0.793	Wind speed	-0.005	0.828
Visibility	0.092	0.055	Visibility	0.092	0.057	Visibility	0.068	0.167
Pressure	-0.721	0.086	Pressure	-0.755	0.075	Pressure	-0.912	0.034
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.711	0.139	Day 1	0.720	0.077	Day 1	0.866	0.002
Day 2	0.702	0.156	Day 2	0.522	0.220	Day 2	0.455	0.139
Day 3	0.662	0.190	Day 3	0.731	0.087	Day 3	0.303	0.355
Day 4	0.443	0.393	Day 4	0.241	0.593	Day 4	0.451	0.195
Day 5	0.328	0.528	Day 5	0.679	0.114	Day 5	0.865	0.016
Day 6	0.408	0.279	Day 6	0.348	0.284	Day 6	0.482	0.062

ORD_Winter		
Coefficient	Estimate value	Pr(>|Z|)
Intercept	10.207	0.548
Temperature	0.009	0.430
Wind speed	-0.002	0.940
Visibility	0.121	0.031
Pressure	-0.449	0.424

Table 11 Variable estimations of logistic regression models developed for DTW

DTW_Spring								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-0.392	0.981	Intercept	-1.005	0.950	Intercept	1.363	0.934
Temperature	0.007	0.379	Temperature	0.008	0.315	Temperature	0.009	0.254
Wind speed	-0.046	0.099	Wind speed	-0.055	0.050	Wind speed	-0.044	0.117
Visibility	0.044	0.450	Visibility	0.050	0.409	Visibility	-0.002	0.967
Pressure	-0.036	0.947	Pressure	-0.023	0.966	Pressure	-0.105	0.848
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	-0.203	0.663	Day 1	0.098	0.791	Day 1	0.580	0.036
Day 2	-0.099	0.834	Day 2	-0.296	0.470	Day 2	0.028	0.934
Day 3	-0.591	0.250	Day 3	-0.117	0.771	Day 3	0.258	0.459
Day 4	-0.376	0.456	Day 4	-0.273	0.529	Day 4	-0.043	0.915
Day 5	-0.212	0.675	Day 5	0.493	0.220	Day 5	0.213	0.618
Day 6	-0.553	0.124	Day 6	-0.513	0.107	Day 6	0.057	0.853
DTW_Summer								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	24.168	0.197	Intercept	24.947	0.189	Intercept	19.153	0.325
Temperature	0.005	0.714	Temperature	0.003	0.831	Temperature	0.005	0.717
Wind speed	0.005	0.871	Wind speed	0.009	0.754	Wind speed	0.002	0.934
Visibility	0.005	0.911	Visibility	-0.011	0.815	Visibility	0.000	0.994
Pressure	-0.847	0.169	Pressure	-0.868	0.164	Pressure	-0.676	0.289
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.149	0.723	Day 1	0.040	0.905	Day 1	0.129	0.594
Day 2	0.083	0.851	Day 2	-0.074	0.837	Day 2	-0.119	0.670
Day 3	0.102	0.817	Day 3	0.509	0.150	Day 3	0.087	0.769
Day 4	0.607	0.161	Day 4	0.378	0.299	Day 4	0.073	0.822
Day 5	0.493	0.269	Day 5	0.068	0.860	Day 5	0.113	0.745
Day 6	-0.052	0.868	Day 6	0.152	0.567	Day 6	-0.097	0.681

Table 11 (cont.)

DTW_Autumn								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-4.079	0.813	Intercept	-6.155	0.723	Intercept	-5.310	0.762
Temperature	0.031	0.0002	Temperature	0.031	0.0002	Temperature	0.031	0.0002
Wind speed	-0.015	0.613	Wind speed	-0.021	0.488	Wind speed	-0.018	0.554
Visibility	0.109	0.059	Visibility	0.140	0.020	Visibility	0.120	0.044
Pressure	0.013	0.982	Pressure	0.084	0.885	Pressure	0.046	0.937
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.094	0.868	Day 1	-0.216	0.650	Day 1	0.135	0.667
Day 2	-1.492	0.077	Day 2	-1.402	0.029	Day 2	-0.408	0.292
Day 3	0.249	0.664	Day 3	-0.163	0.745	Day 3	-0.348	0.385
Day 4	0.283	0.619	Day 4	0.086	0.861	Day 4	-0.010	0.980
Day 5	-0.319	0.609	Day 5	-0.910	0.116	Day 5	-0.207	0.644
Day 6	-0.481	0.294	Day 6	-0.851	0.032	Day 6	-0.529	0.114

DTW_Winter		
Coefficient	Estimate value	Pr(>|Z|)
Intercept	-49.404	0.046
Temperature	0.097	0.00001
Wind speed	-0.043	0.308
Visibility	0.084	0.254
Pressure	1.438	0.078

Table 12 Variable estimations of logistic regression models developed for JFK

JFK_Spring								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-3.948	0.001	Intercept	-4.062	0.001	Intercept	-3.281	0.006
Temperature	0.029	0.0003	Temperature	0.028	0.0004	Temperature	0.029	0.000
Wind speed	-0.005	0.807	Wind speed	-0.005	0.830	Wind speed	-0.012	0.581
Visibility	-0.039	0.360	Visibility	-0.045	0.294	Visibility	-0.027	0.538
Pressure	0.039	0.368	Pressure	0.045	0.301	Pressure	0.027	0.546
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.595	0.142	Day 1	0.568	0.110	Day 1	0.500	0.041
Day 2	0.561	0.175	Day 2	0.558	0.130	Day 2	0.348	0.197
Day 3	0.948	0.025	Day 3	0.824	0.028	Day 3	0.216	0.472
Day 4	0.431	0.337	Day 4	0.170	0.683	Day 4	-0.104	0.770
Day 5	0.609	0.181	Day 5	0.494	0.243	Day 5	-0.139	0.730
Day 6	0.516	0.115	Day 6	0.604	0.037	Day 6	0.214	0.392
JFK_Summer								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-0.789	0.577	Intercept	-0.060	0.966	Intercept	-0.108	0.939
Temperature	-0.001	0.956	Temperature	0.003	0.861	Temperature	0.002	0.893
Wind speed	-0.027	0.249	Wind speed	-0.029	0.228	Wind speed	-0.027	0.267
Visibility	0.005	0.925	Visibility	0.030	0.544	Visibility	0.023	0.654
Pressure	-0.005	0.917	Pressure	-0.031	0.539	Pressure	-0.024	0.649
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.955	0.018	Day 1	0.538	0.105	Day 1	0.266	0.295
Day 2	0.481	0.263	Day 2	0.028	0.938	Day 2	0.211	0.444
Day 3	0.885	0.039	Day 3	0.387	0.287	Day 3	0.071	0.809
Day 4	1.229	0.004	Day 4	0.507	0.162	Day 4	0.093	0.762
Day 5	0.339	0.460	Day 5	0.328	0.400	Day 5	-0.145	0.672
Day 6	0.514	0.119	Day 6	0.045	0.870	Day 6	-0.005	0.981

Table 12 (cont.)

JFK_Autumn								
Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)	Coefficients	Estimate value	Pr(>|Z|)
Intercept	-16.918	0.150	Intercept	-20.144	0.093	Intercept	-22.468	0.061
Temperature	0.024	0.001	Temperature	0.025	0.000	Temperature	0.025	0.0001
Wind speed	0.019	0.279	Wind speed	0.017	0.329	Wind speed	0.013	0.458
Visibility	0.192	0.001	Visibility	0.207	0.001	Visibility	0.219	0.0001
Pressure	0.423	0.276	Pressure	0.532	0.179	Pressure	0.608	0.123
Days after precipitation Precipitation ≥0.5 inch			Days after precipitation Precipitation ≥0.3 inch			Days after precipitation Precipitation ≥0.1 inch		
Day 1	0.190	0.637	Day 1	0.068	0.840	Day 1	0.121	0.632
Day 2	0.404	0.329	Day 2	0.268	0.452	Day 2	0.002	0.993
Day 3	0.414	0.327	Day 3	-0.109	0.771	Day 3	-0.128	0.666
Day 4	0.551	0.195	Day 4	0.250	0.500	Day 4	-0.043	0.889
Day 5	-0.189	0.684	Day 5	-0.398	0.334	Day 5	-0.917	0.023
Day 6	0.071	0.832	Day 6	-0.156	0.595	Day 6	-0.335	0.187

JFK_Winter		
Coefficient	Estimate value	Pr(>|Z|)
Intercept	-0.438	0.710
Temperature	0.023	0.038
Wind speed	-0.045	0.018
Visibility	0.060	0.228
Pressure	-0.062	0.223

2.2.4 Discussion

The overall investigation of this study in the six airports suggested that local weather can affect the bird strike occurrence. As addressed previously, temperature showed positive effects in spring, autumn and winter in most airports, and showed negative effects in summer at LAX. The reason probably is that under cold/cool weather conditions, higher temperature (warmer weather) may attract more birds feeding on the airfiled, increasing bird activity and the chance of bird-airplane collisions. However, under hot weather conditions, higher temperature could decrease the bird activity on airfield because of overheating, which lowers the possibility of bird strikes.

The study of precipitation effects showed that bird strikes were more likely to occur on certain days (e.g., 1 day or 3 days) after precipitation. The possible reasons may include: (1) there are fewer airplane movements on rainy dates; (2) heavy rain or storms may drive earthworms (*Lumbricidae*) to the ground surface, improving the feeding success of birds; and (3) the standing water after the precipitation also creates attraction to birds.

Wind speed was negatively related to reported bird strike status in autumn at LAX and winter at JFK, possibly because high wind speed was associated with low bird activities in particular seasons of two airports. Visibility is commonly assumed to affect the ability of birds to detect approaching airplanes. The intuition is that bird strikes increase as visibility decreases. However, this study showed that better visibility increased the chances of bird strikes in winter at ORD and autumn at JFK, which is counter-intuitive. The possible reasons include, first, low visibility affects airport operations, prompting the use of lights that may help birds avoid airplanes; and second, low visibility may affect flight operations, resulting in fewer flights under bad visibility condistions than good ones, as suggested in previous study (Manktelow 2000).

In summary, the study in the six selected airports concludes that local weather has some effects on bird strike status. Although these effects have been addressed in previous studies, few statisitcal analyses are available to date. This section provides quantitative evidence using regression analysis based on large sets of data, demostrating the exisitence of such effects. The results provide important guidance for bird-hazard mangement at airports. For example, airport management should consider field drainage to minimize the development of temporary standing water caused by rainfall, which is an important bird attractant. Moreover, the quantitative relationships between meteorological factors and bird strike status resulted from this work can be used as a fundation to create a bird strike risk assessement model, which predicts the occurrence of bird strikes under different weather conditions.

CHAPTER 3
BIRD STRIKE SEVERITY

Bird strike severity measures the consequence of a bird strike. It is usually described by the level of airplane damage, passenger injury and effects on airport operations (e.g., flight delay). In order to decrease the risk of damaging bird strikes, quantification of factors that contribute to a strike consequence is needed. As discussed in Chapter 1, a set of factors, such as bird size, airplane mass, engine type, airplane flight phase, and strike position of an airplane may affect bird strike severity. This study is to examine the impacts that these factors may pose on bird strike severity. Because of the data limitation of strike related human injury and airport operation, airplane damage data was used to approximately represent strike severity levels.

3.1 Methodology

The FAA wildlife strike database categorizes airplane damage as: no damage, minor damage, substantial damage and destroyed (FAA, 2010). Two categories: substantial damage and destroyed, were combined in the analysis, because strikes of destroyed damage were very rare. Hence, the likelihood of three severity categories caused by a bird strike was examined based on a list of independent variables and given that the strike has occurred. The discrete outcome was modeled by multinomial logit regression (MNL), which has been applied to vehicle-accident severity analysis (Lee and Mannering, 2002; Carson and Mannering, 2001). MNL compares multiple discrete outcomes through a combination of binary logistic regressions. This analysis treated no damage as the reference and compared minor damage to no damage and serious damage to no damage. For each independent variable, there were two comparisons. MNL provided a set of coefficients for each of the two comparisons. The coefficients for the reference level were all zeros. The estimated coefficients were used to compute the probability that strike damage belonged to each of the three categories. The damage was assigned to a severity category which was associated with the highest probability. Hence, the probability of bird strike n resulting in severity i, can be expressed as the probability of severity $S_{i,n}$ is greater than all other $S_{i,n}$. Formally, it is given by equation (3):

$$p_n(i) = p(S_{i,n} \geq S_{I,n}) \quad \forall I \neq i \tag{3}$$

Where,

$P_n(i)$ is the probability of a bird strike n of severity i;

$S_{i,n}$ denotes severity category i, which can be formed linearly, as shown in equation (4):

$$S_{i,n} = \beta_i X_{i,n} + \varepsilon_{i,n} \tag{4}$$

Where,

$X_{i,n}$ is a vector of explanatory variables such as airplane type, speed, bird size and struck location;

β_i is a vector of estimable coefficients on the explanatory variables;

$\varepsilon_{i,n}$ is an unobservable error term.

By assuming $\varepsilon_{i,n}$ is generalized extreme value (GEV) distributed, the probability of a bird strike being of severity i with MNL can be derived as equation (5):

$$p_n(i) = \frac{\exp(\beta_i X_n)}{\sum_{\forall I} \exp(\beta_I X_n)} \tag{5}$$

With MNL, the error term $\varepsilon_{i,n}$ is assumed to be independent from one severity category to another, and selected explanatory variables should not be highly correlated.

3.2 Data

The data used in this study is from FAA wildlife strike database, which is managed using Microsoft Access. The database contains wildlife strike records reported voluntary from airlines, airports, pilots and other sources since 1990. There are more than 121,000 wildlife strikes reported from civil airlines and the United States Air Force (USAF) between 1990 and 2010.

For each wildlife strike record, there are about100 related variables. This study used bird strikes report for civil airlines (or commercial airports) from 1990 to 2010. Variables of airplane characteristics (e.g., airplane mass), bird characteristics (e.g., bird size), struck positions of an airplane (e.g., struck windshield), time of the day and weather conditions (e.g., precipitation) were selected. Variable type and description were summarized in Table 13.

Table 13 Variables selected in the analysis

Variable	Data Type	Remarks (Coding)
Airplane mass	Categorical	1 if an airplane weight is over 27,000kg, 0 otherwise
Turbofan engine	Categorical	1 if it is turbofan engine, 0 otherwise
Single engine	Categorical	1 if it is a single engine airplane, 0 otherwise
Time of day	Categorical	1 if it is day and dawn, 0 if it is night and dusk
Airplane flight speed (knot)*	Numeric	
Airplane flight altitude (feet)*	Numeric	
Flight phase	Categorical	1 for landing; 2 for takeoff; and 3 for en-route
The number of birds involved	Categorical	1 if >2 birds struck the airplane, 0 otherwise.
Bird size	Categorical	1 for large birds; 2 for medium size birds; and 3 for small birds
Struck engine	Categorical	1 if struck engine, 0 otherwise
Struck wing	Categorical	1 if struck wing, 0 otherwise
Struck nose	Categorical	1 if struck nose, 0 otherwise
Struck tail	Categorical	1 if struck tail, 0 otherwise
Struck windshield	Categorical	1 if struck windshield, 0 otherwise
Struck fuselage	Categorical	1 if struck fuselage, 0 otherwise

Table 13 (cont.)

Variable	Data Type	Remarks (Coding)
Struck light	Categorical	1 if struck light, 0 otherwise
Struck propeller	Categorical	1 if struck propeller, 0 otherwise
Struck radome	Categorical	1 if struck radome, 0 otherwise
Warned	Categorical	1 if warned, 0 otherwise

*Note: 1 knot=0.5144m/s. 1 foot=0.305m.

3.3 Model Estimation Results

The models were estimated using R version 2.13.0 (R Development Core Team, 2011). As addressed previously, three severity categories were considered: no damage, minor damage and serious damage. The severity level of no damage was selected as the reference level. The estimation results for minor and serious damage were summarized in Table 14.

Table 14 MNL estimation results of bird strike severity conditioned on no damage

Variable	Minor Damage			Serious Damage		
	Coefficient	Wald Chi-Square	Pr(>|t|)	Coefficient	Wald Chi-Square	Pr(>|t|)
Severity-specific constant	-2.5795	462.8232	<0.001	-3.5768	356.9940	<0.001
Airplane Characteristics						
Airplane mass	0.5596	348.5382	<0.001	0.4745	92.8165	<0.001
Turbofan engine	0.7155	110.710	<.0001	0.138	20.257	0.4970
Single engine airplane	0.4709	102.4683	<0.001	0.6781	80.9600	<0.001
Airplane flight speed (knot)	0.00658	58.3722	<.0001	0.00291	4.2916	0.0383
Airplane flight altitude (feet)	0.000042	6.5725	0.0104	0.00005	2.1475	0.0428
Flight phase (Landing)	-0.2854	47.1202	<.0001	-0.6153	70.7018	<.0001
Flight phase (Takeoff)	0.0508	1.4136	0.2345	0.3368	21.6918	<.0001
Bird Characteristics						
The number of birds	0.1511	20.1869	<.0001	0.3086	38.6035	<.0001
Bird size (medium)	0.0568	2.7084	0.0998	-0.0917	2.4967	0.1141
Bird size (Large)	1.4093	1281.1638	<.0001	1.8700	939.9347	<.0001

Table 14 (cont.)

Variable	Minor Damage			Serious Damage		
	Coefficient	Wald Chi-Square	Pr(>|t|)	Coefficient	Wald Chi-Square	Pr(>|t|)
Struck position of the airplane						
Struck engine	1.3522	419.6421	<.0001	3.2752	1083.2194	<.0001
Struck nose	-0.2388	12.0461	0.0005	-0.6762	25.4558	<.0001
Struck wing	1.0738	317.2849	<.0001	0.6915	49.4338	<.0001
Struck tail	1.1736	82.5339	<.0001	1.1123	35.7692	<.0001
Struck windshield	-0.7487	102.8004	<.0001	-0.0785	0.4345	0.5098
Struck fuselage	-0.5845	50.1798	<.0001	-0.2594	4.2470	0.0393
Struck light	3.4972	329.5835	<.0001	2.7522	82.2181	<.0001
Struck propeller	-0.6416	30.4305	<.0001	-0.8204	27.6233	<.0001
Struck radome	0.4583	144.8258	<.0001	0.1363	1.0995	0.2944
Other Characteristics						
Time of day (Daytime)	0.0227	0.6713	0.4126	-0.0274	0.3625	0.5471
Warned	-0.0529	3.5761	0.0586	-0.0723	2.6011	0.1068

Comparing with effects on no damage category, the estimation results indicated that: airplanes weighting less than 27000kg and those powered by single engines, increasing airplane flight speed, takeoff flight phase, large and flocking birds, strikes occurring at engine, wing, tail and light increased the chance of serious damage with a significance of 95% ($P < 0.05$). Variables such as landing flight phase, strikes occurring at nose, propeller and fuselage decreased the likelihood of serious damage, which indicated an increased chance of no damage. The rest of selected variables did not show any significant influence on serious damage conditioned on no damage.

Regarding minor damage compared with no damage category, airplanes weighting less than 27000kg and those powered by a single engine, increasing airplane flight speed and altitude, strikes reported with radome, engine, wing, tail and lights, and large and flocking birds increased the probability of minor damage, which indicated an decreased chance of no damage($P < 0.05$). Variables such as landing flight phase, strikes occurring at windshield, nose, propeller and fuselage, and strikes with warnings were negatively associated with minor damage , which indicated a positive association with no damage($P < 0.05$).

In summary, variables such as airplanes weighting less than 27000kg and those powered by single engines, increasing airplane flight speed are positively associated with both minor and serious damage. While landing flight phase, warned status, and strikes occurring at nose, propeller and fuselage are positively correlated to no damage.

3.4 Discussion

Airplanes weighing less than 27,000kg significantly increased the probability of minor and serious damage compared to no damage. The reason probably is large airplanes, which are weighing more than 27,000kg, are more capable of withstanding the impact from a bird strike and sustaining no damage. Single engine airplanes were positively correlated with both minor and serious damage, probably because this type of airplane may completely lose power and result in serious consequences if birds struck and damaged the only engine. Turbofan engine increased the chance of minor damage. An explanation is that turbofan engine is quiet and has a large frontal area, which makes the airplane more vulnerable to bird strikes than airplanes powered by other types of engines.

The positive effect of takeoff flight phase on minor damage was not significant, but the effect on serious damage is. Takeoff is a critical flight phase during which engines are operating at full power, weight and speed are high, altitude is low, and options for safe landing are limited. Therefore, if a bird or a group of birds struck an airplane during this phase, the consequence would be serious. Airplane flight speed and bird size posed positive effects on minor and serious damage. The positive effects of the two variables can be interpreted by the kinetic energy equation, which was described previously (Section 1.2.1). Bird strikes occurred at high altitudes were more likely to result in damage than those occurred at low altitudes. Reasons may include: first, these strikes were mostly caused by migratory birds, which commonly have large body mass and move in flocks and at high altitude; and second, airplanes usually travel at higher speeds at high altitude than they do at low altitude (Dolbeer, 2006).

Regarding strike position of an airplane, engine related strikes can easily cause minor and serious damage, because they may completely destroy the engine/engines of an airplane or cause the airplane to go out of control, resulting in disastrous consequences. For example, in January 2009, the Flight 1549 of the U.S. Airways was forced to land on the Hudson River in New York, because both engines were destroyed after struck by Canada geese. Beside engine, wing is also a sensitive component because of its effect on airplane balance. For time of the day, the estimation results were similar as that suggested in (Dolbeer, 2006): daytime was positively related to minor and no damage, while nighttime was associated with serious damage. Finally, with no surprise, warned bird strikes were less likely to cause damage, which indicated the importance of strike warning systems at airports.

CHAPTER 4
CONCLUSIONS AND FUTURE WORK

4.1 Conclusions

This study provides a series of empirical and methodological assessments that examine the effects of bird strike contributory factors on strike occurrence and severity. Logistic and Multinomial regression models were applied respectively and were estimated with full information maximum likelihood to yield statistically efficient results. All of the assessments were conducted using R, and the outcome quantitatively demonstrated relationships between strike occurrence and related factors as well as relationships between severity and its contributory factors.

The study at SEA showed that bird strike occurrence is positively associated with both bird track density and airplane movement frequency. The results indicates that keeping birds off airport operation areas (e.g., runways and taxiways), particularly when air traffic is busy, is very important.

The evaluation of weather effects in the six airports suggested that local weather can affect bird strike occurrence. Temperature showed positive effects at most airports in cool seasons which include spring, autumn, and winter. In LAX, temperature showed negative effects in summer when the temperature is high. Based on the study of three precipitation levels ($\geqslant$1.27 cm, $\geqslant$0.76 cm, and $\geqslant$0.25 cm), the risk of birds strikes was increased after the rainfall at most of the airports, either 1 days after or 3 days after. Wind speed showed negative effects in autumn at LAX and in winter at JFK. Visibility posed positive effects in winter at ORD and in autumn at JFK. Pressure showed positive effects in autumn at SEA. These results provide important guidance for weather related bird-hazard mangement at airports. For example, airport management should consider field drainage to minimize the development of temporary standing water after rainfall.

The study of bird strike severity demonstrated that smaller airplanes, single engines, increasing airplane flight speed, takeoff, large and flocking birds, strikes occurring at engine, wing, tail and light increased the propensity toward both serious and minor damage. Altitude was proved to be significant in minor destroying strikes. Variables such as landing flight phase, warned status, and strikes occurring at nose, propeller and fuselage are commonly related to no damage.

Overall, the findings of these studies, which quantitatively demonstrate the effects of related variables on bird strike occurrence and severity, are suggestive but limited in a few ways. First of all, the bird strike data is limited in both content and quality; hence, the current estimation results may not be ready to be applied for predictions in the real world. Second, bird strike underreporting and unobserved correlations between strike severity categories were not considered because of the lack of such information. As more data, especially high quality data, becomes available, the analysis will provide a better understanding of bird strikes and associated consequences. For example, if combined with data of reported bird strikes, bird density, airplane movement frequency, strike severity factors and weather, this study can be extended to provide an integrated assessment of bird strike threat incorporating both occurrence and severity, and the integrated model can be adopted by commercial airports in the United States, providing support to reduce bird strikes. Therefore, in spite of such limitations, this study provides a tool that can be used for airport bird hazard management and airplane design with an emphasis on engine and airframe. It also sheds light on the importance of accurately managing bird strike reports.

4.2 Future Work

4.2.1 Bird strike underreporting

As mentioned previously, bird strike database suffers from underreporting, particularly for strikes of no damage and minor damage. As a result, the bird strike data can be regarded as outcome-based samples with an unknown population share of the severity categories. An outcome based sample might be overrepresented by strikes of higher severity categories and therefore result in biased model estimations. Besides, due to underreporting, days with strikes (strike status= “1”) may be categorized as no strike days (strike status= “0”). The inconsistence of bird strike reporting can affect the assessment of factor related to bird strike status and cause biased estimate results. The effects of strike underreporting were not considered in this study and the corresponding investigation was set as a future task when related information becomes available.

4.2.2 Data correlations

The study of bird strike severity assumed that different severity categories were independent from each other. However, there may be immeasurable and unobserved effects between those categories. If such effects do exist, a nested logit model, which groups severity categories that share unobserved effects together, will be more appropriate than multinomial logit regression. Due to the limitations of current bird strike database, applying a nested logit model was set as a future work.

4.2.3 Integrated assessment

There were three investigations conducted separately to examine the effects of different contributory factors on bird strike occurrence and severity. The study results are suggestive but are limited at the same time, because they cannot be applied in an integrated assessment. For example, when assessing the effects of bird density and airplane movement, meteorological variables were not considered directly, even though the number of birds and airplane movement on airfield may reflect the weather conditions in some way. Similarly, when analyzing the effect of meteorological variables, bird density and airplane movement were ignored. In order to assess and predict bird strike occurrence and the severity when a bird strike does occur, an integrated assessment, which integrates all of the contributory factors, is needed. To develop such a comprehensive assessment, the estimation results of the three investigations can be used as a basis; meanwhile, sufficient data on bird strike reports and corresponding data on bird density, bird size, airplane movement, airplane type and meteorological variables (e.g., rainfall, temperature and et al.) collected when bird strikes occurred are also required. Currently, obtaining these data sets is challenging. However, in the future, the integrated assessment can be accomplished when those data becomes available.

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