Monthly analyses of convection-related irregular flights and their linear projections for the future climate in China

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Abstract
Convective weather such as thunderstorms and rain is one of the main causes of irregular flights including delays, cancelations, turnbacks and diversions. In China, summer (April–September) flights accounted for 94% of irregular flights due to convective weather in 2016–2019. The impact of summer convective weather conditions on irregular flights is however not well understood. In this research, we find that thunderstorms, as indicated by the lifted index (LI), are greatly related to these irregular flights over Southeast China. The global climate model ensemble indicates there will be robust increases in the occurrence of convective weather environments in response to further global warming. We also find that as the LI is decreasing over time, the likelihood of thunderstorm-related irregular flights is increasing. Such an increase indicates there will be a 17% increase in irregular flights by the end of the century.

1. Introduction
Irregular flights exist across the world, result in billions of dollars of losses for airlines and affect the plans of millions of passengers (Belcastro et al 2016). Weather, especially convective weather, poses threats to aviation safety and flight on-time performance (Kaplan et al 2006, Hentzen et al 2018). In China, 79% of flights are disrupted due to the convective weather from 2016 to 2019 according to the daily air operation records (CAAC 2020). Convective weather such as thunderstorms, lightning, heavy rain and strong wind can result in major irregular flights in air travel, leading to delays, cancellations, turnbacks and diversions of flights. Such weather can damage in-flight planes and airports, air traffic control centres, communication towers and navigation beacons (Yair 2018). Therefore, it is necessary to explore the impact of convective weather on irregular flights to help reduce the costs incurred by airlines and the anxiety of passengers.

Due to climate change, many meteorological factors that potentially affect aviation have also changed. Previous research suggests that both future increasing temperatures and strong winds will decrease aircraft performance (Coffel et al 2017, Zhou et al 2018, Gratton et al 2020). Changes in wind also affect travel time length and clear air turbulence (Williams and Joshi 2013, Karnauskas et al 2015, Kim et al 2016, 2020, Williams 2016). Increasing research suggests that the occurrence and intensity of convective weather have been amplified due to climate change and will continue to increase in the future (Diffenbaugh et al 2013). There is a critical gap in our understanding of how future changes in the frequency, distribution and intensity of thunderstorms will affect future aviation. Therefore, research exploring the future trend of irregular flights is important (Belcastro et al 2016).

The purpose of this research is to explore the effect of climate change on convective weather, providing information greatly needed for aviation. To achieve this goal, we first analyse the irregular flights situation in China from 2016 to 2019.
irregular flights and predict the impact of these key factors in this region by the end of this century. The lifted index (LI) and convective available potential energy (CAPE) are measurements of the environmental conditions to produce severe thunderstorms (Pucik et al 2017, Yair 2018). Therefore, we use moderate-to-heavy rain-, LI- and CAPE-related variables in this work to indicate the likelihood of convective weather.

2. Methods and data

2.1. Data

Daily data on flight delays, cancellations, turnbacks and diversions were obtained from the Operation Supervisory Center of Civil Aviation Administration of China (CAAC). The irregular situations are determined by on duty air traffic controllers and on duty airflow controllers. The daily operation report includes the number of scheduled flights, the number of all irregular flights and the number of irregular flights due to convective weather (CAAC 2020). The total number of scheduled flights in 2016–2019 (excluding the December data in 2019) is over 14.7 million (figure S2). The irregular flights due to convective weather is determined and recorded by dispatchers of airlines, air traffic controllers and pilots according to the real-time weather condition. Note that both domestic and international flights are included. The turnbacks and diversions flights are categorized in one group. The category for irregular flights in this work could be subjective to people (i.e. dispatcher, controller) and regulation (i.e. airline, pilot).

The typhoon data are obtained from the China Meteorological Administration (CMA) Tropical Cyclone Data Center (Ying et al 2014) (http://tcddata.typhoon.org.cn/dlrdqx_zl.html) and the China Weather (http://typhoon.weather.com.cn/). The weather-related variables including precipitation, air temperature and specific humidity were obtained from ten Coupled Model Intercomparison Project, Phase 5 (CMIP5) models (table S1) for the Representative Concentration Pathway 8.5 (RCP8.5) ‘business-as-usual’ scenario, indicating a high-emission of greenhouse gas. These ten models provide 4D atmospheric variables, including data for eight air pressure layers (1000 hPa, 850 hPa, 700 hPa, 500 hPa, 250 hPa, 100 hPa, 50 hPa and 10 hPa). All model data are gridded to a 1° × 1° resolution.

2.2. Methods

The target region in this work is Southeast China, which refers to the east area of the Hu Line of China (figure S1). This region covers 43% of the national area, but 94% of the population (Naughton 2007). Due to the huge population, this region is also more economically advanced with far more airport flights compared to the other region (Li et al 2015).

We focus on summer months (April–September) when thunderstorms are most active and intense. To investigate the response of thunderstorms to climate change, we use the R package ‘airThermo’ to calculate CAPE and LI. A high CAPE (>1500 J kg⁻¹) or a low LI (≤−2 °C) indicates a high potential of thunderstorms (Pucik et al 2017, Singh et al 2017). Note that high CAPE and low LI do not guarantee to have severe thunderstorms because there are several other meteorological factors to be involved in severe thunderstorms and their impact to aviation operations. In addition, moderate and heavy rain greatly affects runway conditions and is also associated with thunderstorms. Therefore, we use moderate and heavy rain-, LI- and CAPE-related variables as candidate variables to represent the convective weather conditions. We applied a bias-correction method (Piani et al 2010) to correct the modelled precipitation.

2.2.1. Geostatistical regression model

We use a geostatistical regression model (GRM) to represent the relationship between the number of irregular flights and selected weather covariates at a monthly resolution. GRM accounts for both the autocorrelation in the observations and multicollinearity among covariates (Mueller et al 2010, Yadav et al 2010). GRM is particularly useful when temporal correlation is present within the regression residuals. If correlation is present but not modelled, traditional statistical inference techniques (e.g. multiple linear regression) may result in incorrect identification of a significant relationship (Faraway 2014) and misleading conclusions. Irregular flights (z) can be represented as the sum of a deterministic component and a stochastic term:

\[ z = X + z_{res}, \]  

where is a known matrix of auxiliary variables including constant, \( \beta \) is a vector of unknown drift coefficients on these variables and \( z_{res} \) is a vector of residuals. The stochastic term \( z_{res} \) is modelled as temporally correlated residuals. A covariance function (Chiles and Delfiner 1999), which quantifies the degree to which the temporal correlation between a pair of residuals decays as a function of their separation time lag \( t \) is defined as

\[ Q(t) = \begin{cases} \sigma^2 + \sigma^2_0, & t = 0 \\ \sigma^2 \exp \left(-\frac{t}{\tau}\right), & t > 0, \end{cases} \]  

where \( \sigma^2 \) is the variance of the portion of the residual irregular flights variability that is temporally correlated, \( \sigma^2_0 \) is the practical correlation range and \( \sigma^2_0 \) is the variance of the portion of the variability that is not temporally correlated (e.g. measurement error). These three model parameters were optimized by fitting the theoretical model to the empirical covariance of the residuals using restricted maximum likelihood.
by minimizing the cost function below (Mueller et al 2010)

\[ L \propto -\frac{1}{2}(z - X\beta)^\top Q^{-1}(z - X\beta). \]  

(3)

The best estimate of drift coefficients (\( \hat{\beta} \)) of the auxiliary variables were obtained as (Chiles and Delfiner 1999)

\[ \hat{\beta} = (X^\top Q^{-1}X)^{-1}X^\top Q^{-1}z, \]  

(4)

where T denotes a matrix transpose. The coefficient of determination \( R^2 \) is calculated as

\[ R^2 = 1 - \frac{\| z - X\hat{\beta} \|^2}{\| z - \bar{z} \|^2}, \]

(5)

where \( \bar{z} \) represents the mean of the observations.

2.2.2. Bayesian information criterion

We use the group Bayesian information criterion (BIC) to identify the model (i.e. the subset of candidate explanatory variables) that has the strongest power of explaining the number of irregular flights (Zhou et al 2015). BIC considers both the goodness of fit and the number of variables in a candidate model (Anderson et al 1998, Mueller et al 2010, Zhou et al 2013) and is defined as

\[ \text{BIC} = -2\ln(L) + p\ln(n) \]  

(6)

where \( L \) is likelihood of the observations. If the residuals are correlated and normally distributed, the negative natural logarithm of the likelihood becomes (Mueller et al 2010)

\[ -\ln(L) = \frac{1}{2}\ln|Q| + \frac{1}{2}z^\top \left( Q^{-1} - Q^{-1}X(X^\top Q^{-1}X)^{-1}X^\top Q^{-1} \right)z. \]  

(7)

Overall, the model with the lowest BIC is considered as the best model. However, given the relatively small sample size here, we used a BIC difference of 2 as the threshold for choosing a smaller model with a higher BIC over a larger model with a lower BIC (Raftery 1995). As many covariates are strongly collinear and representative of similar types of driving processes, we include at most one variable from each of the two categories of variables in the selected model (table S2).

3. Results

3.1. Irregular flights situation in China from 2016 to 2018

From 2016 to 2019, there were about 108,000, 137,000, 109,000 and 148,000 annual irregular flights caused by convective weather. The irregular flights included 82% flight delays, 14% flight cancelations as well as 4% flight turnbacks and diversions (figure 1). During these four years, 94% irregular flights in China occurred from April to September, which indicates that the effect of convective weather on flights mostly occurred during this time period. Irregular flights occurred the least from October to March, as the atmospheric situation is most stable during this time in China. The most irregular flights occurred during the warm season because the major international airports in China are mostly located in mid- and low-latitude areas, where the convective weather is more intense in summer (e.g. thunderstorms, rainfall) than in winter (e.g. blizzards, snow).

Large number of flight cancelations were mainly due to typhoons. The extremely high flight cancellation rate in August 2019 was due to the Super Typhoon Lekima, which experienced landfall in Zhejiang Province in the middle of Southeast China. Although there were super typhoons in other years (table S3), the number of flight cancelations was not as large. This is because these typhoons experienced landfall in the southern area of China, including Guangzhou and Xiamen, did not cause large spatial effects for flights. In addition, most irregular flights occurred at airports of Southeast China, which has a relatively high number of airports and airlines. This area is also more economically developed and has a greater population than other areas of China. From 2016 to 2019, there are more days that are affected by convective weather in Southeast China than the other area. (figure S1).

3.2. Weather variables affect irregular flights in Southeast China

We explored the convective weather situation, including rain and thunderstorm-related variables (table S2). We analysed the relationship between these variables and irregular flights in the Southeast China region instead of at individual airports or airlines because the convective weather around both airports and airlines affect flights. Both the spatial extent and severity of the weather factors influenced the flight on-time performance.

Among the variables examined in table S2, irregular flights numbers were mostly explained by the mean LI over the examined region according to our group BIC and GRM results (figures S3 and S4). The relationship between the monthly irregular flights (\( F \), 1000 flights) from April to September 2016–2019 and the monthly LI (LI, °C) is shown as the equation below.

\[ F = -5.93 \times \text{LI} + 36.51. \]  

(8)

This model explained 66% (i.e. \( R^2 \)) of the variability in irregular flights. That is, the variance of the fitting numbers account for the 66% of variance of the original numbers. The irregular flights in equation (8) refers to those removing the irregular
flights during the six super typhoon events (table S3), because we noticed that super typhoons could cause exceptionally large numbers of delays, cancellations or turnbacks and diversions. When these irregular flights due to typhoon events were not removed, the model explained 62% of the variability. As expected, the monthly irregular flights were negatively correlated with the monthly LI. A negative LI indicates that there is a large chance of experiencing a severe thunderstorm, which would further disturb on-time flights. These results suggest that monthly LI could be a better indicator than any CAPE or rain-related variable for irregular flights in Southeast China.

3.3. Future irregular flights in Southeast China
During warm season (April–September), the mean LI of Southeast China will decrease (i.e. become more unstable) from 2.96 °C at present (2006–2025) to 2.52 °C by the end of century (2081–2100) in response to the RCP8.5 forcing pathway (figures 2(a) and (b)). At present, the lowest LI is in Yunnan, Guangxi and Hainan Province (the black box in figure 2(a)). LI robustly decrease (i.e. more unstable) in most regions of Southeast China, ranging from 2% to 199% (figure 2(c)) or from −0.93 °C to −0.04 °C (figure 2(d)). The largest and most robust decreases will occur over the central southeast China. East Guangxi Province (the black box in figure 2(c)) will exhibit the largest relative decrease, whereas in Huabei Plain especially Shandong Province (the black box in figure 2(d)) will exhibit the largest absolute decrease. Such results indicate there will be more potential irregular flights due to convective weather in the future.

As the LI changes, the irregular flights may also change based on their relationship indicated in equation (1). If all other related factors remain at the present values, we find that anticipated changes in future LI alone will lead to a 17% (3.1 thousand per month in Southeast China) irregular flights increase during warm season (April–September) by the end century (figure 3). Such an increase is robust under the RCP8.5 scenario. All other related factors here refer to the total number of annual flights, flight management efficiency and aircraft design etc.

4. Discussion
In China, most popular airlines and airports are located in Southeast China, which is greatly affected by thunderstorms and heavy rains during the warm
season. LI is the weather factor that is most correlated with irregular flights. The simulated LI shows a high likelihood of increasing thunderstorms over the century, which indicates there will be more irregular flights due to convective weather in the future. As the civil aviation administration is improving flight on-time management efficiency, weather forecasting skill, and flight technologies, the impact of convective weather may become minor. Our results could serve as a reference for airports in improving management and for passengers in making future travelling plans. Due to the increasing trend of monthly averaged convective weather conditions, fewer flight travels during summer in the future are suggested.

One caveat of this work is that we did not consider other spatial and temporal scales of modes in atmosphere due to the limited irregular flight data. Here, we only consider convective weather conditions. Other weather conditions, such as fog and blizzards, also affect flight on-time performance. As shown in our research, super typhoons are the main cause of high rates of cancelled flights and their landfall location matters. For the future prediction, effect of super typhoons is not considered, because the CMIP5 models are not able to predict typhoon activities. The research on how these weather conditions affect the flight performance is also required. In addition, we focus on the analysis of the entire busy region in this research. Different airports and airlines have specific characteristics and weather conditions. More research on the analysis of individual airports is needed in the future.
Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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