# Assessing the Impact of Flight Activity on Urban $NO_2$ Pollution During The COVID-19 Pandemic in China

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## I. Introduction

Air pollution represents one of the most pressing environmental challenges facing urban areas worldwide, with significant implications for public health, climate change, and urban sustainability [1]. Among the various contributors to urban air pollution, aircraft emissions have been increasingly recognized as a significant source of nitrogen dioxide ($NO_2$) and other pollutants. The aviation industry's rapid growth in recent decades has raised concerns about its environmental footprint, particularly in densely populated urban centers near major airports.

The 2020 COVID-19 pandemic presented an opportunity to study the relationship between air traffic and urban air quality, as global travel restrictions were implemented to contain the spread of the virus, air traffic volumes decreased dramatically, creating a natural experiment to examine how changes in flight activity impact atmospheric pollutant concentrations. China, being among the first countries to implement strict lockdown measures and subsequently experience varying degrees of recovery in air travel, provides an ideal case study for this analysis [6].

Understanding the spatial and temporal relationships between flight trajectories and urban $NO_2$ concentrations is crucial for several reasons. First, it can help quantify aviation's contribution to urban air pollution under normal operating conditions. Second, it can inform air traffic management strategies and policy decisions aimed at mitigating adverse environmental impacts. Finally, it can provide insights into how future changes in aviation technology and flight patterns might affect urban air quality and public health.

**II. Research Question**

How can spatial and temporal variation in flight trajectories explain changes in urban $NO_2$ concentrations during the COVID-19 pandemic in China?

**III. Methods**

1. **Data Sources Collection**
   a. **Flight trajectory data**: Obtained from the OpenSky Network [2], providing comprehensive information on flight paths, altitudes, origins, and destinations for the period spanning January 2019 - December 2020.
   b. **Satellite $NO_2$ data**: Sourced from the Copernicus Sentinel-5P TROPOMI [3], which provides high-resolution measurements of tropospheric $NO_2$ concentrations.
   c. **Wind speed data**: Monthly wind speed components (u10 and v10) were obtained from the monthly ECMWF ERA5 [4], which provides global atmospheric conditions.
   d. **Administrative boundaries**: City-level boundaries for China were extracted from the GADM [5], providing the spatial framework for analyzing data.
2. **Data Processing and Analysis**
   a. **Flight data preparation**: Flights to/from 58 major Chinese airports were filtered from global data (2019–2020), categorized by four COVID-19 phases: pre-COVID (Jan-Dec 2019), early outbreak (Jan-Feb 2020), disruption (Mar-May 2020), and recovery (Jun-Dec 2020), and used to compute average flight altitudes.

b. **Satellite data processing**: Sentinel-5P $NO_2$ rasters were averaged by phase, clipped to China, and city-level $NO_2$ means were extracted.

c. **Wind data integration**: ERA5 wind components (u10, v10) were used to calculate wind speed, aggregated by phase, and merged with flight and pollution data for analysis.

**3. Variable Selection and Rationale**

a. **Flight count**: Serves as a proxy for aviation activity and $NO_x$ emissions. More flights typically lead to higher $NO_2$ levels due to increased fuel combustion, therefore, a positive relationship with $NO_2$ is expected.

b. **Average Flight Altitude:** Higher altitudes may reduce ground-level pollution due to better dispersion and greater distance from surface receptors. Aircraft also emit more efficiently at cruising altitudes.

c. **Wind Speed:** Wind enhances pollutant dispersion, shortens residence time, and affects chemical mixing, in which the speeds are linked to lower $NO_2$ concentrations near emission sources.

d. **Flight Count × Wind Speed:** The interaction captures how wind conditions moderate the pollution impact of flights, in which under low wind, emissions might accumulate locally, while high wind disperses them more quickly, reducing local concentration spikes.

**4. Statistical Modelling**

A fixed-effects panel regression model was constructed to analyze these relationships:

$$NO2_{it} = \alpha + \beta_1 \cdot Flights_{it} + \beta_2 \cdot Altitude_{it} + \beta_3 \cdot Wind_{it} + \beta_4 \cdot (Flights_{it} \times Wind_{it}) + \gamma_i + \delta_t + \varepsilon_{it}$$

where:

- $NO2_{it}$: Mean $NO_2$ concentration in city i during phase t (dependent variable)

- $Flights_{it}$: Number of flights in/out of city i at time t
- $Altitude_{it}$: Average altitude of flights in city i at time t, measured in feet or meters
- $Wind_{it}$ : Mean wind speed in city i at time t, derived from ERA5 u10 and v10 components
- ($Flights_{it} \times Wind_{it}$): Interaction term capturing how wind speed moderates the impact of flights on $NO_2$
- $\gamma_i$ : City-specific fixed effects accounting for unobserved characteristics
- $\delta_t$: Time (phase) fixed effects capturing variation across COVID-19 periods
- $\varepsilon_{it}$: Error term capturing unobserved factors.

This specification allows for isolating the effects of aviation activity on $NO_2$ concentrations while accounting for the complex role of wind in pollution formation, transformation, and transport.

## III. Results

**Regression Analysis of Flight Activity and $NO_2$ Concentrations**

| Variable | Estimate | Std. Error | t-value | Pr( > \| t \| ) |
|---|---|---|---|---|
| flight_count | $2.6810 \times 10^{-9}$ | $9.5700 \times 10^{-10}$ | 2.8009 | 0.0054** |
| wind_speed | $1.1474 \times 10^{-6}$ | $1.6168 \times 10^{-6}$ | 0.7097 | 0.4784 |
| avg_altitude | $3.3300 \times 10^{-10}$ | $3.3300 \times 10^{-10}$ | 0.4886 | 0.6255 |
| flight_count:wind_speed | $-2.9580 \times 10^{-9}$ | $1.1590 \times 10^{-9}$ | –2.5528 | 0.0111* |

*Note: significant codes 0.001 ‘**’, 0.05 “*”*

| | |
|---|---|
| **Adjusted $R^2$** | 0.83602 |
| **Within $R^2$** | 0.003751 |

**Table 1.** Output Summary from Fixed-effects Panel Regression Model

As we can see from **Table 1**, the model revealed significant relationships between flight activities and $NO_2$ concentrations across Chinese cities during different phases of the COVID-19 pandemic. It has achieved an adjusted $R^2$ of 0.83602, indicating that approximately 83.6% of the variation in $NO_2$ concentrations was explained by the included variables and fixed effects.

Flight count demonstrated a statistically significant positive relationship with mean $NO_2$ concentrations ($\beta = 2.6810 \times 10^{9}$, $p = 0.005$), confirming that higher numbers of flights were associated with increased $NO_2$ levels in urban areas. This relationship was consistent across the different pandemic phases, suggesting that aviation emissions directly contribute to urban air pollution regardless of other temporal factors.

While average flight altitude showed a positive coefficient ($\beta = 3.3300 \times 10^{-10}$), this relationship was not statistically significant ($p = 0.625$). This suggests that within the range of altitudes observed in the dataset, variations in flight altitude alone did not consistently predict changes in ground-level $NO_2$ concentrations.

Wind speed as an independent variable also did not show a statistically significant direct effect on $NO_2$ concentrations ($\beta = 1.1474 \times 10^{-6}$, $p = 0.479$). However, the interaction term between flight count and wind speed revealed a significant negative relationship ($\beta = -2.9580 \times 10^{-9}$, $p = 0.011$). This indicates that the effect of flight activity on $NO_2$ concentrations was moderated by wind conditions, specifically, the impact of flights on $NO_2$ levels diminished as wind speed increased.

## Spatial and Temporal Patterns in $NO_2$ Distribution

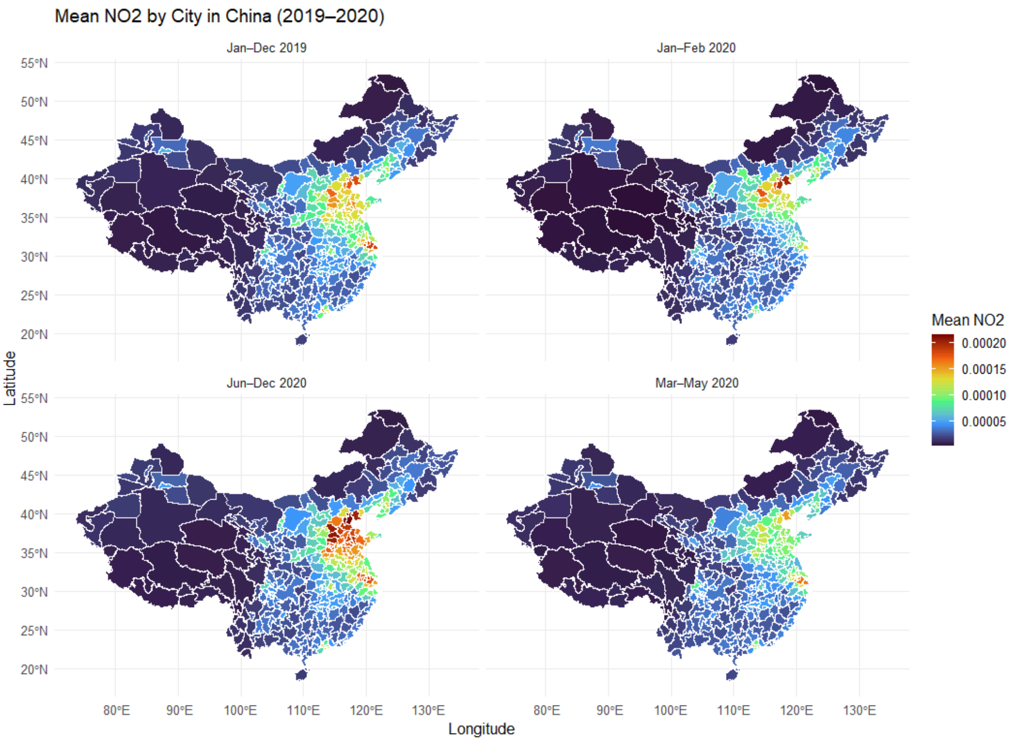


**Figure 1.** Temporal Changes in Mean $NO_2$ Concentrations Across Chinese Cities During COVID-19 Phases

As shown by **Figure 1,** there were distinct spatial patterns where the highest $NO_2$ concentrations were consistently observed in major urban and industrial centers, particularly in eastern China around Beijing, Shanghai, and the Pearl River Delta region.

Temporal analysis showed noticeable changes in $NO_2$ distribution across the pandemic phases. While pre-COVID patterns (Jan-Dec 2019) established a baseline of relatively high $NO_2$ concentrations in urban centers, the early outbreak phase (Jan-Feb 2020) exhibited slight reductions in these areas. The disruption phase (Mar-May 2020), when stringent lockdown measures and travel restrictions were implemented, displayed the most pronounced decrease in $NO_2$ concentrations across most cities.

Interestingly, the recovery phase (Jun-Dec 2020) showed a rebound in $NO_2$ levels in many urban areas, with some regions exhibiting concentrations that exceeded pre-pandemic levels. This pattern aligns with the resumption of domestic flights and economic activities in China while international travel remained restricted, potentially leading to intensified domestic aviation activity in certain hubs.

**IV. Conclusion**

This study provides empirical evidence of the relationship between flight activities and urban $NO_2$ concentrations in China during the COVID-19 pandemic. The findings demonstrate that flight count is a significant predictor of $NO_2$ pollution levels, with this relationship being moderated by wind speed. These results underscore the environmental impact of aviation on urban air quality and highlight the potential benefits of aviation management strategies that account for meteorological conditions.

The significant negative interaction between flight count and wind speed suggests that the environmental impact of aviation activities is context-dependent, with meteorological factors playing an important role in determining pollution outcomes. This has important implications for air traffic management, particularly in terms of flight scheduling during different weather conditions to minimize pollution impacts on urban populations.

While the analysis did not find a significant direct relationship between flight altitude and $NO_2$ concentrations, this does not necessarily negate the importance of altitude in pollution dynamics. The lack of statistical significance may reflect limitations in the data or the complexity of altitude-pollution relationships that were not fully captured in the model.

The spatial and temporal analysis of $NO_2$ concentrations across China during different pandemic phases revealed that pollution levels are responsive to changes in aviation activity, but this relationship is embedded within broader patterns of economic activity and policy interventions. The rebound in $NO_2$ levels during the recovery phase, despite continued international travel restrictions, highlights the significant contribution of domestic flights to urban air pollution.

Future research should explore the relationship between flight activities and other pollutants, such as particulate matter and ozone, to provide a more comprehensive understanding of aviation's environmental footprint. Further investigation into the role of flight altitude in pollution dispersal is warranted, potentially using more granular flight trajectory data and advanced atmospheric dispersion models. Long-term monitoring of the relationship between flight patterns and air quality as the aviation sector continues to recover and evolve post-pandemic would provide valuable insights for sustainable aviation planning.

**References:**


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