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Count Models to Represent the Impacts of Weather and Infrastructure on Flight Disruptions

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ABSTRACT

We explore the application of count models to represent the relationship between flight disruptions and weather. Throughout the world, flights are regularly disrupted by delays at airports and in the terminal airspace, and less frequently by diversions and cancelations. Many delay studies have been conducted for large American and European airports, in part due to the availability of high-quality data. However, such high-quality data is not as readily available for other airports throughout the world. In this study, we build excess-zero count models using a publicly available dataset for Iqaluit Airport in Northern Canada, to determine the influence of different weather components on disruption counts. Visibility and crosswind speeds are shown to have the largest influence on flight disruptions. We also applied the models using ASPM flight data for Anchorage Airport; we systematically degraded the data to match completeness of the Iqaluit data to test the models. Our results verify that an excess-zero model using incomplete data yields results similar to that of a count model with complete data, demonstrating that an excess-zero model can overcome data incompleteness to yield acceptable results. Although count models have been applied extensively in the transportation literature, we believe this to be the first application to flight disruptions, and the first quantitative model of operations at a northern Canadian airport. We demonstrate that challenges in data availability, the case for most airports throughout the world, can be addressed with novel statistical modeling applications, and thus, delay studies can be conducted for almost any airport.

Keywords: Excess zero models, Weather-related flight disruptions, Airport infrastructure, Northern Canada, Iqaluit Airport, Anchorage Airport

INTRODUCTION

Disruptions, including diversions, cancelations and particularly delays, have become an almost expected experience in air travel worldwide, with potentially enormous costs to society (*1*–*3*). Researchers have built empirical models, using statistical analysis and machine learning, to better understand the key determinants and features (temporal and geographic scope) of these delays for many major American and European airports and airspace (*4*, *5*), for which high quality operations data has been available. There has been less data availability for other markets throughout the world, and thus, there exist few quantitative studies of these markets (*6*).

Airports in Northern Canada are small, with limited infrastructure and relatively minor flight demands. Despite this, airports like Iqaluit Airport (YFB) in the territory of Nunavut provide critical access and serve as a hub connecting small, highly remote communities throughout a vast geographic region. In fact, air transport is the only year-round mode of transport in Nunavut for resupply of food, fuel, medical, and other necessary goods, and the only mode in winter given that there are no overland connections between Nunavut and the rest of Canada. Hence, flight disruptions can have extreme social and economic impacts on the communities they serve (*7*). Targeted infrastructure improvements can reduce the operational impacts of inclement weather at these airports, but the availability of high-quality data and public funding are limited to support such improvements. A 2017 report by Canada's Office of the Auditor General confirmed that many northern airports had deficient and outdated infrastructure, and that improvements were required, but that there was no empirical evidence to support the allocation of limited funds (*7*).

Thus, the objective of this study is to explore the use of count models to quantitatively map the impacts of weather on flight disruptions. We investigate how these models are able to further illuminate the extent of the relationship between flight disruptions and weather conditions, using datasets that are available to the public online, but may not necessarily be complete or of the quality available from the FAA's Aviation System Performance Metrics (ASPM) database. Count models have been useful in the face of data limitations in other areas of transportation engineering (*8*–*12*); we are interested in how model results may inform infrastructure investment decisions at airports like Iqaluit. Specifically, we build a simple negative binomial count model as well as excess-zero (zero-inflated/hurdle) count models of disruptions using FlightStats data from Iqaluit Airport. We also apply the same models to Anchorage Airport, to test model quality using both complete and (artificially constructed) incomplete ASPM datasets. Our results verify that an excess-zero model using incomplete data yields results similar to that of a count model with complete data, showing that an excess-zero model can overcome data incompleteness to yield acceptable results. This further demonstrates that delay studies can be conducted for almost any airport throughout the world using such models.

Although count models have been applied extensively in the transportation literature (traffic safety), we believe this to be the first documented application to airport disruptions, and is the first step in the further model building with this dataset, including a multivariate model of disruptions, network analysis, and data science applications.

LITERATURE REVIEW

There is extensive existing literature on assessing and modeling flight delays and cancelations at airports, the majority of which focuses on large airports in the U.S. and Europe (*4, 5*). Researchers have developed models of delay propagation within an airline (*13, 14*) and throughout networks (*15–19*) and models of how changing airport delays are attributed to changing demand and throughput (*20*). Rebollo and Balakrishnan used random forest algorithms to predict short term departure delays over the U.S. air network (*21*).

Weather conditions have been clearly identified as a primary driver of flight disruptions (*22*, *23*). A study of several Brazilian airports showed a 216% increase in delays in extreme weather conditions (*6*). Weather variables like wind speed, temperature, and thunderstorms were used in regression models of delays at Heathrow Airport (*24*) and estimate airfield capacity at Newark Liberty International Airport and San Diego International Airport (*25*). A study of Frankfurt Airport showed that an average of 740 minutes of flight delays could be attributed to a single thunderstorm (*26*). Low visibility and ceilings due to the morning marine strata frequently cause Ground Delay Programs at San Francisco International Airport, whereas wind is the dominant cause of operational degradations at Portland International Airport (*27*). Various models of flight cancelations (and of both cancelations and delays) have also been developed (*28–32*).

While much of the literature on weather-driven operational degradation focuses on large airports and in air networks exacerbated by demands that exceed capacities, there are no readily available flight disruption statistics for Canada, particularly the northern regions where airports are small, with limited infrastructure, and relatively minor flight demands. Despite this, extreme weather in the northern regions of Canada is a pervasive factor in the flight delays that significantly affect the local communities that rely on the air transport. A comprehensive report on the weather and geography of the Canadian territories suggests that weather causes 75% of flight delays (*33*); however, no studies have been performed using an air operations analysis approach in Northern Canada. Infrastructure improvements can reduce the operational impacts of inclement weather, but decision-makers need high quality supporting evidence to allocate limited resources. Empirically-based flight operations models can help in this regard; count models are particularly useful in the face of data limitations. Count models have been applied in many areas, including medicine (*34*), political science (*35*), ecology (*36*), agricultural science (*37*) and transportation engineering (*8–12*, *38*). In transportation, count models have been applied to estimate trip frequency (*11*, *12*), traffic collisions, and crash frequency (*8–10*, *38*). We recognize that flight disruptions, as a physical process of random discrete events, are analogous to roadway collisions. Thus, we have applied this modelling approach.

In this study, we applied disruption count models at two airports. We first apply our models using readily available but incomplete FlightStats data at Iqaluit Airport (YFB) in Nunavut, a northern territory of Canada. We then apply the models using ASPM data at Anchorage Airport (ANC) in Alaska, to verify model quality and applicability.

METHODOLOGY – COUNT MODELS

A flight disruption can be a random, discrete, and non-negative event. The negative binomial (NB) distribution can be used to represent flight disruption counts and is more appropriate than Poisson (P) for over- or under-dispersed data. The deterministic generalized linear regression model for expected flight disruption count per time period t at airport a $(\mu_{a,t})$ with log link is:

$$ln(\mu_{a,t}) = \alpha_{a,t} + \sum_{j=1}^{k} \beta_{a,t,j} X_{a,t,j} \tag{1}$$

where $\alpha_{a,t}$ and $\beta_{a,t,j}$ are estimated coefficients on the independent variables, for the time period t, and $X_{a,t,j}$ are independent variables $(j = 1 \dots k)$, and $\mu_{a,t}$ is the dependent variable (the expected daily count of disrupted flights).

The probability of observing a non-negative flight disruption count on a given time *t* is expressed as:

$$P: f(y_{a,t}) = P(y_{a,t}) = \frac{\exp(-\mu_{a,t}) {\mu_{a,t}}^{y_{a,t}}}{y_{a,t}!} \tag{2}$$

$$NB: f(y_{a,t}) = P(y_{a,t}) = \frac{\Gamma(y_{a,t} + \theta_a^{-1})}{\Gamma(\theta_a^{-1}) y_{a,t}!} \left(\frac{1}{1 + \theta_a \mu_{a,t}}\right)^{\theta_a^{-1}} \left(\frac{\theta_a \mu_{a,t}}{1 + \theta_a \mu_{a,t}}\right)^{y_{a,t}} \tag{3}$$

where $f(y_{a,t})$ is the probability of observing a day t with a flight disruption(s), $y_{a,t}$, θ_a is the dispersion parameter, $\mu_{a,t}$ is the dependent variable (expected daily count of disrupted flights), and $\Gamma(\cdot)$ is the gamma function.

In our dataset, zero counts can arise from two situations i) having a day with no flight disruptions or ii) having a day with no delay records (which are converted to zero). Both zero-truncated hurdle models and zero-inflated (ZI) count models account for excess zeros in a dataset (*36*–*38*); each model has two components (count component with log link and excess-zero component with logit link) to do so.

The hurdle model assumes that excess zeros are generated in a different process than non-zero counts, and these zeros can be modeled independently of the count values. Therefore, the "zero" state includes situations in which a zero is recorded (true-zero state) as well as those where the observation is missing (excess-zero state). Non-zero observations follow a Poisson or negative binomial distribution. **Equation 4** shows the probability of observing a zero or non-zero flight disruption count, according to the hurdle model:

$$P(y_{a,t}) = \begin{cases} \mathrm{g}_1(y_{a,t}) & y_{a,t} = 0 \\ \left(1 - \mathrm{g}_1(y_{a,t})\right) \cdot \mathrm{g}_2(y_{a,t}) & y_{a,t} > 0 \end{cases} \tag{4}$$

where $\mathrm{g}_1(y_{a,t})$ is the probability of being in the zero state (both true-zero and excess zero) and $\mathrm{g}_2(y_{a,t})$ the probability of being in the truncated positive count state.

The probability of the count being zero $\mathrm{g}_1(y_{a,t})$ over non-zero is expressed with the following generalized linear regression model with a logit link.

$$\text{logit}\left(\mathrm{g}_1(y_{a,t})\right) = ln\left(\frac{\mathrm{g}_1(y_{a,t})}{1-\mathrm{g}_1(y_{a,t})}\right) = \gamma_{a,t} + \sum_{j=1}^{k} \delta_{a,t,j} Z_{a,t,j} \quad (5)$$

where $\gamma_{a,t}$ and $\delta_{a,t,j}$ are estimated coefficients, and $Z_{a,t,j}$ are independent variables (may or may not be same as $X_{a,t,j}$).

The zero-inflated (ZI) model is a modified hurdle model where all observed counts, zero or greater, are generated by one process (that, again, follows a Poisson or negative binomial distribution) and the no-count state by another:

$$P(y_{a,t}) = \begin{cases} \mathrm{g}_3(y_{a,t}) + \left(1-\mathrm{g}_3(y_{a,t})\right) \cdot f(y_{a,t}=0) & y_{a,t}=0 \\ \left(1-\mathrm{g}_3(y_{a,t})\right) \cdot f(y_{a,t}) & y_{a,t}>0 \end{cases} \quad (6)$$

where $g_3(y_{a,t})$ is the probability of being in a excess-zero state and $f(y_{a,t})$ is the probability of being in the count state (true-zero and positive count) from **Equation 2** and **Equation 3**.

A large number of zeros in a dataset does not automatically justify the use of an excess-zero count model over a simple count model. Vuong's test (**Equation 7**) is used to determine whether the presence of excess zeros is statistically significant at airport *a* (*39–41*).

$$V_a = \frac{\sqrt{n_a}\left[\frac{1}{n_a}\sum_{t=1}^{n_a} m_{a,t}\right]}{\sqrt{\frac{1}{n_a}\sum_{t=1}^{n_a}\left(m_{a,t}-\overline{m_a}\right)^2}} = \frac{\sqrt{n_a}\cdot\overline{m_a}}{S_{m,a}} \quad (7)$$

where n_a is sample size for airport *a* with a mean $\overline{m_a}$ and standard deviation S_{m_a}. $m_{a,t}$ can be expressed as:

$$m_{a,t} = ln\left[\frac{f_1(y_{a,t})}{f_2(y_{a,t})}\right] \quad (8)$$

where $f_1(y_{a,t})$ is the probability density function of excess-zero count model (**Equation 4** or **Equation 6**) and $f_2(y_{a,t})$ is the probability density function of simple count model (**Equation 2** or **Equation 3**). An excess-zero count model is considered to be a better fit than a simple count model with similar distribution (Poisson or negative binomial) when $V_a > V_{critical}$. $V_{critical}$ is 1.96 at a 95% confidence interval (*41*). The model selection process is summarized in **Figure 1**.

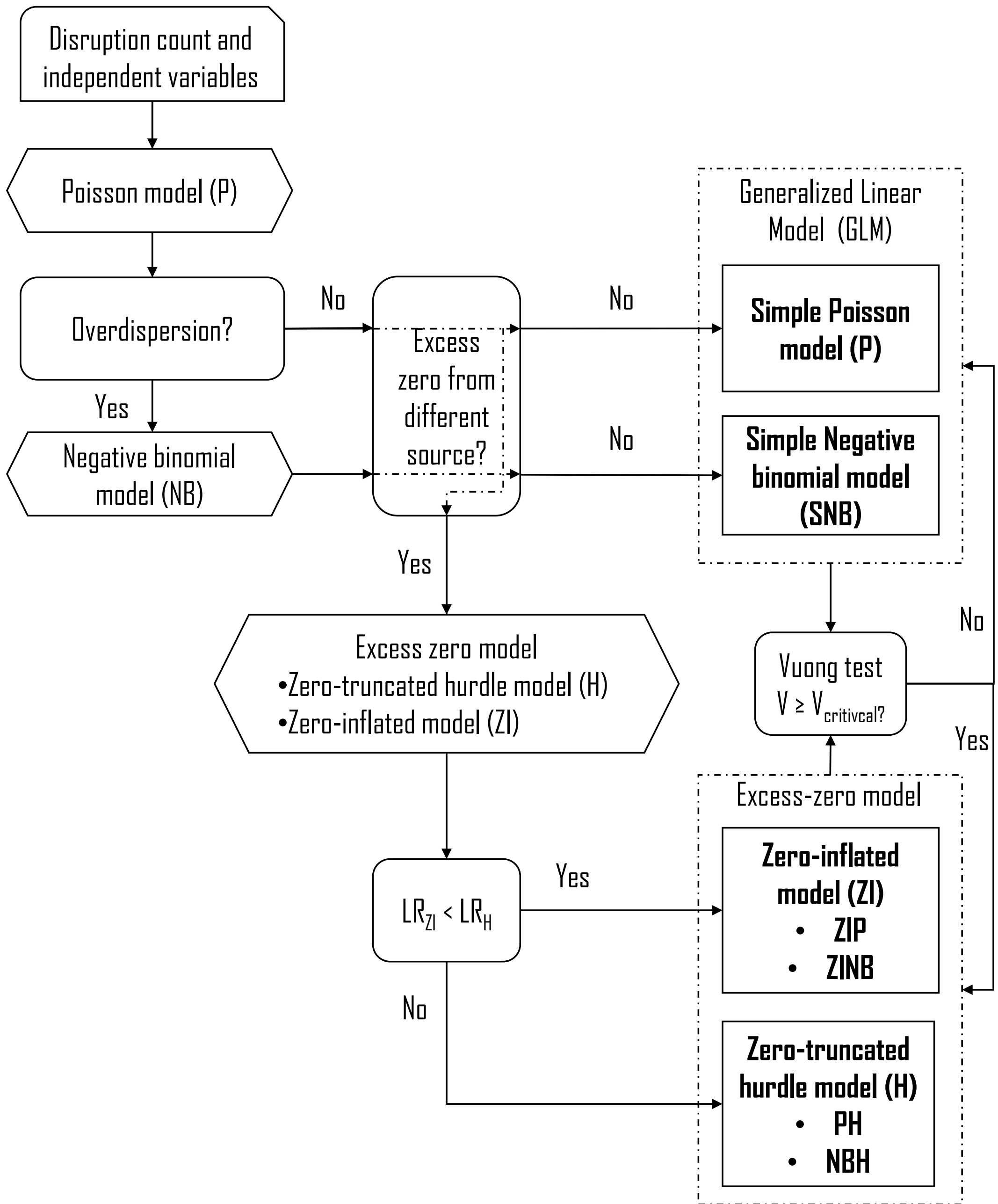

Figure 1 How to select an appropriate count model

DATA AND ANALYSIS

Iqaluit Airport (YFB) serves the capital city of the Canadian territory of Nunavut. Iqaluit is the only territorial or provincial capital city in Canada without overland access to other communities or the rest of the country. This coastal airport has only one runway (paved) aligned into a valley with approach and threshold lighting, 24-hour METAR and TAF operation, ILS with RVR 1200 (1/4sm), and precision approach path indicators for aircraft with eye-to-wheel height up to 45' (*42*). There is a long history of flight delays and cancelations due to weather and infrastructure issues, like thawing permafrost, ILS failure, and poor visibility. With nearly 19,000 aircraft movements (*43*) serving 156,641 passengers (*44*), YFB has the highest passenger per capita ratio in Canada (*45*) and serves as a hub connecting smaller remote communities throughout the territory; thus, it is an important airport for many Nunavummiut, disruptions have had significant social consequences (*46*, *47*).

Anchorage Airport (ANC) in Alaska is a mid-sized American airport with high cargo volumes. It has three runways serving over five million passengers and approximately three million metric tons of cargo annually (*48*). In 2015, 17.2% of flights were delayed, 0.9% were canceled, and 0.2% diverted (*3*). We chose to model ANC due to its northern coastal location similar to YFB.

Data Description

Historical flight operations data for YFB was purchased from FlightStats (www.flightstats.com), a flight data services company. The FlightStats (FS) dataset contains records for scheduled flights as well as (a relatively small number of) charter flights that file flight plans (i.e., IFR flights). We used the data attributes 'departure_airport_iata_code,' 'arrival_airport_iata_code,' and 'diverted_airport_iata_code' to filter for departure, arrival and diverted flights at YFB; this yielded us 20,050 flights operating at YFB from October 1, 2015, through October 31, 2017. A quick check of the FlightStats dataset for another (smaller) territorial airport, against flight data provided by an airline for that same airport, showed the exact same number of flights. This gave us confidence that there is unlikely to be missing flight records in the YFB FlightStats data. We referred to fields 'actual_runway_departure' and 'actual_runway_arrival' to identify flight departure and arrival times respectively. When data for these fields were missing, we replaced them with 'est_runway_departure' and 'est_runway_arrival'. We obtained flight and weather data for ANC from the FAA's Aviation System Performance Metrics (ASPM) database.

We obtained publicly available historical weather data from Environment Canada, gathered from meteorological stations managed by both NAV Canada (NAVCAN) and Environment Canada for 2015-2017. The weather data for YFB includes hourly records of ceiling, visibility, dew point, wind speed and direction, station pressure, and dry bulb temperature as well as daily recordings of total rainfall, total snowfall, total precipitation, and snow on the ground. To create our daily dataset, we included the minimum, maximum, average, and median of each hourly weather variable identified above.

Operation and weather data for ANC were obtained from ASPM using the "Download/Airport" Section (https://aspm.faa.gov/). The data contains quarter-hourly airport operations and weather data from 2012 to 2018. Among the 72 operational fields in the data, we used counts of arrival and departure flights for efficiency computation ('EFFARR' and 'EFFDEP') and counts of the Official Airline Guide (OAG)-based airport arrival and departure delay ≥ 15 minutes ('DLAARR15' and 'DLAOFF15'). We used the weather variables of visibility, temperature, wind speed, and wind angle.

Data Processing

YFB

The 25-months of FlightStats data for YFB includes 10,194 arrivals, with 146 of these consisting of flights diverted to YFB, and 9,856 departures, including 10 diverted back to YFB (due to problems en route or at the destination airport). Of the flights scheduled to arrive at YFB, 51 were diverted to other airports. There was an average of 26 flight operations (arrivals and departures) per day and records showed only large aircrafts (according to FAA definition) operated at the airport. We observed some inconsistencies in recorded flight status and diversion airports, as well as some missing values. Thus, we developed a decision process (**Figure 2**) to address the above discrepancies and missing data, and ultimately identify a flight's status as disrupted or not disrupted. A flight disruption is attributed to an airport when (1) an arriving or departing flight is canceled, (2) an arriving or departing flight is delayed for 15 minutes or more, or (3) a flight scheduled to arrive is diverted to an alternate airport.

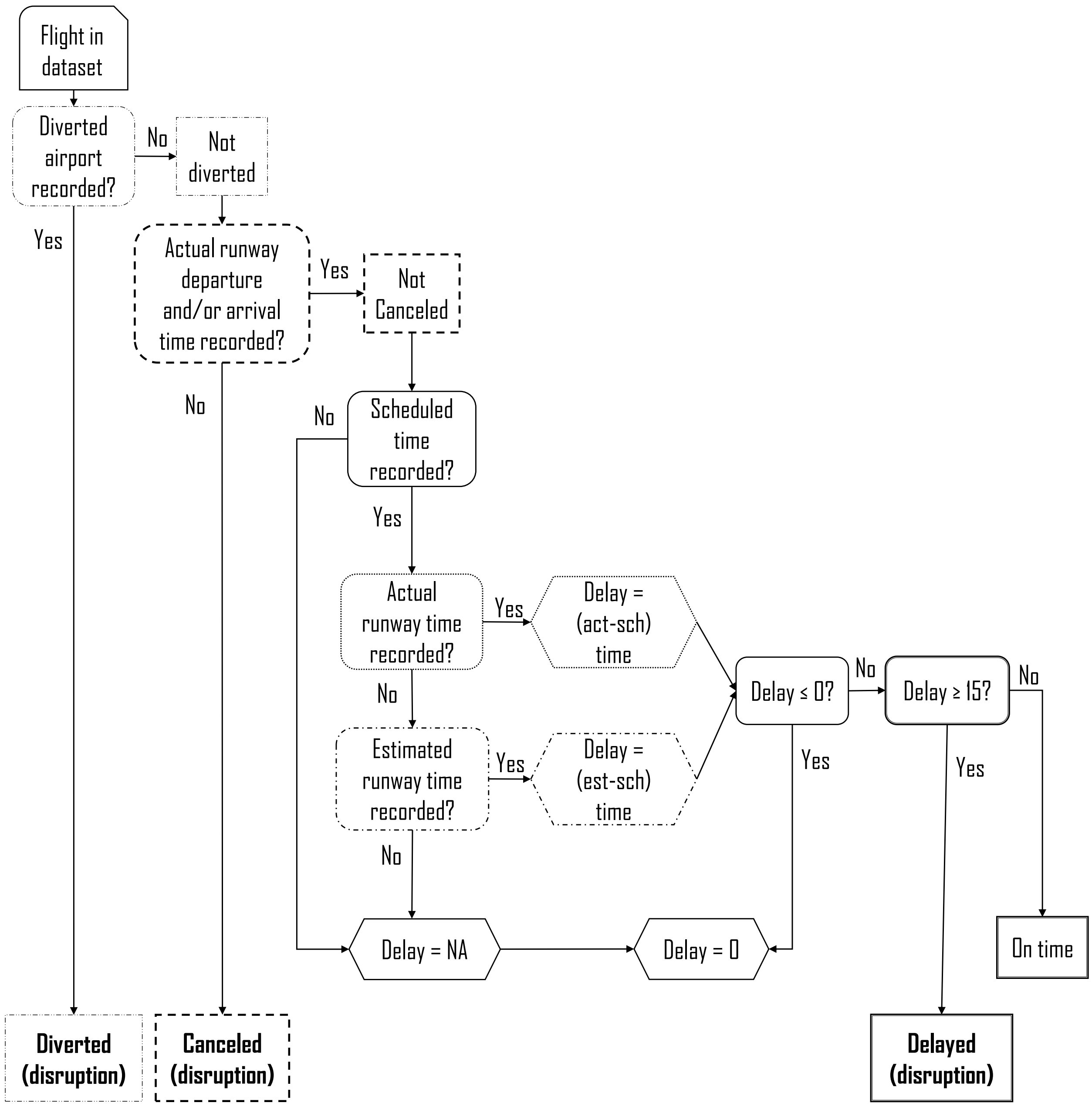

Figure 2 Flowchart for determining flight disruption of FlightStats data

Delayed flights are the primary contributor to flight disruption counts at YFB, with 35.7% of departure flights and 16.2% of arrivals delayed (≥15 minutes) during the study period. The lower number of disrupted arrivals is the result of prioritizing arrivals over departures, as flights are inherently safer on the ground than in the air due to a number of conditions, including fuel capacity (*49*). Flight cancelations are the second highest contributor to disruptions, making up 13% and 10% of arrival and departure flights, respectively. **Figure 3** shows a histogram of the daily disruptions counts.

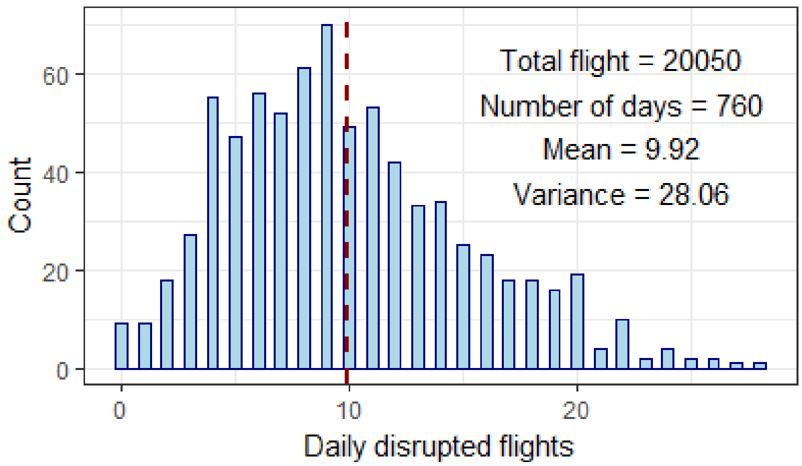

Figure 3 Histogram of daily flight disruptions at YFB

The daily flight disruptions count is overdispersed, with variance greatly exceeding the mean. Hence, the negative binomial distribution is likely to be a better fit for this data compared with the Poisson distribution. The overdispersion and zeros due to different causes indicate that an excess-zero negative binomial model might be appropriate.

Christmas Day (December 25) of 2015 and 2016 were the only days in the 762-day study period with no flights at YFB. We removed these two days from our dataset. The final dataset contained 20,050 flight records over 760 days; of these 20,050 flights, 1,764 had missing arrival and/or departure times.

ANC

The ASPM data for ANC contained 245,472 quarter-hourly records of 1,210,734 flights from 2012 to 2018. Recall that the quarter hourly ASPM data does not contain canceled flights nor identify diverted flights, and thus we can only count delayed flights (which we will refer to as disruptions herein for ease). The average daily flight count for ANC was 473 flights/day while YFB's was 26 flights/day. If we looked at daily disruptions for ANC, as we did for YFB, we would be highly unlikely to observe a day at ANC without flight delays (i.e. we would be unlikely to observe a true zero count). On the other hand, if we were to look at hourly disruptions for both, we would run into a problem with YFB insofar as hours with disruption counts would be very rare. As a result, we chose to model hourly disruption flight counts at ANC, and daily for YFB. There is no night flight curfew at ANC, with the airport authority instead using its 'Noise

Compatibility Program' to reduce noise impacts (*50*). Serving an average of 20 flights per hour, delay counts at ANC are also overdispersed.

With the same reasoning for removing Christmas Day at YFB, we removed 18 hours with no flights at ANC and were left with 61,350 hours of data. **Figure 4** shows a histogram of the hourly disruptions counts.

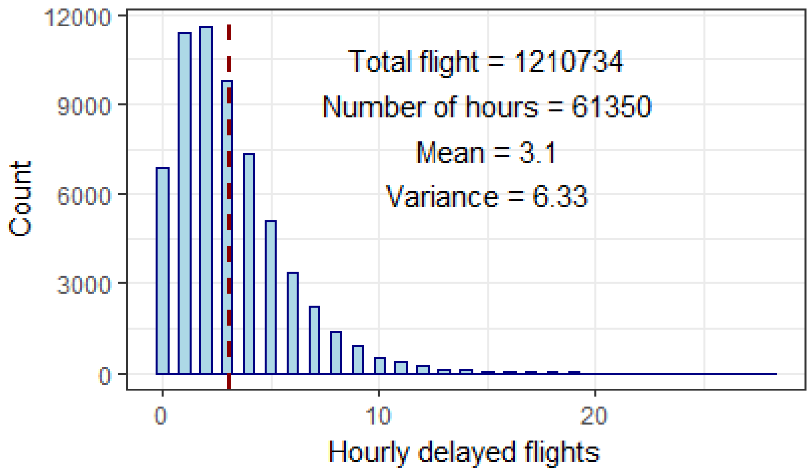

Figure 4 Histogram of hourly flight disruptions at ANC

Modeling Approach

Flight disruption counts at an airport (per day at YFB; per hour at ANC) are modeled as discrete, non-negative and random events using the count models introduced earlier. A flight record falls into one of the following categories:

1) Disrupted (non-zero count-state),
2) Not disrupted, or on-schedule (true-zero state), and
3) Missing information, and thus, converted to zero (excess zero states).

Of arrival and departure flights at YFB, 55% and 51% were on-schedule, respectively, falling into category (2) above. Additional zeros due to (3) would contribute to the impression of a higher number of on-schedule flights (YFB arrival and departure flight records in categories (2) and (3) number 70% and 54%, respectively). The ANC dataset has no missing information – there is nothing in category (3).

The non-zero count-state of the YFB disruption count data likely follows a negative binomial distribution as it is overdispersed. Nonetheless, we developed a Poisson model and tested for dispersion. Both the hurdle (**Equation 4**) and zero-inflated (**Equation 6**) models are appropriate to model disruption counts, especially because we have missing observations in our dataset. This is equivalent to applying count models to traffic crash data with missing observations (i.e., situation (3) above). We tested both models as discussed in the following section, developing them using different combinations of dependent variables. **Table 1** provides a list of the candidate variables tested. Data preparation, data analysis, and modeling were performed using the free statistical software RStudio; the "pscl", "MASS", and "stats" packages in RStudio were used to estimate the count models (*51*).

TABLE 1 Candidate Explanatory Variables

Category	Primary variable	Candidate variables
Operations	Flight	Arrivals, departures, total (arr+dep)
	Flight distance	% long (> 4000km), % medium (1500km-4000km), % short (< 1500km)
	Aircraft type	% heavy, % large, % medium, % small
	Seasonality	Month, season
Weather	Visibility	Min, max, average, median (daily & hour of operation)
	Wind speed	Min, max, average, median (daily & hour of operation)
	Crosswind speed	Min, max, average, median (daily & hour of operation)
	Head/tailwind speed	Min, max, average, median (daily & hour of operation)
	Temperature	Min, max, average, median (daily & hour of operation)
	Station pressure	Min, max, average, median (daily & hour of operation)
	Dewpoint	Min, max, average, median (daily & hour of operation)
	Precipitation	Total rain, total snow, total precipitation (rain+snow), snow cover

As we aggregated the YFB data over a day, we could represent the weather conditions (visibility, temperature, etc.) for the day, and thus their impact on daily disruption counts, using different representations of the data like daily average, average over operating hours, daily minimum, daily maximum, standard deviation, etc. Thus, we started with an exhaustive list of nearly 290 candidate variables in order to understand which of the above quantities would be significant to disruptions. We applied correlation and multicollinearity tests followed by the backward stepwise selection method (*52*) to reduce the candidate variables set, as is standard practice in regression analysis. One operations-related and three weather-related variables were finally chosen for inclusion in the count models. The selected operations variable is the total flight count. With more scheduled flights, a higher likelihood of disruption is anticipated for two reasons. First, more scheduled flights mean there are simply more flights "available" to disrupt. Second, flight demands that approach or exceed an airport's capacity lead to disruptions (i.e., congestion), consistent with observations at high demand airports (*20*). The three weather variables include 1) minimum visibility during operating hours (0700-2300), 2) maximum crosswind speed during operating hours, and 3) total daily precipitation.

For ANC, we used total flights per hour (summation of 'EFFARR' and 'EFFDEP'), minimum hourly visibility, maximum hourly crosswind speed, and minimum hourly temperature as independent variables. ASPM does not contain precipitation records. Also, as it provides complete operational data, zero inflation is not expected in the dataset. For comparability, we induced excess-zeros in the ASPM data maintaining the similar pattern of missing zeros in FS data for YFB. We have achieved this by randomly converting delay records for 9% of total flights of ANC (108,966 flights) to zero (category 3 in Modeling Approach) and distributing them in a manner ensuring over 90% of the aggregated study period (55215 hours) contained excess-zero.

RESULT AND DISCUSSION

We first estimated the simple Poisson count model (generalized linear model (GLM) with log link) on total daily flight disruptions at YFB, to perform a dispersion test given that **Figure 3** indicated overdispersion. The test determined a dispersion value of 1.70 and confirmed that the disruption count data were overdispersed at a 99% significance level. Therefore, we developed a simple negative binomial count model (SNB). As there was more than one source of zero counts in the data, we estimated both a zero-truncated negative binomial hurdle (NBH) (**Equation 4**) and a zero-inflated negative binomial (ZINB) (**Equation 6**) with explanatory variables of total flights, visibility, crosswind speed, and daily precipitation.

Vuong's test (**Equation 7**) was used to determine whether the excess-zero models (ZINB and NBH) were superior to the simple count model in fit (**Figure 1**). Vuong's z-statistics were 1.44 and 1.39 for NHB and ZINB respectively, indicating that both these excess-zero models are favorable over the simple negative binomial (SNB) model at a 90% confidence level. The shape parameter, θ, is also significant (95% confidence) for both models, again confirming data overdispersion. According to both the Akaike Information Criterion (AICc) and log-likelihood values, both excess-zero models have similar goodness-of-fit. The results are shown in **Table 2**.

TABLE 2 Results of YFB Daily Disruption Count Models

	SNB		NBH		ZINB	
	Coefficient	**z-value**	**Coefficient**	**z-value**	**Coefficient**	**z-value**
Count model						
(Intercept)	-2.097	-8.522	-1.980	-8.000	-1.965	-7.977
ln(#Flight)	1.351	18.331	1.313	17.733	1.309	17.757
Min Visibility (mile)	-0.020	-10.377	-0.019	-10.043	-0.019	-10.045
Max Crosswind (knot)	0.019	4.952	0.020	5.163	0.020	5.126
Precipitation (mm)	0.013	2.873	0.013	2.921	0.013	2.935
$\ln(\theta)$	2.63	7.610	2.708	19.713	2.709	19.736
Excess-zero model						
(Intercept)	-	-	0.147^{+}	0.130	-0.916^{+}	-0.580
Min Visibility (mile)	-	-	-0.130	-3.096	0.137^{*}	2.537
#Flight	-	-	0.273	4.482	-0.256	-3.167
Model parameters						
θ	13.85		14.99		15.012	
Log-likelihood	-2120.87		-2114.68		-2114.98	
AICc	4253.8		4247.6		4248.2	

** Significant at 95% confidence level; all others are significant at 99%.*
+ Intercepts of excess-zero model component are not significant.

In the NBH model, the zero-truncation component uses binomial logit to represent whether a positive count (distributed negative binomial – GLM with log link) has occurred or not. All estimated parameters have expected signs, and all but the intercept in the excess-zero model are statistically significant at 95% confidence level. The excess-zero model component results of the NBH model indicate that a one-mile increase in the daily minimum visibility leads to a 12.2% decrease in the odd ratio $\Pr(y > 0)/\Pr(y = 0)$. This means that when comparing flight disruption between two days, the day that experiences the lower minimum visibility is more likely to have a disruption, given all other variables remain constant. Similarly, the odd ratio of observing flight disruptions in a given day increases 31% with higher flight volumes. When all explanatory variables are zero (or nearly zero, for instance, #flights = 1), the daily expected disruption count is nearly zero as well ($e^{-1.98+1.313*\ln(1)} = 0.14$). However, with 10 scheduled flights, the expected daily flight disruption count increases to 2.8; with 20 scheduled flights, the expected disruption count is 7.1. If we increase visibility by one mile, then we can expect a 1.9% decrease in daily disruptions. Similarly, increasing crosswind speed and precipitation by one unit each increase expected daily disruption count by 2% and 1.3% respectively. These (statistically significant) models' estimates for weather variables on disruption count appear small. This could be attributed to the fact that very extreme weather events (i.e. very low visibilities, very high crosswinds and heavy rain/snow) are also infrequent. As a result, the effects of these extreme events may be "washed out"; an analysis targeted at these events may be more insightful given the extreme consequences of such events. Despite that, seemingly small decreases in operational capacity can have significant impacts on airport efficiency as the impacts of disruptions grow non-linearly (*32*). Besides, the operational impacts of many adverse weather conditions can be lessened with improved maintenance (i.e., snow clearing), navaids, and lighting, which can be poor to non-existent at many airports throughout northern Canada.

In ZINB, the GLM (with log link and negative binomial count model) is applied to represent both true zero and positive disruption counts. The signs on all coefficients are intuitive and similar to those of the NBH model. The sign on the ZINB excess-zero component is opposite that of the excess-zero component of NBH; this is because the ZINB excess-zero component finds the probability of excess zeros versus true zeros and positive counts, whereas the NBH hurdle component finds the probability of positive counts versus excess zeros and true zeros. The ZINB model results indicate that the probability of observing excess zeros in the data increases by 15% with a one-mile visibility increase, suggesting that the dataset contains more missing entries during better weather conditions. This would be a curious result except that, during data cleaning, we observed that good weather days also tended to have flights with more fields missing in the original FlightStats dataset. Also, the probability of observing excess zero from missing records (odd ratio) is low at busier airports as it decreases by 29% with one unit increase of flight volume. However, the NBH model provides the best fit and results as we are interested in understanding the impacts of the different variables on daily total disruption counts, particularly focusing on when disruptions occurred.

For ANC, we also applied different delay count models to the hourly aggregated data. The data also indicated overdispersion, with dispersion value 1.49 for complete data and 2.2 for zero-induced data respectively at a 99% significant level. Thus, we proceeded with the negative binomial count models (simple, hurdle and zero-inflated). Insignificant odd ratio supports the inapplicability of ZINB/NBH model to complete ASPM data whereas Vuong's test result suggests that for incomplete ASPM data ZINB/NBH is preferred over SNB. The results are shown in **Table 3**.

TABLE 3 Results of ANC Hourly Delay Count Models (With Complete and Incomplete ASPM)

	Complete data		Zero-induced incomplete data			
	SNB		NBH		ZINB	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Count model						
(Intercept)	-0.793	-35.86	-1.237	-29.97	-1.275	-35.54
ln(#Flight)	0.806	123.58	0.882	70.31	0.893	72.45
Min Visibility (mile)	-0.046	-46.19	-0.052	-35.53	-0.051	-35.72
Max Crosswind (knot)	0.007	9.21	0.010	9.02	0.010	9.66
Min Temperature (°C)	-0.004	-12.64	-0.005	-9.97	-0.006	-12.15
ln(θ)	1.864	15.80	1.244	49.06	1.243	49.23
Excess-zero model						
(Intercept)	-	-	-0.358	-8.44	-0.434	-6.31
Min Visibility (mile)	-	-	-0.085	-24.21	0.067	12.91
#Flight	-	-	0.089	77.63	-0.074	-35.49
Model parameters						
θ	6.45		3.47		3.46	
Log-likelihood	-125163.1		-106414.4		-106288.3	
AICc	250338		212846.8		212594.7	

All estimates are significant at 99% confidence level

The result shows that higher counts of flight delays are correlated to higher (natural log of) hourly flight volume, higher crosswind speeds, lower visibility, and lower temperature. Unlike YFB (**Table 2**), crosswind speed at ANC has a smaller influence on delay than that of visibility (**Table 3**). There could be two explanations for this. First, intersecting runways at ANC would allow for a runway to be used when winds create crosswinds on the other, and vice versa, thus reducing the impacts of winds. However, with only one runway at YFB, with strong crosswinds, the airport would not be able to accommodate any operations. Second, with high cargo volumes, we expect that larger aircraft operate at ANC, which are less susceptible to crosswinds. However, the purpose of developing the model is not to identify and compare the influencing factors; rather verify the applicability of excess-zero models (ZINB and NBH) to the incomplete dataset. A simple exploration of incremental data removal demonstrated that model parameters did not change significantly when removing up to about 15% of ANC flight data. Beyond 15%, we started to observe significant changes in coefficient values. Further analysis was not conducted because only 9% of flights at YFB had missing data, and we induced the same number of excess zeros into the ANC data. Comparing the result of simple count models for the complete dataset and excess-zero count models for the incomplete dataset (**Table 3**), it can be confirmed that both yield similar results for ANC. This suggests that the data incompleteness can be address by adopting a ZINB/NBH model over SNB.

Since we replaced some delayed flight records from ASPM to excess zeros (category 3 in Modeling Approach) to obtain a similar structure of FS data for YFB. The result from **Table 3** supports our hypothesis that the excess-zero count models are handling the missing zeros in the YFB dataset adequately and providing results (**Table 2**) that we can confidently say are a true reflection of YFB operations.

CONCLUDING REMARKS

This research investigated the novel application of empirical count models to represent relationships between flight disruptions and weather conditions at airports, using data of varying completeness and quality. We estimate models for Iqaluit Airport (YFB) in Nunavut, Canada using publicly available but incomplete data from FlightStats, and for Anchorage Airport (ANC) in Alaska, United States using high quality data from FAA's ASPM database. Our work was motivated by the need quantitatively map the strength of the relationships between flight disruptions and weather (and infrastructure) at northern Canadian airports, where infrastructure is deficient and outdated (severely hampering their ability to support reliable air services when weather conditions deteriorate), data is limited, and the Canadian government has no quantitative information to guide investment allocation decisions across these airports – yet, air transportation is an essential service to sustain communities. Furthermore, climate change is opening up northern Canada and Arctic waters to increased tourism and freight movement, requiring support via air transport services. At the same time, it created further challenges in providing these services due to even greater weather volatility, and runway surface degradation from melting permafrost foundations (leading to higher mitigation and maintenance costs) (*53*).

The results from applying a zero-inflated negative binomial model and negative binomial hurdle model at YFB indicate that flight disruptions are correlated to flight counts, minimum visibility, maximum crosswind speed, and precipitation. However, due to the incompleteness of the YFB FlightStats data, we further explored model building with ANC ASPM data. After systematically degrading the data to match YFB data completeness, we found that the application of an excess zero model to the incomplete dataset yields similar results as applying simple count models to complete data, determining that an excess-zero model can overcome data incompleteness to yield good-quality results. This demonstrates that challenges in data availability – the typical case for most airports throughout the world – can be addressed with novel statistical modeling applications. We believe this method can be applied to other airports throughout Northern Canada and the world, given the availability of weather and airport infrastructure data.

The YFB results show that low visibility is an issue with respect to operational disruptions. If this is to be addressed, installation of improved lighting systems, navaids and/or landing equipment (a cost borne by the airport authority, NAV Canada, and the federal Airports Capital Assistance Program) should be considered to facilitate and/or improve operations in low-visibility conditions. Because ANC has multiple runways, it was found that crosswind speeds are less disruptive than low visibility on flight delays. However, YFB is highly susceptible to winds, with only one runway aligned into a valley from the coast. This model offers a method by which to monitor the impact of crosswinds (a combination of wind speed and angle with runway) on disruptions, particularly as the effects change over time; the only way to mitigate the effects of crosswinds is to construct a new runway, and this could be considered by governments particularly as YFB grows in size and importance (tourism, shipping, etc.). Overall, this model offers empirical evidence to effectively identify and target the types of infrastructure investments needed at airports, which will lead to more efficient use of limited funds by both the territorial and federal governments.

Our study was limited by a lack of data on runway configurations used and the occurrence of other operational issues (snow clearing, lighting outages, staffing shortfalls, etc.). It would be beneficial, in future studies, to work closely with the airport authority to gain access to such data if it is collected. Analytic capacities for each of the two runway configurations, in good and poor visibility, weighted by the probability of use given winds, can be calculated (with further assumptions). Empirical estimation of capacity would be hindered by the above data limitations; thus, in this paper, we chose to focus on disruptions as YFB operates well below capacity in good conditions. We can further build on this research by exploring other data science applications to further unpack the relationship between highly disrupted days and severe weather conditions. We continue to work with a northern airline to explore their operational data to support network-level operational disruptions models. Our larger vision is to develop analysis tools that can support governments (and operators) in allocating infrastructure improvement funds in a well-targeted, effective manner while addressing the potential threats from climate change.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: S. J. Ohi, A. M. Kim; data collection: A. M. Kim; analysis and interpretation of results: S. J. Ohi; draft manuscript preparation: S. J. Ohi, A. M. Kim. All authors reviewed the results and approved the final version of the manuscript.

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Figure 1 How to select an appropriate count model

Figure 2 Flowchart for determining flight disruption of FlightStats data

Figure 3 Histogram of daily flight disruptions at YFB

Figure 4 Histogram of hourly flight disruptions at ANC

TABLE 1 Candidate Explanatory Variables

Category	Primary variable	Candidate variables
Operations	Flight	Arrivals, departures, total (arr+dep)
	Flight distance	% long (> 4000km), % medium (1500km-4000km), % short (< 1500km)
	Aircraft type	% heavy, % large, % medium, % small
	Seasonality	Month, season
Weather	Visibility	Min, max, average, median (daily & hour of operation)
	Wind speed	Min, max, average, median (daily & hour of operation)
	Crosswind speed	Min, max, average, median (daily & hour of operation)
	Head/tailwind speed	Min, max, average, median (daily & hour of operation)
	Temperature	Min, max, average, median (daily & hour of operation)
	Station pressure	Min, max, average, median (daily & hour of operation)
	Dewpoint	Min, max, average, median (daily & hour of operation)
	Precipitation	Total rain, total snow, total precipitation (rain+snow), snow cover

TABLE 2 Results of YFB Daily Disruption Count Models

	SNB		**NBH**		**ZINB**	
	Coefficient	**z-value**	**Coefficient**	**z-value**	**Coefficient**	**z-value**
Count model						
(Intercept)	-2.097	-8.522	-1.980	-8.000	-1.965	-7.977
ln(#Flight)	1.351	18.331	1.313	17.733	1.309	17.757
Min Visibility (mile)	-0.020	-10.377	-0.019	-10.043	-0.019	-10.045
Max Crosswind (knot)	0.019	4.952	0.020	5.163	0.020	5.126
Precipitation (mm)	0.013	2.873	0.013	2.921	0.013	2.935
$\ln(\theta)$	2.63	7.610	2.708	19.713	2.709	19.736
Excess-zero model						
(Intercept)	-	-	0.147^{+}	0.130	-0.916^{+}	-0.580
Min Visibility (mile)	-	-	-0.130	-3.096	0.137^{*}	2.537
#Flight	-	-	0.273	4.482	-0.256	-3.167
Model parameters						
θ	13.85		14.99		15.012	
Log-likelihood	-2120.87		-2114.68		-2114.98	
AICc	4253.8		4247.6		4248.2	

* *Significant at 95% confidence level; all others are significant at 99%.*

$^{+}$ *Intercepts of excess-zero model component are not significant*

TABLE 3 Results of ANC Hourly Delay Count Models (With Complete and Incomplete ASPM)

	Complete data		Zero-induced incomplete data			
	SNB		NBH		ZINB	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Count model						
(Intercept)	-0.793	-35.86	-1.237	-29.97	-1.275	-35.54
ln(#Flight)	0.806	123.58	0.882	70.31	0.893	72.45
Min Visibility (mile)	-0.046	-46.19	-0.052	-35.53	-0.051	-35.72
Max Crosswind (knot)	0.007	9.21	0.010	9.02	0.010	9.66
Min Temperature (^{o}C)	-0.004	-12.64	-0.005	-9.97	-0.006	-12.15
ln(θ)	1.864	15.80	1.244	49.06	1.243	49.23
Excess-zero model						
(Intercept)	-	-	-0.358	-8.44	-0.434	-6.31
Min Visibility (mile)	-	-	-0.085	-24.21	0.067	12.91
#Flight	-	-	0.089	77.63	-0.074	-35.49
Model parameters						
θ	6.45		3.47		3.46	
Log-likelihood	-125163.1		-106414.4		-106288.3	
AICc	250338		212846.8		212594.7	

All estimates are significant at 99% confidence level