What causes bird-building collision risk? Seasonal dynamics and weather drivers

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Abstract

Bird-building collisions are a major source of wild bird mortality, with hundreds of millions of fatalities each year in the United States and Canada alone. Here, we use two decades of daily citizen-science monitoring to characterize day-to-day variation in building collisions and determine the factors that predict the highest risk times in two North American cities. We use these analyses to evaluate three potential causes of increased collision risk: heightened migration traffic during benign weather, increased navigational and flight errors during inclement weather, and errors in response to reflective glass. The seasonal phenology of collisions was consistent across sites and years, with daily collision rates approximately two-fold higher in autumn as compared to spring. During autumn migration, day-to-day variation in collision rates is best explained by weather conditions around dawn with four major drivers: no precipitation, high atmospheric pressure, cold temperatures, and clear skies. In spring, collision risk was best predicted by either overnight or morning weather, driven by a lack of precipitation and warm temperatures. Based on these results, we hypothesize that collisions are influenced by two main weather-driven mechanisms. First, benign weather causes an increase in migration traffic in both spring and autumn, creating greater opportunity for collisions to occur. Second, cold clear conditions cause an additional increase in collision risk for autumnal migrants. These conditions may be particularly hazardous in autumn because of the high abundance of naïve and diurnal migrants at that time of year. Our analysis also establishes that a relatively small proportion of days (15%) are responsible for 50% of the total collision mortality within a season, highlighting the importance of targeting mitigation strategies to the most hazardous times.

1. Introduction

Birds have been in a marked decline, and North America has lost an approximate 29% of bird abundance since the 1970s (Rosenberg et al., 2019). One factor that may contribute is the widespread mortality caused by birds colliding with buildings and windows, particularly during migration (Arnold & Zink, 2011; Loss, Will, Loss, & Marra, 2014; Loss, Will, & Marra, 2015). Indeed, recent meta-analyses have estimated that 365–988 million birds are killed in collisions each year in the USA, while another 16–42 million are killed in collisions each year in Canada (Loss et al., 2014; Machtans et al., 2013). Collision risk varies greatly across landscapes, buildings, seasons, days, and times of day. Given that collisions occur during flight, an important driver of this variation may be weather because weather influences migration decisions, flight and navigational errors, and the visual appearance of glass. Understanding the day-to-day dynamics of these collisions is important for two reasons: it allows us to better predict times that will have elevated risk, and it provides insight into potential causal mechanisms that can inform mitigation. This knowledge is important for aeroecology and aeroconservation, which are underrepresented areas of study (Davy, Ford, & Fraser, 2017; Horton, Van Doren, Stepanian, Farnsworth, & Kelly, 2016).

An early study by Klem reported qualitative descriptions of weather conditions on days when 83 collisions occurred at two houses (Klem, 1989). More recently, a study by Loss et al. examined how weather influenced collisions of American Woodcocks at a single urban site, and found that Woodcock collisions increased during inclement weather (Loss et al., 2020; Riding, O'Connell, & Loss, 2021). To build on these early studies, a broad analysis is needed that covers a greater range of species over longer timeframes. Here, we address this gap by leveraging a large dataset of over 60,000 collisions, representing two decades of daily monitoring by citizen scientists in two large metropolitan areas (Toronto, Canada, and Chicago, USA). Our goal is to evaluate the influence of weather and atmospheric conditions on daily variation in avian collision rates in these urban environments.

There are several non-exclusive mechanisms by which weather and atmospheric conditions might influence collision risk for birds. The first possibility is that weather-induced changes in migration traffic (defined as the abundance of migrating birds in the air) can influence the occurrence of collisions. Consistent with this hypothesis, avian collision rates were recently shown to correlate with times of higher migration traffic (Elmore et al., 2021; van Doren et al., 2021). Increased migration traffic is commonly driven by benign weather during both spring and autumn migration periods (Bozó, Csörgõ, & Heim, 2018; Erni, Liechti, Underhill, & Bruderer, 2002; Welcker & Vilela, 2019). During spring, the strongest predictor of migration traffic is often warmer temperatures (Bozó et al., 2018; Haest, Hüppop, & Bairlein, 2020; Hamer et al., 2021; Schekler & Sapir, 2021; Van Doren & Horton, 2018; Welcker & Vilela, 2019). By contrast, in autumn, the effects of temperature on migration traffic are less clear, with different studies finding positive, negative, or no associations between temperatures and migration traffic (Bozó et al., 2018; Erni et al., 2002; Loss et al., 2020; Nilsson et al., 2019; Schekler & Sapir, 2021; Welcker & Vilela, 2019). If weather-induced changes in migration traffic are a major driver of avian collisions, then we expect higher collision rates to occur on days with benign conditions in both spring and fall (low wind speeds, low precipitation, and high atmospheric pressure), with additional risk posed by warm temperatures in spring.

A second mechanism by which weather and atmospheric conditions might influence collision risk is by increasing the probability that birds make errors during flight. For example, inclement weather may negatively impact visual guidance and the ability of birds to detect and respond appropriately to important navigational landmarks and obstacles (Marques et al., 2014). Inclement weather could also increase physiological stress through depletion of energy reserves, making birds more likely to make fatal errors. This is occasionally observed in mass casualty events; for example, in the fall of 2020, winter storm conditions led to a mass bird casualty event in the southwestern USA (Johnson, 2020). Inclement weather may also compound the detrimental effects of artificial light at night (ALAN) on birds' navigational abilities. Studies have shown that ALAN can be an important driver of building collisions (La Sorte & Horton, 2021; Lao et al., 2020; van Doren et al., 2021; Winger et al., 2019), and can affect birds up to an altitude of 4 km (Van Doren et al., 2017). In general, if weather-induced flight and navigational errors are a major driver of collisions, then we then expect higher collision rates to occur on days with high wind speeds, high precipitation, and cold temperatures, all of which may increase stress and disrupt sensory performance.

A third mechanism by which atmospheric conditions might influence collision risk is by affecting the visual appearance of glass windows. The appearance of glass has been found to be an important proximate driver of collisions, based on positive associations between collision rates and the extent of glass on buildings (Riding, O'Connell, & Loss, 2020), and experiments demonstrating that visual deterrents and acoustic signals placed on or in front of windows can prevent collisions (Boycott, Mullis, Jackson, & Swaddle, 2021; Klem, 2009; Klem & Saenger, 2013). The appearance of glass is also influenced by weather: on days with clear skies, glass reflects more light and creates brighter images of the surroundings. These highly reflective conditions may increase the probability that birds are deceived by reflected images. If weather-induced changes in the appearance of glass are an important driver of collisions, then we expect collision rates to be elevated on days with reduced cloud cover.

In addition to the mechanisms above, we also consider the possibility that the phase of the moon may influence daily variation in collision risk (Norevik, Åkesson, Andersson, Bäckman, & Hedenström, 2019). The moon can be a navigational beacon for some nocturnal migrants and may facilitate flight at night (Miles, Money, Luxmoore, & Furness, 2010; Syposz, Gonçalves, Carty, Hoppitt, & Manco, 2018). In addition to its potential effects on migration traffic, it is also possible that lunar illumination may interact with ALAN and/or other sources of navigational disruption that may influence collision risk. We therefore include lunar illumination in our analysis, although we have no *a priori* predictions as to the direction of any potential lunar effects.

Here, we analyze the correlations between weather and day-to-day variation in building collisions for a broad range of North American bird species. Our analysis considers six variables: air temperature, wind speed, precipitation, atmospheric pressure, cloud cover, and lunar illumination. We examine these potential drivers using data on over 60,000 collisions involving 138 species – our goal is to identify the general drivers of collisions in urban environments, rather than species-specific effects. We first use these data to estimate day-to-day variation in collision rates and compare spring and autumn. Second, we evaluate if daily collision rates are

best explained by weather conditions at four different times of day: morning, dawn, overnight, or the previous evening. Third, we describe the relationships between collision rates and the six weather predictor variables, comparing these effects across seasons (spring and autumn) and study locations (Toronto and Chicago). By comparing the results across two cities, our aim is to identify the major drivers of risk. This is important for better predicting collision events as well as understanding the causal mechanisms that drive them. Ultimately, with increased knowledge, improved mitigation and aeroconservation measures will be possible (Davy et al., 2017).

2. Methods

2.1 Collision rates

To estimate daily collision rates, we obtained data on the number of collision casualties recorded per day from two large metropolitan areas: Toronto, Canada (43.74 N, 79.37 W) and Chicago, USA (41.88 N, 87.63 W). Both cities have a long-term daily collision monitoring program that has provided the basis for important continent-wide estimates of the extent and causes of collision mortality (Arnold & Zink, 2011; Colling, Guglielmo, Bonner, & Morbey, 2022; Cusa, Jackson, & Mesure, 2015; Evans Ogden, 1996; Loss et al., 2014; Machtans et al., 2013; van Doren et al., 2021; Winger et al., 2019). The data from Toronto were collected by FLAP Canada (Fatal Light Awareness Program, www.flap.org) and in Chicago by the Chicago Bird Collision Monitors and McCormick Place monitors (www.birdmonitors.net) (Winger et al., 2019). For the purpose of this study, we focused on a 10-year period from each city with daily records on the number of collision casualties detected (years 2009 to 2018 in Toronto, and 2006 to 2015 in Chicago). This dataset represents 31,051 casualties in Toronto and 33,493 in Chicago. The Chicago dataset focused on casualties from the passerine order (89 identified species), whereas the Toronto dataset was predominantly passerines, with some additional non-passerines also recorded (138 identified bird species, 93% of which were passerines). All processing and analyses of the data were performed in R 3.6.3.

Because the vast majority of building collisions occur during migration, we limited our analysis to daily casualty records from the spring (March–June) and autumn (August–November) within each city (Fig. 1). The number of days in our sample was 798 days in spring and 964 in autumn for Toronto, and 721 days in spring and 936 in autumn for Chicago.

2.2 Weather and atmospheric conditions

To investigate the relationships between weather conditions and collision rates, we obtained hourly weather station data on six atmospheric parameters: air temperature (C), wind speed (km/h), precipitation (mm/h), atmospheric pressure (kPa), cloud cover (%), and lunar illumination (%). Hourly temperature, wind speed, precipitation, pressure, and cloud cover data were obtained from www.openweathermap.org. All cloud cover estimates were expressed as a percent of full cloud cover, such that a value of 100% indicates a completely overcast sky. Lunar illumination values represent a measure of lunar phase and were obtained from the R package lunar 0.1-04; a value of 0% indicates the new moon and 100% indicates a full moon.

We assume that collisions recorded on a given day may have occurred at any time in the previous 24 hours, with weather during the previous 12-14 hours hypothesized to have the greatest influence (Evans Ogden, 1996; Lao et al., 2020). Therefore, we summarized the weather

data into four time periods: (i) the previous evening, defined as the average of hourly weather conditions from 2000 to 2300 on the previous day; (ii) the overnight period, defined as the average of hourly conditions from 0000 to 0300; (iii) dawn, defined as the average of hourly conditions from 0400 to 0700; and (iv) morning, defined as the average of the hourly conditions from 0800 to 1100 (all local times). As an example, for collisions recorded on April 10, 2009, the corresponding local morning temperature would be calculated as the average from 0800-1100 on April 10, 2009, whereas the previous evening temperature would be calculated as the average from 2000-2300 on April 9, 2009.

2.3 Migration phenology

Collision rates have a well-defined phenological peak each spring and autumn migration season, corresponding with migration phenology (Fig. 1). To quantify this baseline temporal variation, we fit a cubic spline to the daily number of casualties as a function of day of the year within each city-year-season, with 0.6 as the smoothing parameter (Fig. 1B). The resulting spline fits represent the expected phenological variation in casualties for a given season and year, at a given city site. We used these phenology estimates as a covariate in our statistical analysis of day-to-day variation in collision rates (see details in section 2.4 below). Hence, our analysis evaluates if local daily weather can explain day-to-day variation in collision rates, after accounting for the expected seasonal pulse due to the timing of migration in a given year.

2.4 Statistical analysis of collision rates and weather

We used mixed-effects regression models to evaluate sources of variation in daily collision rates. The response variable was the daily number of collisions recorded, log-transformed to meet the assumptions of linear regression. All models were fit in R using the lme4 1.1-23 and lmerTest 3.1-2 packages. Our first goal was to describe seasonal differences in collision rates. To do this, we fit a model for each city with season as the only fixed effect predictor and year as the random effect to account for non-independence of data within the same year.

Our next goal was to evaluate which weather time period was the best predictor of collision rates for each city-season. To do this, we compared four candidate models: a previous evening model, an overnight model, a dawn model, and a morning model. As fixed effect predictors, each model included migration phenology, as well as the six weather conditions described in section 2.2 above (the morning model contained local weather conditions for the morning time period, whereas the dawn model contained local weather conditions for the dawn period, etc). In all models, year was included as a random effect. Models were fit with maximum likelihood and compared using Akaike's Information Criterion (AIC). We also used the MuMIn package 1.43.17 to calculate Akaike weights. The Akaike weight is a measure of the relative strength of the evidence for a given model in a model set, expressed as a probability ranging from 0 to 1; the weights for all models in a set sum to 1. Hence, if a model has an Akaike weight of 1, it indicates complete certainty that the model is best supported within its model set. If two models receive similar Akaike weights, it indicates that they are equivalently well-supported. We performed these analyses separately for each city-season (i.e., spring in Toronto, spring in Chicago, autumn in Toronto, and autumn in Chicago).

Next, we examined the coefficient estimates from the best-supported models. We used mean-centred and standardized variables (response and predictor) to allow comparison of effect sizes

within and across models. We also obtained p-values using Satterthwaite's method in the lmerTest package. As a measure of the total variance in collision rates explained by the fixed effects in each model, we calculated R^2_{GLMM} using the MuMIn package. As an additional check on our results, we verified that day of the week was not a significant predictor of collision rates in our analyses, and we confirmed that all conclusions were unchanged when controlling for day of the week.

3. Results

3.1 Seasonal and day-to-day variation in collision rates

The incidence of collisions was approximately twice as high in autumn as compared to spring (Fig. 1A). In Toronto, there was a 2.2-fold greater incidence of collisions in autumn ($p < 0.0001$, n = 1,762 days over 10 years), and in Chicago, a 1.7-fold greater incidence in autumn ($p < 0.0001$, n = 1,657 days over 10 years) as compared to spring. Within each season, there was substantial day-to-day variation in collision rates (Fig. 1B). Notably, a relatively small number of days account for a large proportion of the seasonal total (Fig. 2). For example, at both locations, the 12 worst days typically account for about 50% of the seasonal total, and the three worst days typically account for between 20-22% of the seasonal total. Collision risk peaked in the 17th week in spring (end of April and beginning of May) and the 39th – 40th week in autumn (beginning of October) in both cities.

3.2 Drivers of autumn collisions

Dawn weather was the best predictor of autumn collision rates in both cities (Akaike weight > 0.99 for both cities; Tables S1-S2). Collisions increased on autumn days that had a lack of precipitation at dawn, with high atmospheric pressure, cold temperatures, and clear skies (i.e., reduced cloud cover) at that time of day (Fig. 3A and Table 1). In Chicago, autumn collision risk was also weakly associated wind speed, such that collision rates were higher on days with less wind (Table 1).

3.3 Drivers of spring collisions

In spring, morning weather was the best predictor of collision rates in Toronto (Akaike weight = 0.92), whereas overnight weather was best-supported in Chicago (Akaike weight > 0.99; Tables S3-S4). Despite this difference in the most important time period, spring collisions were mainly driven by a lack of precipitation and warm temperatures in both cities (Fig. 3B and Table 2). In Toronto, spring collisions also increased on days with less wind and more cloud cover (Table 2). In Chicago, where overnight conditions were identified as a major driver, there was also a very weak association between spring collisions and lunar illumination: collisions rates were slightly elevated under a darkened moon phase (Table 2).

4. Discussion

Bird building collisions follow a consistent seasonal phenology with strong peaks in the spring and autumn migration seasons (Fig. 1). Autumn migration is particularly hazardous (Fig. 1A), with collisions rates approximately twice as severe as spring. The increased risk of collision mortality in autumn could be due the presence of a large number of first-time migrants (Newton, 2007). This idea is corroborated by Sabo, et al., who found that local birds were able to learn the

hazards of windows and to avoid them (Riding et al., 2021; Sabo, Hagemeyer, Lahey, & Walters, 2016).

We also found that a relatively small number of days are responsible for a large burden of total collision mortality within a site; for example, 50% of the recorded collisions occur in just 15% of days within a season (Fig. 2). This finding is consistent with previous studies of migration pulses, wherein a small number of days account for the majority of individual movements, highlighting the importance of understanding drivers of day-to-day variation (Lin et al., 2019; Van Doren & Horton, 2018).

During spring, we found that day-to-day variation in collision rates was best explained by weather conditions in either the morning (Toronto) or overnight time period (Chicago; Tables S3-S4), consistent with recent reports that collisions peak overnight and during early morning hours (Colling et al., 2022; Riding et al., 2021; van Doren et al., 2021). We speculate that in our study, differences in the most predictive weather period across the two sites may be due geographic differences in the time period of greatest migration traffic. Despite this difference, we found broad consistencies in the relationships between spring collisions and several major weather variables (Fig. 3B). Specifically, collision risk was greatly elevated on days with a lack of precipitation and warmer temperatures in the spring. Based on this result, we conclude that the biggest driver of spring collisions is weather-induced changes in migration traffic (Elmore et al., 2021; Hamer et al., 2021). On warm, dry days, there is an increased abundance of birds in the air, and this increases the opportunity for collisions to occur.

During autumn, variation in collision rates was best predicted by the weather conditions at dawn across both sites (Tables S1-S2), with broad consistency in the major weather drivers across sites. Autumn collision mortality was elevated on days that were dry at dawn, with high atmospheric pressure, cold air temperature, and clear skies (Fig. 3A). These results suggest that autumn collisions may be driven by a combination of three potential mechanisms: an increase in migration traffic at dawn during dry, high atmospheric conditions, an increase in flight errors that may be caused by cold but otherwise benign conditions, and an increase in errors in response to glass under clear skies.

In both seasons, we found evidence for some site-specificity of weather effects. First, we found a weak association between a darkened spring moon phase and increased collision rates in Chicago, consistent with the finding that overnight conditions were a strong predictor for spring collisions at that location. Lunar illumination was a weaker predictor than precipitation and temperature, however (Fig. 3B). Second, we found that calm winds were associated with higher autumn collision rates in Chicago, and higher spring collision rates in Toronto (Fig. 3). Although the wind effects were found in different seasons in our two respective study sites, the consistency emphasizes that collision risk is most elevated under conditions that are otherwise benign for flight. While inclement weather can drive rare mass casualty events (Johnson, 2020; Newton, 2007) or species-specific risks (Loss et al., 2020), the greatest overall burden occurs on days with fair weather. Although we did not examine wind direction in this study, we predict that wind direction may have site- and season-specific effects that interact with wind speed, because strong winds in a favourable direction may be associated with greater migration traffic.

Our analysis here focused on identifying the immediate causes of daily collision risk, as this is most valuable for predicting days of greatest risk in the future. It is important to note that even though inclement weather may not be the direct cause of most collisions, it may still be a contributing factor. For example, inclement weather may cause birds to make suboptimal choices for stopover landing areas, e.g., in urban regions or other areas that pose greater mortality risk (Jenni & Schaub, 2003). This may indirectly influence collision rates if birds later attempt to leave the urban area at the next benign weather opportunity (Clipp et al., 2020; Van Doren et al., 2017). This could be due to the greater number of birds forced to initiate flights in a hazardous environment. It is also possible that ALAN may compound the effects of inclement weather, as both may be disorienting factors (Arnold & Zink, 2011; Evans Ogden, 1996; La Sorte & Horton, 2021; Lao et al., 2020; van Doren et al., 2021).

Overall, our correlational analysis reveals that the vast majority of urban collisions occur on fair weather days consistent with migration traffic as a major driver. We also found consistency in the major driving factors across our two study sites. In autumn, collisions mainly occur on days that are dry and cold with high pressure and clear skies at dawn, pointing to the importance of both migration traffic and flight errors. In spring, collisions mainly occur on dry, warm days, again highlighting the role of migration traffic as a major driver. It is important to note that these results are limited to two urban landscapes. A key question for future work is whether the same patterns occur in residential and suburban sites, which are responsible for a large burden collision mortality across North America (Loss et al., 2014; Machtans et al., 2013). Increased understanding of the conditions and mechanisms that drive bird-building collisions is vital in working towards prevention. As pointed out by Gelb and Delacretaz, there are high-collision sites that are responsible for most of the mortality (Gelb & Delacretaz, 2009). With this knowledge, focused action on these sites during the days with highest risk would yield the greatest improvements.

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DATA ACCESSIBILITY

All data and R scripts are available at: https://figshare.com/s/5c455f2a5c763682a737
The repository will be made public when the final version of the study is published.

AUTHOR CONTRIBUTIONS

RD and KMS designed the study; RD, KMS, PP and AA collected the data; RD and KMS analyzed the data and wrote the manuscript.

COMPETING INTERESTS

We have no competing interests.

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FIGURE LEGENDS

Figure 1. Seasonal phenology of bird collisions with buildings. (A) Daily collision rates recorded in two cities, Toronto and Chicago, during the spring (green) and autumn (red) migration periods (horizontal lines show the means). Collision rates are consistently higher during autumn migration, as compared to spring. Note that the span of studied years differs for the two sites. (B) To evaluate atmospheric and weather drivers of collision rates while controlling for seasonal phenology, we first determined the expected rate of collisions by fitting a cubic spline to each seasonal peak (shown by the green and pink lines in B). This procedure was repeated for each site-season dataset; examples from the Toronto dataset are shown here. Next, we analyzed the daily collision rate while controlling for the expected phenological pulse each season. Hence, the analysis tested if atmospheric conditions explain fluctuations above or below the seasonal expected rate of collisions.

Figure 2. Most collision risk is concentrated within a small number of days. These plots show the cumulative proportion of total seasonal mortality for (A) Toronto and (B) Chicago. To perform this analysis, days were first ranked by severity within each site-season (1st = most severe, etc.). Then, each day's cumulative proportion of the seasonal total was plotted with lines connecting data from a given site-season. The steep increase in these cumulative proportion curves illustrates how most collisions can be attributed to a small number of severe days within a season. Each season represents four months: spring = March through June, and autumn = August to November.

Figure 3. Collision risk is driven by weather conditions that are largely benign for flight. (A) In autumn, high collision rates are consistently observed on days with little to no precipitation, high atmospheric pressure, cold temperatures, and clear skies (reduced cloud cover). (B) In spring, high collision rates are associated with a lack of precipitation and warm temperatures. Collisions are also more common on days with less wind, though these effects may be location- and season-specific. Cold temperatures are the only challenging weather condition associated with collision risk, and only in autumn. Each panel in (A) and (B) shows the predictions of the best-supported model when all other predictors are set to the mean value. The inner shaded region shows the 95% CI for the line-of-best fit. The outer shaded region shows the 50% prediction interval of the model. Red is used for predictors that had a statistically significant association with collision rates in the full model. See Tables 1-2 and S1-S4 for additional details of this analysis.

Table 1. Autumn collision rates in relation to weather. Autumn collision rates are strongly associated with the weather at dawn. A lack of precipitation, high atmospheric pressure, cold temperatures, and clear skies (reduced cloud cover) all predict high collision risk. To facilitate comparison of effect sizes, the response variable and all predictor variables were centered and standardized to have mean = 0 and SD = 1. Predictors are indicated in bold where the slope is statistically significant. See Tables S1-S2 for additional details of this analysis.

	Toronto – DAWN n = 964 days in 10 years				Chicago – DAWN n = 936 days in 10 years		
Predictor	Estimate	95% CI	p	Predictor	Estimate	95% CI	p
Temperature	**–0.11**	**[–0.15, –0.07]**	**< 0.0001**	**Temperature**	**–0.05**	**[–0.10, –0.01]**	**0.02**
Wind	–0.01	[–0.05, 0.03]	0.58	**Wind**	**–0.05**	**[–0.09, –0.001]**	**0.047**
Precipitation	**–0.10**	**[–0.14, –0.06]**	**< 0.0001**	**Precipitation**	**–0.09**	**[–0.13, –0.04]**	**< 0.0001**
Atmos. pressure	**0.14**	**[0.09, 0.18]**	**< 0.0001**	**Atmos. pressure**	**0.06**	**[0.01, 0.11]**	**0.01**
Cloud cover	**–0.05**	**[–0.09, –0.01]**	**0.01**	**Cloud cover**	**–0.05**	**[–0.10, –0.01]**	**0.02**
Lunar illum.	–0.03	[–0.07, 0.003]	0.08	Lunar illum.	–0.02	[–0.07, 0.01]	0.19

Table 2. Spring collision rates in relation to weather. Spring collision rates are highest on days with a lack of precipitation and warm temperatures at both sites. In Toronto, spring collisions were best predicted by the morning weather, whereas overnight weather was the best predictor of spring collisions in Chicago. Additionally, mornings with reduced wind speeds and cloudy skies in Toronto, and nights with reduced lunar illumination in Chicago, were also weakly predictive of collision risk. To facilitate comparison of effect sizes, the response variable and all predictor variables were centered and standardized to have mean = 0 and SD = 1. Predictors are indicated in bold where the slope is statistically significant. See Tables S3-S4 for additional details of this analysis.

	Toronto – MORNING n = 798 days in 10 years				Chicago – OVERNIGHT n = 721 days in 10 years		
Predictor	Estimate	95% CI	p	Predictor	Estimate	95% CI	p
Temperature	**0.10**	**[0.04, 0.15]**	**< 0.0001**	**Temperature**	**0.34**	**[0.28, 0.40]**	**< 0.0001**
Wind	**–0.08**	**[–0.13, –0.03]**	**0.002**	Wind	0.02	[–0.04, 0.08]	0.56
Precipitation	**–0.08**	**[–0.12, –0.03]**	**0.001**	**Precipitation**	**–0.07**	**[–0.13, –0.02]**	**0.01**
Atmos. pressure	0.03	[–0.03, 0.08]	0.31	Atmos. pressure	–0.06	[–0.12, 0.007]	0.08
Cloud cover	**0.07**	**[0.02, 0.12]**	**0.008**	Cloud cover	0.03	[–0.03, 0.09]	0.34
Lunar illum.	0.03	[–0.02, 0.07]	0.24	**Lunar illum.**	**–0.07**	**[–0.12, –0.01]**	**0.02**

Figure 1

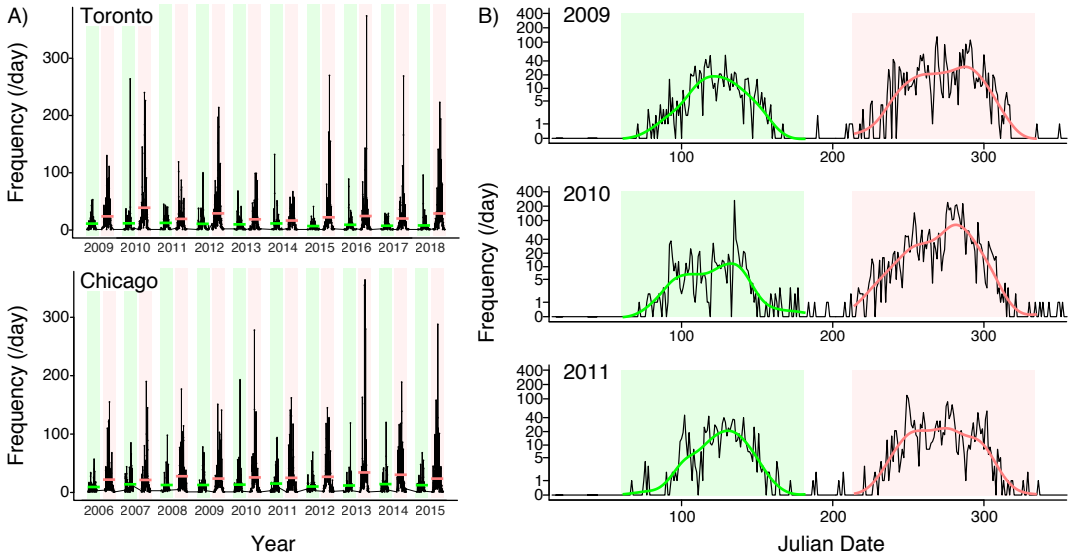

A)
Toronto
Chicago
Frequency (/day)
Year
B)
2009
2010
2011
Julian Date

Figure S1

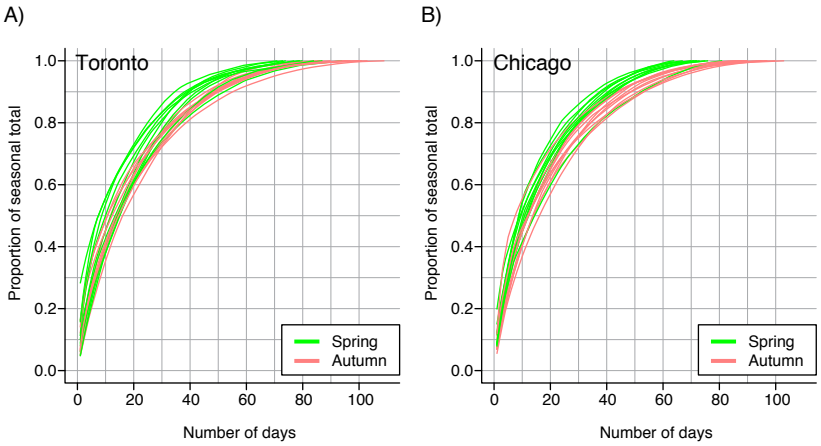
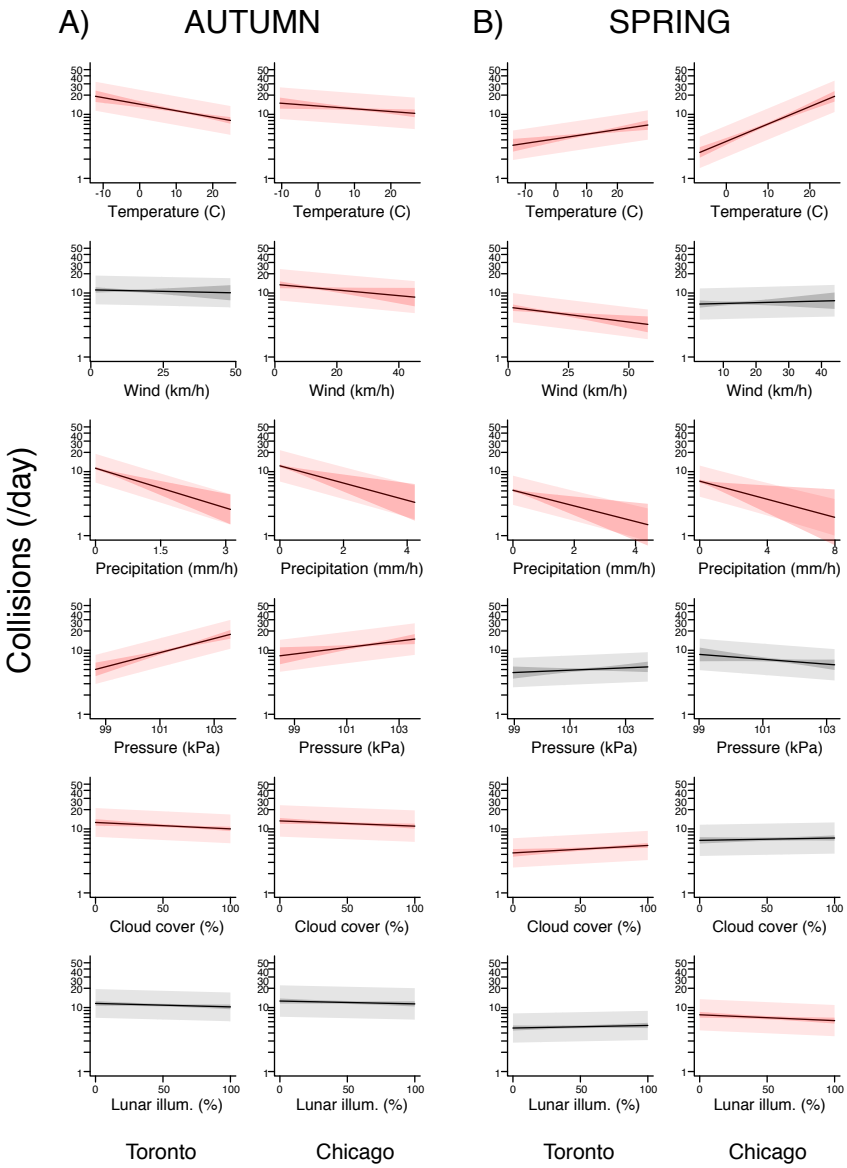

A)
Toronto
Proportion of seasonal total
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
100
Number of days
Spring
Autumn
B)
Chicago
Proportion of seasonal total
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
100
Number of days
Spring
Autumn

Figure 2


A)
AUTUMN
B)
SPRING
Collisions (/day)
Temperature (C)
Wind (km/h)
Precipitation (mm/h)
Pressure (kPa)
Cloud cover (%)
Lunar illum. (%)
Toronto
Chicago
Toronto
Chicago