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The impact of COVID-19 on wildlife strike rates in the United States

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Abstract: Shortly after the COVID-19 pandemic impacted air traffic, industry bodies warned of the potential increase in wildlife strike risk. Prior to the pandemic, wildlife strikes were already a concern to the industry. We sought to evaluate industry warnings using interrupted time series analysis of wildlife strike trends in the United States. Using pre-pandemic wildlife strike trends, we compared a forecast of the expected monthly strike rates through the COVID-19 impact period (March 2020 to December 2020) to the actual wildlife strike rates for the same period. Our results showed an increase in wildlife strike rates in 5 out of the 10 months analyzed, supporting the need for careful consideration of wildlife strike risk through the industry's recovery.

Key words: air traffic, aviation, bird strike, COVID-19, time series analysis, United States, wildlife strike

The outbreak of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and its associated disease, COVID-19, had a significant impact on aviation globally. As nations responded to the health emergency, global air traffic was cut. Local lockdowns, border restrictions, traveler uncertainty, and economic decline made flight operations either unfeasible or uneconomic (Hotle and Mumbower 2021). At its worst, U.S. domestic movements were <30% of their pre-COVID-19 levels and had only returned to approximately 60% by the end of 2020 (Airlines for America 2021).

The potential for the air traffic and financial downturn to have an impact on wildlife hazard management at airports was highlighted in industry guidance within months of the dramatic decline. Both the International Civil Aviation Organization (ICAO 2020) and the European Union Aviation Safety Agency (EASA 2020) identified the reduction in air traffic and impact on wildlife hazard management resources as having the potential to adversely impact aviation safety. These concerns were echoed by industry groups including the Flight Safety Foundation (FSF 2020) and the Australian Aviation Wildlife Hazard Working Group (AAWHG 2020).

Either through an increased presence of wildlife on quieter airports, an inability of airport operators to maintain their wildlife control programs, or a combination of these (ICAO 2020), airport operators were warned the risk of wildlife strike could increase (EASA 2020). Wildlife strikes are collisions between aircraft and wildlife that are considered a serious concern for the aviation industry in both safety and economic terms (Metz et al. 2020). Since the early days of modern heavier-than-air flight, wildlife strikes, often called bird strikes, have resulted in death, destruction, damage, and other negative effects on flights. As of October 27, 2021, 534 fatalities and 618 aircraft hull losses were attributed to wildlife strikes (Shaw and Dolbeer 2021). While such catastrophic outcomes are rare, relatively lower impacts, such as damage and diversions, cost the worldwide industry >$1.2 billion USD annually (Allan 2000) and the U.S. industry $205 million USD in 2019 (Dolbeer et al. 2021).

Given the impact of wildlife strikes on the aviation industry and the warnings issued by regulators and industry bodies, this study sought to confirm if the global disruption caused by COVID-19 coincided with an interruption to the long-term wildlife strike trends in the United States. If such an interruption was identified, this would validate the concerns raised by ICAO and others as well as support subsequent research into more specific relationships between the COVID-19 disruption and wildlife strikes.

In the United States, where wildlife strike reports have been centrally collated since 1995, long-term trends show a steady increase in reported wildlife strikes through the end of 2015 (Dolbeer et al. 2018). However, this trend is not attributed to an increase in actual wildlife strikes but to improvements in reporting practices, generally, and at airports, in particular (Dolbeer 2015, Dolbeer et al. 2018). Other drivers behind wildlife strike trends include successful conservation efforts leading to increases in hazardous bird populations and quieter aircraft types that reduce the detection and avoidance capability of wildlife (Dolbeer et al. 2021). The impact of increasing air traffic movements can be removed by using wildlife strike rate, typically expressed in the United States in terms of strikes per 100,000 aircraft movements.

The focus of wildlife strike risk management falls on the airport environment as >90% of reported wildlife strikes occur during the phases of flight that occur within the vicinity of the airport (ICAO 2017, Dolbeer et al. 2021). In addition to airports being a point of convergence for operating aircraft, the airport environment consists of a variety of habitats that are attractive to wildlife, as noted by DeVault et al. (2013).

For these reasons, certificated airports are required to monitor wildlife hazards and, when a hazard is detected, take immediate action. Such action may include the development and implementation of a wildlife hazard management plan (WHMP; Federal Aviation Administration [FAA] 2018). The procedures designed to control the wildlife hazard are a significant component of a WHMP and include designation of responsible personnel, ongoing monitoring, control measures, and communication protocols. During COVID-19-related lockdowns and as a result of the economic situation, there existed the potential for these procedures to be disrupted (EASA 2020, ICAO 2020).

Therefore, we focused our study on the certificated airport environment due to the potential for both air traffic reductions and disrupted wildlife hazard control measures to have a measurable effect on established wildlife strike reporting trends. There was little direct research found on the potential relationships at play in this scenario. Dolbeer and Begier (2012) found no relationship between aircraft movements and adverse-effect wildlife strikes. In a similar vein, Soldatini et al. (2010), noted that, for some species, aircraft and other human disturbances may have a negligible effect. The potential reason for this lack of research lies in the apparent "unprecedented impact" of COVID-19 on air traffic (Airports Council International 2021).

The nature of wildlife strike report trends lends itself to the use of time series analysis. Where observations of a variable have or can be taken sequentially in time, they may be ordered by time and subjected to the statistical techniques encompassed by time series analysis (Yaffee and McGee 2000, Box et al. 2015). The aggregation of time-stamped wildlife strike data into monthly totals and the subsequent division by monthly totals for air traffic movements provides a univariate time series of wildlife strike rate along a uniform timeline based on months.

While aggregating wildlife strike data into annual or monthly totals is common in wildlife hazard research, a review of wildlife strike literature identified minimal research using time series analysis techniques. Ruhe (2000) used time series migration patterns in examining the efficacy of bird count practices, and Shwiff and Sterner (2002) used time series analysis as part of developing a framework for cost-benefit analysis of wildlife hazard management programs. Kelly et al. (2000) briefly mentioned time series analysis in their paper on weather radar and the avian hazard advisory system; however, it was only in the context of future research.

The nature of the social impact brought on by the COVID-19 pandemic lends itself to the use of interrupted time series analysis techniques. This approach has been used in the analysis of suicide (Bergmans and Larson 2021, Leske et al. 2021), alcohol purchases (Anderson et al. 2020), and childhood body mass index increases (Weaver et al. 2021) resulting from COVID-19-related policies and social effects. We employed these techniques to identify if the impact of COVID-19 on air traffic and the aviation industry in the United States coincides with an increased wildlife strike rate.

Methods

We used the Box-Jenkins approach as outlined by Yaffee and McGee (2000) and Dimri et al. (2020) combined with a process known as interrupted time series analysis to conduct our study (McDowall et al. 1980). The approach uses a pre-interruption (pre-COVID-19) time series model to develop a counterfactual model against which post-interruption (post-COVID-19) observations may be compared.

Data sources and preparation

The wildlife strike report data we used for this study were sourced from the FAA Wildlife Strike Database (FAA 2021*a*). The wildlife strike report sample was limited to the period 2014 to 2020 (inclusive, n = 100,846) and was not filtered for adverse outcome such as negative effect on flight, damage, or injury. This would ensure that the reported data represented a high proportion of wildlife strike events (Dolbeer 2015, Metz et al. 2020) and that sufficient time periods would be available for use in the development of the time series model.

We downloaded air traffic data from the Bureau of Transportation Statistics (BTS 2021). This data consisted of flights undertaken by U.S. carriers with revenue >$20 million per year and by foreign carriers servicing >10,000 passengers per month to and from the United States (BTS 2021). The data were structured as monthly totals for domestic flights, international flights, and total flights. Since wildlife strike rates are based on aircraft movements, total movements were calculated as the monthly domestic flights total multiplied by 2, for each take-off and landing, plus the monthly international flights total, for the corresponding take-off or landing occuring within the United States.

Because the wildlife strike database included reports from operators not included in the BTS data, airports not located in the United States, non-certificated airports in the United States, reports not attributable to either, and reports of strikes >457.2 m (>1,500 feet) above airport elevation, those records that could not be confirmed as having occurred at a U.S. certificated airport and involving a tracked carrier were excluded from the time series analysis.

We applied filters to the FAA Wildlife Strike Database to extract the final data to be used in the creation of the wildlife strike time series (n = 35,649). To assist in the visualization and identification of the air traffic downturn, we created monthly time series for wildlife strike numbers, air traffic movements, and wildlife strike rates. The initial identification of the interruption was made visually using the air traffic movement time series. Despite the announcement of travel restrictions between the United States and China in January 2020 (Corkery and Karni 2020), the total movements for January and February 2020 were similar to the totals for the same months the previous year. March 2020, on the other hand, showed a month-on-month decrease where an increase was expected. This aligns with broader travel advisories issued during that month (FAA 2021*b*). Therefore, the first month of the interrupted time series was set at March 2020 (index row 74).

We separated the complete time series into the pre-interruption period or historical time series (n = 74) and the post-interruption period or COVID-19 time series (n = 10). The historical time series was further divided into a training time series (n = 59) and a test time series (n = 15) for use in verifying the sensitivity of the forecasts produced by the time series analysis model.

Development of ARIMA model

The Box-Jenkins approach to time series analysis is centered around the development of an Autoregressive Integrated Moving Average (ARIMA) model that approximates the behavior of a known time series and facilitates out-of-sample forecasting (Yaffee and McGee 2000). Using Python programming, the pmdarima.auto_arima process (Smith 2020) was applied to the training time series. This automated process identified the optimal model as ARIMA (1, 0, 0)(1, 1, 0)12, which was confirmed through a review of the Akaike Information Criterion (AIC) results showing this model achieved the lowest valid score (AIC = 269.330). The residuals for this model showed a normal distribution and no autocorrelation, which supported the assumption that the identified model was valid.

The ARIMA model's performance was assessed against the test time series with a set of goodness of fit measures calculated (Yaffee and McGee 2000, Hyndman and Athanasopoulos 2018). The results showed acceptable performance in model fitness for the test subset based on the training model forecast (Table 1). Using the complete pre-interruption time series, a forecast from March 2020 through December

Table 1. Goodness of fit measures for the test and interrupted series subsets comparing actual and predicted values of wildlife strike rates in the United States from January 2019 to December 2019 and March 2020 to December 2020, respectively.

	Time series subset	
	Pre-interruption test time series	Interrupted time series
Mean Predicted Error	1.24	5.87
Mean Percentage Prediction Error	3.87%	11.76%
Mean Absolute Error	1.80	5.88
Mean Absolute Percentage Error	7.80%	11.83%
Root Mean Square Error	2.40	8.68
R^2	0.980	0.812
Adjusted R^2	0.978	0.789
Amemiya's adjusted R^2	0.974	0.719

2020 (inclusive) was produced (n = 10). The pmdarima.auto_arima process produced predicted values as well as lower and upper confidence limits (α = 0.05) for each month in the forecast period.

Results

A visual review of the 3 time series constructed from the data showed a clear interruption to both the wildlife strike numbers and air traffic movements beginning in March 2020 (Figure 1). This interruption affected both the time series trend as well as the regular seasonal variations. The wildlife strike rate, however, appeared to maintain a similar trend and seasonality through the post-interruption period when compared to the pre-interruption period (Figure 2). The interrupted time series included the initial "spring" peak in May 2020 and the more pronounced peak from mid-summer through mid-fall (July 2020 to October 2020) before returning to the winter low season.

However, on closer inspection, the wildlife strike rates recorded for May through September (inclusive) exceeded the 95% upper confidence level for each month (Table 2). This indicated that the wildlife strike rate through this period deviated from the pre-interruption forecast and had increased in real terms through spring and summer 2020. These results confirmed that, for at least these 5 months, the wildlife strike rate was adversely impacted following the COVID-19 pandemic interruption.

The diagnostic variation between the performance of the test model versus the counterfactual model also supported this conclusion. The optimal ARIMA model performed well through the pre-interruption test time series with low prediction error and percentage prediction error scores, and high levels of proportion of variance (R^2 = 0.980–0.974; Table 1). In contrast, the forecast for the interrupted period performed markedly poorer. The results for Mean Prediction Error and Mean Percentage Prediction Error highlighted this variation in performance. The model proportion of variance measures showed a corresponding reduction with the Amemiya's adjusted R^2 as low as 0.719. These results supported the conclusion that the actual wildlife strike rate during the COVID-19 impacted period deviated from the pre-interruption trends and forecast.

Discussion

Our analysis showed that the COVID-19 pandemic coincided with an adverse deviation in the wildlife strike rate within the United States through the spring and summer period of 2020. The ARIMA-model-based forecast, acting as a counterfactual to the hypothesized interruption that occurred in March 2020, indicated that wildlife strike rates from May 2020 onward were increasing well above the forecast with monthly rates exceeding the 95% confidence interval of the model through May to September 2020.

These results support the emphasis placed

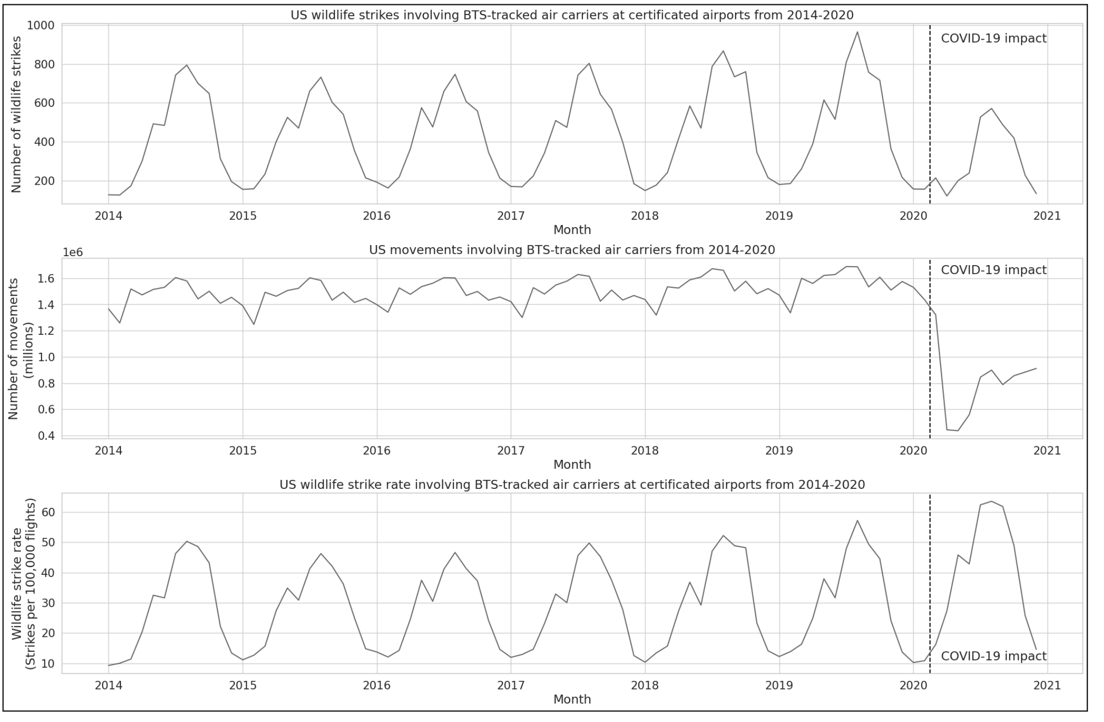

Figure 1. Time series for wildlife strikes, movements, and wildlife strike rates from January 2014 to December 2020 (inclusive) in the United States (data sources: Bureau of Transportation Statistics 2021, Federal Aviation Administration 2021*a*).

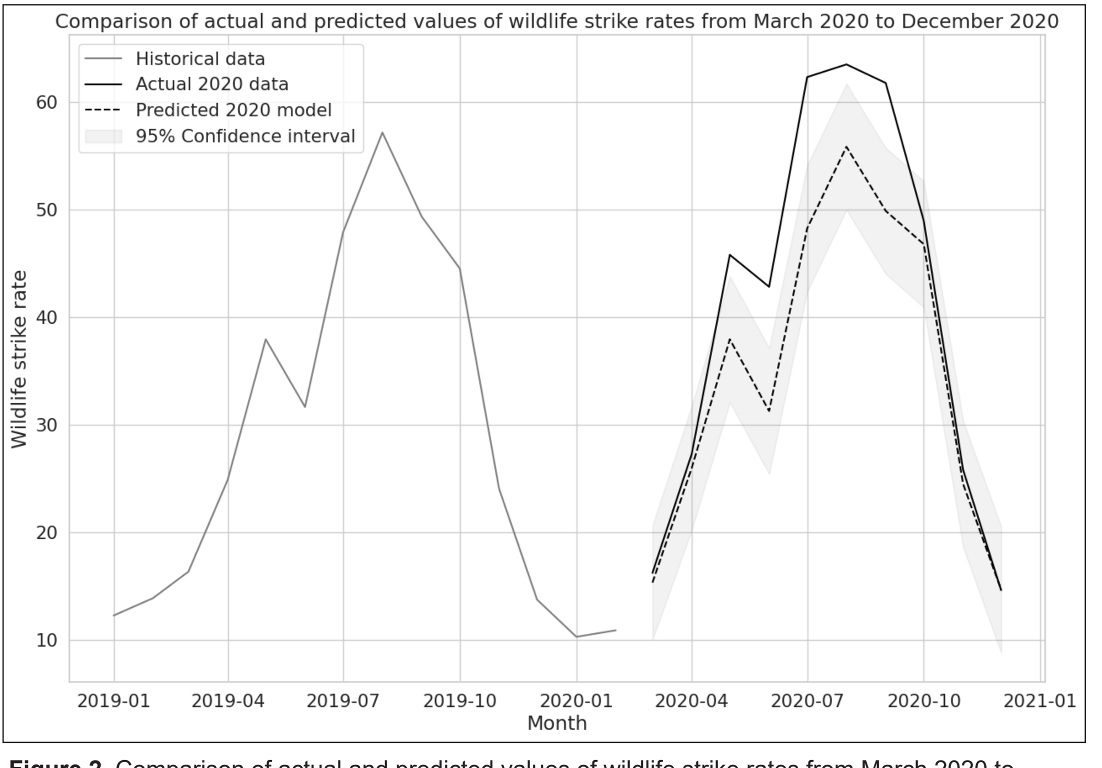

Figure 2. Comparison of actual and predicted values of wildlife strike rates from March 2020 to December 2020 (inclusive) in the United States (data sources: Bureau of Transportation Statistics 2021, Federal Aviation Administration 2021*a*).

Table 2. Comparison of actual and predicted values of wildlife strike rates in the United States from March 2020 to December 2020 based on an Autoregressive Integrated Moving Average (ARIMA) (1, 0, 0)(1, 1, 0)12 model.

Month	Actual value	ARIMA forecast			
		Predicted value	95% Lower confidence level	95% Upper confidence level	Exceed limits
March 2020	16.20	15.03	9.99	20.61	
April 2020	27.28	25.98	20.21	31.75	
May 2020	45.80	37.94	32.09	43.79	*
June 2020	42.83	31.26	25.40	37.13	*
July 2020	62.34	48.26	42.39	54.12	*
August 2020	63.52	55.86	49.99	61.72	*
September 2020	61.79	49.89	44.02	55.75	*
October 2020	48.95	46.79	40.93	52.66	
November 2020	25.80	24.48	18.62	30.35	
December 2020	14.59	14.64	8.77	20.51	

on wildlife hazard management through the COVID-19 pandemic by international, national, and industry bodies (AAWHG 2020, EASA 2020, FSF 2020, ICAO 2020). They highlight the importance of reviewing wildlife control practices impacted by COVID-19, inspecting and surveying the airport environment to assess the wildlife now present, and to revise WHMPs considering these potential changes.

The limitations of this research can be divided into 2 broad categories, the first relating to data completeness and the second regarding causal inferences drawn from the results. With respect to data completeness, wildlife strike data have well-documented issues with under-reporting (Civil Aviation Authority 2006, Dolbeer 2015, Dolbeer et al. 2021). To address this issue, the historical data set was limited to 2014 onward. This data show consistent trends in reporting (overall and seasonal) that support the time series analysis techniques used.

In addition to under-reporting, the complete wildlife strike dataset exceeded the scope of the air traffic movements data set. The filters applied to the wildlife strike data provide for valid analysis of this sector of this industry, but they mask wildlife strike rate changes that may or may not have occurred within the commuter and general aviation sectors and the airports that support them.

On the topic of causal inferences, whether the observed impact is the result of opportunistic adaptations by wildlife at quieter airports (AAWHG 2020) or disruption to wildlife control measures (AAWHG 2020, FSF 2020, ICAO 2020) is not yet clear. While this study includes air traffic movements in its analysis, it is important to note that these results make no inference on the potential causal nature of having reduced traffic at airports, any potential increase in wildlife numbers, and subsequent wildlife strike rates. As the above guidance material notes, any increase in wildlife hazard may result from either reduced traffic levels, changes to wildlife hazard management practices, or other ecological or behavior changes.

Further interrupted time series analyses could identify the relative impact of traffic levels and wildlife hazard management activities on the wildlife strike rate. Data at the airport level may show, if sufficient, more direct relationships between traffic levels and wildlife strike rate or wildlife control measures and wildlife strike rate. While there are data sufficiency limitations in conducting this research, this analysis could deepen our understanding of the causes behind the wildlife strike rate increase observed here.

Management implications

This research and future research may have wider implications than just the impact of CO-

VID-19. It could provide lessons and guidance to individual airport operators experiencing isolated air traffic changes or seeking to make changes to their wildlife hazard management plan. Our analysis of data captured during this historical period could facilitate quasi-experimental findings to support the continued development of research in the wildlife hazard management field.

For now, this validation of the warnings of the aviation safety impact from COVID-19 helps those sectors of the industry still managing the risk of restarting aviation. The ICAO (2021) is currently supporting member states through the challenge posed by airport closures and reduced operations with guidance material, training, and expertise. While wildlife hazard management is just a component of these efforts, the findings outlined above show that the aviation industry has been impacted in profound and subtle ways. Managing the return of pre-COVID-19 air traffic levels will require careful and continued consideration of the risks present in the COVID-19 impact environment.

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