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Aviation's emissions and contribution to the air quality in China

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ABSTRACT

With a rapid increase in air traffic, aviation has become an increasingly important contributor to anthropogenic air pollutants (particularly nitrogen oxides (NO_X)) over China. This study provides the first overall estimation of the aviation emissions from all civil airports in mainland China as well as the associated contribution to ambient air quality. First, aircraft emissions (NOx, sulfur dioxide (SO_2), carbon monoxide (CO), hydro-carbons (HC), particulate matter ($PM_{2.5}$ and PM_{10}), volatile organic carbons (VOCs) and black carbon (BC)) during landing and take-off cycles (below 3 km) are estimated for both recent (2000–2016) and future (2020) scenarios. Second, the corresponding environmental impacts are measured by the Comprehensive Air Quality Model with extensions (CAMx). The results have insightful policy implications for China's aviation planning. (1) Generally, China's aviation emissions and their effect on air quality have been and will continue to increase. (2) Among species, NOx dominated China's aircraft emissions in terms of both emission amount and environmental impact, while $PM_{2.5}$ generated an extensive influence. (3) With respect to spatial distribution, the air quality effect was highly concentrated at emission-intense airports that served economic zones and/or tourist spots.

1. Introduction

The aviation sector, with a fast-growing market demand, has played and will continue to play an increasingly substantial role in China's economic system. According to the Civil Aviation Administration of China (CAAC), aviation has become an important mode of transportation in China, and the annual number of air passengers and amount of freight reached 440 million and 6.68 million tons in 2016, respectively—approximately 2.75 and 1.92-fold above the figures for 2006 (CAAC, 2016). Furthermore, such a developmental tendency will remain, and CAAC (2016) projected annual average increases of 10.4% and 6.2% for air passengers and freight, respectively, during 2015–2020. Accordingly, approximately 720 million passengers and 8.5 million tons of freight are expected to fly in 2020.

Despite its vital role in economy, the aviation sector presents severe environmental concerns, emitting massive amounts of air pollutants, thereby deteriorating the ambient air quality. Aircraft activities, particularly landing and take-off (LTO) cycles (USEPA, 1992), generate a large amount of harmful air pollutants, such as nitrogen oxides (NOx), sulfur dioxide (SO_2), carbon monoxide (CO), hydro-carbons (HC), particulate matter ($PM_{2.5}$ and PM_{10}), volatile organic compounds (VOCs) and black carbon (BC) (Song and Shon, 2012). These emissions interact with each other and adversely impact the ambient atmospheric environment, leading especially to haze or smog weather at the ground level (Mahashabde et al., 2011) and a long-range effect on the ozone layer (Janić, 1999; Brasseur et al., 1998). Furthermore, extended exposure to these harmful air pollutants (particularly $PM_{2.5}$) seriously threatens human health, particularly with respect to heart and lung diseases (Boldo et al., 2006; Franklin et al., 2007; Kampa and Castanas, 2008) and even causing premature death (Yim et al., 2013). Therefore, environmental concerns regarding the aviation sector have received growing and widespread attention.

Given this background, numerous studies have been conducted to explore the impacts of aviation emissions on air quality, and the analytical techniques used generally fall into monitoring and dispersion modelling-based approaches (Unal et al., 2005; Carslaw et al., 2008; Mazaheri et al., 2011; Hu et al., 2009; Hsu et al., 2014). In particular, the monitoring approaches measure the related variables (aircraft activity, meteorology, pollutant concentrations, etc.) and then perform statistical analyses on these measurements to estimate the aviation-

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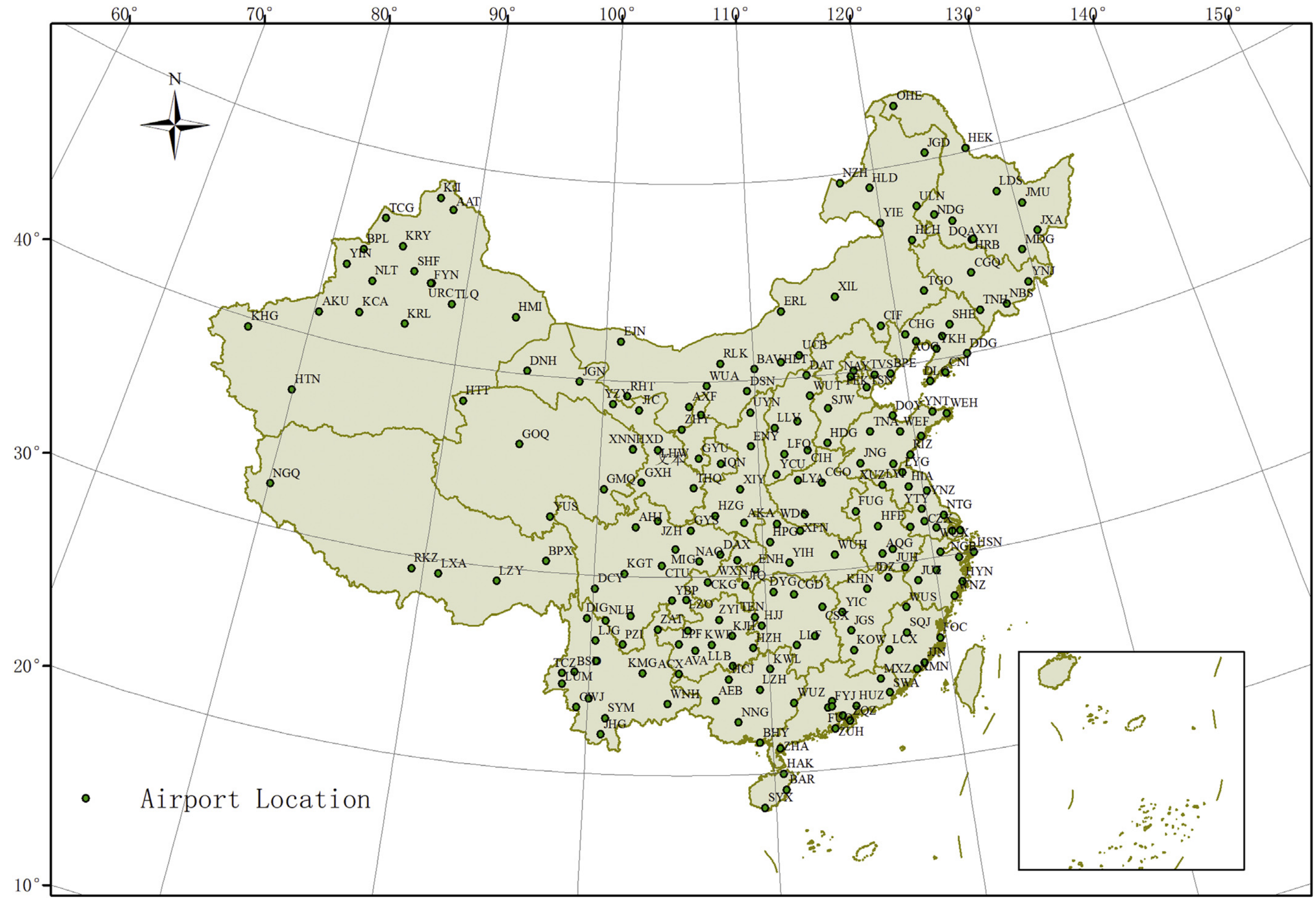


Fig. 1. Civil airports in mainland China.

attributable fractions; these approaches are suitable for analysing individual airports on a small scale (Penn et al., 2015). The dispersion modelling-based approaches employ meteorology and numerical models to simulate air quality on a large scale both horizontally and vertically (Beelen et al., 2010). With respect to their advantages and disadvantages, though highly accurate, the monitoring methods might be somewhat limited to a relatively small scale in terms of the study period, spatial coverage, meteorological conditions and flight activities (Penn et al., 2015). In comparison, the dispersion modelling based methods overcome these limitations (Beelen et al., 2010). Popular dispersion models for studying aviation emissions contribution to air quality include the Comprehensive Air Quality Model with extensions (CAMx) (Foy et al., 2015; Tang et al., 2013), the Community Multiscale Air Quality model (CMAQ) (Brunelle-Yeung et al., 2014), and the American Meteorological Society and Environmental Protection Agency Regulatory model (AERMOD) (Penn et al., 2015). Compared with other models, CAMx, a multi-scale regional chemical transport model, particularly specializes in capturing synergistic effects among multiple pollutants involved in different atmospheric physical processes and chemical reactions (Bossioli et al., 2013). Accordingly, the CAMx model has widely been applied to analysing the impacts of aviation emissions, e.g., in the US (Foy et al., 2015; Tang et al., 2013; Kemball-Cook et al., 2009; Junquera et al., 2005) and Brazil (Borrego et al., 2010).

However, the existing research on China's aviation emissions and their environmental impacts is insufficient. On one hand, an overall estimation of aviation emissions from all China's airports is lacking, to the best of our knowledge. In particular, previous studies were usually restricted to one or several airports in China. For example, Bo et al. (2017) focused on the emissions from Beijing Capital International Airport of China and simulated their impact on the surrounding atmospheric environment. On the other hand, in studies with relatively sufficient samples, such as that by Xia et al. (2008) for 123 airports in China, aviation emissions were calculated, whereas the related contribution to air quality was otherwise ignored. Therefore, the present study intends to fill this gap in the literature and provide an overall inventory of aviation emissions from all the civil airports in mainland China (involving a total of 217 airports) as well as the related contribution to the ambient air quality.

To the best of our knowledge, this study is the first attempt to provide an overall, detailed estimation of aviation emissions from all civil airports in mainland China as well as their corresponding contribution to air quality. In particular, the aircraft emissions (NOx, SO_2, CO, HC, $PM_{2.5}$, PM_{10}, VOCs and BC) from a total of 217 airports in China are calculated for both recent (2000–2016) and future (2020) scenarios. In particular, emissions during the LTO activities below 3 km, accounting for most contributions to the ambient atmospheric environment (USEPA, 1992), are focused on in this study. Furthermore, the environmental impact of China's aviation emissions is simulated using the CAMx model (Foy et al., 2015; Tang et al., 2013).

2. Methodology

This study provided an inventory of aviation emissions from all China's civil airports for both recent (2000–2016) and future (2020) scenarios and estimated the corresponding air quality contributions based on the CAMx model, a multi-scale regional chemical transport model (Bossioli et al., 2013).

Accordingly, two major steps were taken in this study. (1) The first was inventory establishment for aviation emissions, in which the recent (2000–2016) and future (2020) aircraft emissions (NOx, SO_2, CO, HC, $PM_{2.5}$, PM_{10}, VOCs and BC) during LTO cycles (below 3 km) from different civil airports in mainland China were estimated. (2) The second was atmospheric modelling for the air quality contribution, in which the CAMx model was implemented to explore the impacts of China's aviation emissions on the ambient environment. Sections 2.1 and 2.2 elaborate on these two main steps, respectively, together with the related techniques.

2.1. Emission estimation

The aviation emissions for recent (2000–2016) and future years (2020) were computed (i.e., NOx, SO_2, CO, HC, $PM_{2.5}$, PM_{10}, VOCs and BC), as presented in Sections 2.1.1 and 2.1.2, respectively. Fig. 1 displays the geographic locations and codes of the International Air Transport Association (IATA).

2.1.1. Recent emissions

The contribution of aviation emissions to the ambient environment varies greatly across different aircraft activities (Song and Shon, 2012). The LTO cycles have widely been considered to impact the ground-level air quality greatly, which is within the planetary boundary layer (typically below 1–3 km) (Woody et al., 2011; Jacob, 1999). Therefore, this study especially focused on the LTO emissions from the surface to 3 km altitude. A LTO cycle covers two aircraft operations, landing (approach, landing, and taxi-in to the gate) and take-off (taxi-out onto the runway, take-off and climb-out) (ICAO, 1995). Typical estimation methods for aircraft LTO emissions at airports are the Tier 1 and Tier 2 methods (EEA, 2009; IPCC, 2006). The Tier 1 method calculates emissions in terms of the aggregate activity data multiplied by the corresponding average emission factors:

$$E_{i,j,t} = LTO_{i,t} \cdot EF_j, \tag{1}$$

where $E_{i,j,t}$ is the annual emissions of air pollutant j at airport i for year t (in kg), $LTO_{i,t}$ is the total number of LTO cycles conducted at airport i for year t, and EF_j is the general emission factor of air pollutant j per LTO cycle (kg/LTO) (as listed in Table 1). The Tier 2 method relies on detailed data for each aircraft type, engine type, and mode:

$$E_{i,m} = \sum_a \sum_e n_a I_{a,e} F_{a,e,m} E_{e,m,i} t_{m,a}, \tag{2}$$

where $E_{i,m}$ indicates the annual emissions of pollutant i for mode m (kg/y), n_a is the total number of engines of aircraft type a, $I_{a,e}$ is the number of annual LTO cycles for aircraft type a with engine type e, $F_{a,e,m}$ is the fuel consumption for aircraft type a with engine type e in mode m (kg/s), $E_{e,m,i}$ is the emission factor of engine type e in mode m for pollutant i (g/kg), and $t_{m,a}$ is the time in mode m for aircraft type a (s).

A comparison of Eq. (1) and Eq. (2) clearly reveals a considerable difference between the Tier 1 and Tier 2 methods. While the former is based on overall activity data of each airport, the latter requires much more detailed data for each aircraft type and engine type and the mode of each airport. Currently, the detailed data required for Tier 2 are not available for different airports nationwide. Therefore, the Tier 1 method, a simple estimation approach (Romano et al., 1999), was employed in this study. Nevertheless, collecting the missing data and providing a much more precise estimation for China's aviation emissions would be valuable in the near future.

Concerning data sources, the annual numbers of LTO cycles at different airports were collected by CAAC. Data quality control, involving missing data detection, error detection and possible error corrections (Zahumenský, 2004), was conducted for the original data, and the results supported the applicability and usability of the data. Emission factors are widely available, e.g., in the Federal Aviation Administration's Aviation Environmental Design Tool (Kim et al., 2007), FAA-recommended Emissions and Dispersion Modelling System (FAA, 2010), and International Civil Aviation Organization-engine Emission Data Bank (ICAO, 1995). In this study, emission factors for PM_{10}, $PM_{2.5}$, HC, NOx, CO, VOCs and BC were from the Ministry of Environment Protection of the People's Republic of China (MEP, 2011) and that for SO_2 was from Wang et al. (2018), as listed in Table 1.

Table 1
Aircraft emission factors (kg/LTO).

Emission species	PM_{10}	$PM_{2.5}$	HC	NOx	CO	VOCs	BC	SO_2
Emission factor	0.54	0.53	2.68	16.29	9.14	1.95	0.26	1.40

2.1.2. Future emissions

The future scenario for 2020 was designed according to the related planning and historical data (Yang et al., 2017; Ratanavaraha and Jomnonkwao, 2015). In particular, the 13th Five-Year Plan for the Development of Civil Aviation in China projected an upward growth in aviation demand—approximately 0.72 billion passengers and 8.5 million tons of freight are expected to fly in 2020. Accordingly, the overall activity data, i.e., the aggregated LTO numbers throughout mainland China, were assumed to follow similar development towards such expected demands.

Individual trends for different airports were captured based on the historical data for 2000–2016 by using a typical econometric time-series technique, autoregressive integrated moving average (ARMA) (Box and Jenkins, 1976). The ARMA model includes two types of linear-regressions: autoregressive (AR) and moving average (MA). Given a time series y_t, $t \in \mathbf{N}$ (i.e., annual LTO numbers of an individual airport for the period t for this study), the AR regression function is defined as follows:

$$y_t = c + a_1 y_{t-1} + \ldots + a_p y_{t-p} + u_t, \tag{3}$$

where $a_1, \ldots, a_p$ are the AR parameters, c is a constant, p is the order of the AR, and u_t is the white noise (error). The MA model is as follows:

$$y_t = \mu + u_t + m_1 u_{t-1} + \ldots + m_q u_{t-q}, \tag{4}$$

where $m_1, \ldots, m_q$ are the MA parameters, q is the order of the MA, u_t, u_{t-1}, …, u_{t-q} are the white noise terms, and μ is the expectation of y_t. By coupling Eq. (3) with Eq. (4), an ARIMA(p, q) model can be formulated:

$$y_t = c + a_1 y_{t-1} + \ldots + a_p y_{t-p} + u_t + m_1 u_{t-1} + \ldots + m_q u_{t-q}. \tag{5}$$

A least-square estimation was conducted to determine the ARMA parameters, and future values were projected based on Eq. (5) and the historical observations.

It was assumed that there will still be 217 airports in mainland China in 2020 without a new airport built or a constraint on the capacity of each airport (Yim et al., 2013). The future-year estimates did not consider mitigation strategies, technology improvements, policy reforms, or other related notable changes. Introducing the expected activity data into Eq. (1) allows the future emissions to be projected.

2.2. Air quality modelling

The CAMx model, a popular chemistry transport model, was employed to explore the contribution of China's aviation emissions to the air quality for the recent (2016) and future (2020) scenarios (Foy et al., 2015; Tang et al., 2013). Specifically, the CAMx model is a regional chemical transport model and runs based on meteorological data and a well-built inventory of background emissions or target emissions (i.e., aviation emissions that are obtained by the estimation method described in Section 2.1). Meteorology data and background emissions are described in Sections 2.2.1 and 2.2.2, respectively, and Section 2.2.3 presents the air quality modelling.

2.2.1. Meteorological data

In the atmospheric simulation, the meteorological field for 2016 was derived from the Weather Research and Forecasting model (WRF 3.4) (Yim et al., 2013; Wang et al., 2016). In particular, the WRF system covers 20 sigma levels from the surface to 15 km altitude, with a horizontal grid resolution of 36 km. The final operational global analysis dataset from the US National Center for Environmental Prediction (NCEP) and National Center for Atmosphere Research (NCAR) was used to set the initial and boundary conditions of the WRF (Wang et al., 2016). The land use/cover and topographical data were obtained from the 30-s resolution default WRF input dataset. Notably, this study made no attempt to investigate the effect of climate changes on the environmental impacts of aviation emissions, thus accounting for no change in the meteorological fields for 2020 relative to 2016.

2.2.2. Background emissions

Baseline emissions covered all non-aviation anthropogenic and biogenic emissions sources, excluding aviation sources. Anthropogenic emissions of SO_2, NOx, CO, $PM_{2.5}$, NH_3 and VOCs were obtained from the Multi-resolution Emission Inventory for China at a $0.25 \times 0.25°$ resolution (MEIC 1.2, http://www.meicmodel.org) and the Regional Emission inventory in Asia (REAS 2.1) at a $0.25 \times 0.25°$ resolution (Kurokawa et al., 2013). Biogenic emissions were derived from the biogenic emission processor in the Model of Emissions of Gases and Aerosols from Nature (MEGAN 2.0) (Guenther et al., 2006). These background emissions data were further adjusted and updated according to the latest official statistics (Wang et al., 2016; Du et al., 2016). In particular, the sectoral emissions of SO_2, NO_x and PM_{10} were modified according to the Annual Statistic Report on Environment in China (2015). Source-based emissions for each sector were distributed to gridded emissions according to the China Environmental Statistics Yearbooks (2015) and Annual Statistic Report on Environment in China (2015). Spares Matrix Operator Kernel Emissions (SMOKE 3.0) was used to remap these emissions data into the CAMx model.

2.2.3. Simulation

CAMx 6.2.0 (Wang et al., 2014, 2016) was implemented in this study as the atmospheric simulation technique for exploring the contribution of China's aviation emissions to the ambient air quality. In particular, the CAMx model is an efficient, flexible open-source system incorporating frontier technical features required for air quality simulation (ENVIRON, 2014).

As a three-dimensional Eulerian photochemical dispersion model, the CAMx model allows an integrated assessment of gaseous and air pollution on multiple scales from sub-urban to continental (Borrego et al., 2010). The domain (160 × 200 grid cells) studied was centred at (110°E, 35°N) on a Lambert-projected map of East Asia (see Fig. 1) with a horizontal grid resolution of 36 km. In existing studies, the resolution was usually set to 36 km in the air quality modelling at a national level, e.g., for the US (Woody et al., 2011; Arunachalam et al., 2011) and China (Wang et al., 2016). Therefore, the resolution of 36 km was used in this study. Nevertheless, enhancing horizontal resolution is an important direction to further improve our simulation model. The vertical axis covered 20 sigma levels ranging from the surface to 15 km altitudes (i.e., the whole vertical column layer of CAMx model), in which 15 sigma levels were included in altitude below 3 km. Other model parameters, such as physical processes and chemical mechanisms, are listed in Table 2. A 10-day spin-up simulation was conducted to produce initial conditions, and the boundary condition of the global chemistry transport model MOZART was used (Wang et al., 2016). For the planet boundary layer (PBL), the CAMx model used a post-processor (VERTAVG) to read the input files of CAMx Kv, height, temperature, and pressure for determining the PBL depth for each grid column at each hour and then to average chemical process analysis variables and concentrations over multiple layers within the depth of the PBL.

In this simulation, the most harmful air pollutants, i.e., NOx, SO_2, and $PM_{2.5}$, were of specific interest (USEPA, 2011). To estimate the impact of China's aviation emissions on the air quality, four scenarios were designed, simulated and compared, as listed in Table 3. For each scenario, the corresponding emission inventory, together with the meteorological data and environmental conditions, was introduced into CAMx as the model input. Accordingly, CAMx simulated the emissions, dispersion, physical processes and chemical reactions by the Eulerian continuity equation and generated the time-dependent volume-averaged pollutant concentration in each grid cell as the final result of various physical and chemical interactions operating on that volume. The environmental impact of aviation emissions can be computed in terms of incremental concentrations (in $\mu g/m^3$) and incremental rates (%) under the scenarios with aviation emissions (i.e., A-16 and A-20) relative to the respective baselines without aviation emissions (i.e., BAU-16 and BAU-20).

Table 2
Numerical methods employed in CAMx.

Process	Numerical Method
Horizontal advection	PPM
Vertical diffusion	Standard K Theory
Dry settlement parameterization scheme	WESELY89
Chemical mechanism of liquid phase	RADM-AQ
Gas phase chemical mechanism	SAPRC99
Aerosol module	CF Scheme
Thermodynamic equilibrium model of aerosol	ISORROPIA

Table 3
CAMx modelling scenarios.

Scenario	Emissions	Year
BAU-16	Background emissions	2016
A-16	Background emissions + aviation emissions	2016
BAU-20	Background emissions	2020
A-20	Background emissions + aviation emissions	2020

For model evaluation, previous studies (i.e., Wang et al., 2014; Wang et al., 2016; Du et al., 2016; Chen et al., 2016; Li et al., 2015) have evaluated the CAMx simulation output. To verify the simulation results, real monitoring data (i.e., concentrations of NOx, SO_2, $PM_{2.5}$, aerosol nitrate and aerosol sulfate) from 3 monitoring stations in Beijing, Tianjin and Shijiazhuang and 15 stations in the acid deposition monitoring network for East Asia were introduced (Wang et al., 2014, 2016; Du et al., 2016). Statistical analyses were conducted to compare the simulations from our model and the observations at monitoring stations, including the Pearson correlation coefficient (*R*), normalized mean bias (*NMB*), normalized mean error (*NME*) and root-mean-square error (*RMSE*) (Yu et al., 2006). The comparison results indicated that our simulated concentrations for different species (i.e., NOx, SO_2, $PM_{2.5}$, PSO_4 and PNO_3) showed reasonable agreement with observations in terms of *R* (around the mean of 0.71), *NMB* (−20.78%), *NME* (47.43%) and *RMSE* (1.73 $\mu g/m^3$).

3. Results and discussion

According to the two steps of the methodology, an overall, detailed inventory of China's aviation emissions was first produced, with the results reported in Section 3.1. Then, the corresponding contribution to the air quality was estimated based on the CAMx simulations, as discussed in Section 3.2.

3.1. Aviation emissions

For a clear discussion, the estimation results for China's aviation emissions were analysed from the temporal, species and spatial perspectives.

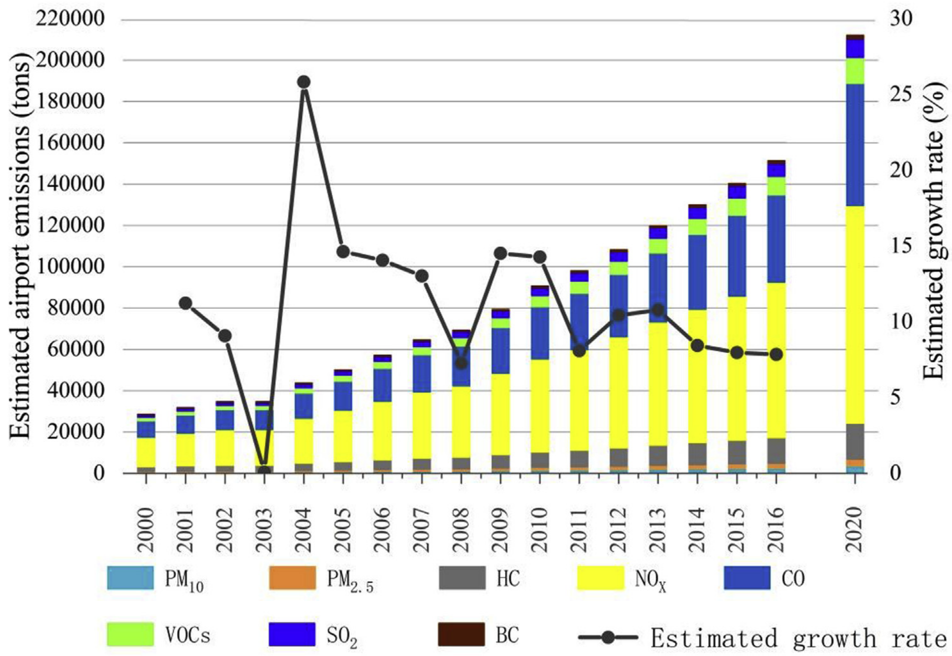


Fig. 2. Estimated aviation emissions (bars, right axis) and growth rate (lines, left axis) in China.

Concerning temporal evolution, Fig. 2 illustrates the overall growth of China's aircraft emissions during 2000–2016. In particular, the total amount of all targeted pollutants from China's civil airports climbed from approximately 28,588 tons in 2000 up to 151,369 tons in 2016, with the annual growth rates ranging between 0.08 and 25.84%. Not surprisingly, such a rising trend is consistent with the continuously fast-growing demand for civil aviation—with average annual growth rates of 13.52% for air passengers and 10.42% for freight during 2000–2016. Two obvious inflection points occurred in 2003 and 2008, when the growth rate of China's aviation emissions fell sharply, though they rebounded quickly. The hidden reasons might be related to the occurrence of acute respiratory syndrome (SARS) during 2002–2003 and the global financial crisis during 2008–2009, which suppressed China's aviation demand severely. In the future scenario, according to China's 13th Five-Year Plan, the aviation demand will still rise; thus, China's aviation emissions might continue to grow, with the predicted overall amount in 2020 being approximately 1.40 times the 2016 level.

From a species perspective, Fig. 2 reveals that NOx dominated China's aircraft emissions, followed by CO and HC, while BC accounted for the smallest share. For example, the aviation emissions of NOx, CO, HC, VOCs, SO_2, PM_{10}, $PM_{2.5}$ and BC throughout mainland China were estimated to be approximately 75246, 42219, 12379, 9007, 6374, 2494, 2448 and 1201 tons in 2016, respectively, making up approximately 49.71, 27.89, 8.18, 5.95, 4.21, 1.65, 1.62 and 0.79% of the aggregated amount. It is worth noting that these proportions didn't change over time due to a limitation of the Tier 1 method in which a fraction of each species in the total emissions is assumed to be a constant. Nevertheless, our result highlighting NOx as the top prevailing aviation emission is consistent with the results of previous studies (e.g., Penner, 1999; ICAO, 2007). Unfortunately, NOx has widely been acknowledged to be one of the most harmful air pollutants, as a determining factor in forming acid rain (Brasseur et al., 1998) and ground-level ozone or smog (Mahashabde et al., 2011). Therefore, efficient measures are strongly recommended to curb such a large magnitude of NOx emitted from China's airports, especially for improving air quality and associated public health.

Regarding the spatial distribution, Fig. 3 displays the detailed emissions at the 217 airports in China, and two insightful findings are of particular note. On one hand, China's aviation emissions are concentrated intensively at certain airports. For example, the top 20 emission-intensive airports out of the 217 accounted for approximately 57.37% of China's total aviation emissions in 2016, with the aggregated amount of NOx, SO_2, CO, HC, $PM_{2.5}$, PM_{10}, VOCs and BC reaching approximately 86,848 tons. Among these airports, Beijing Capital International Airport (PEK) yielded the highest proportion (approximately 6.56% in 2016), closely followed by Shanghai Pudong International Airport (PVG) (5.19%) and Guangzhou Baiyun International Airport (HGH) (4.17%). On the other hand, these emission-intensive airports are mostly around metropolitan areas with a high level of economic development (e.g., PEK and PVG) and/or tourist areas (e.g., HGH, Kunming Changshui International Airport (KMG) and Sanya Phoenix International Airport (SYX)). The hidden reasons for this phenomenon are easy to understand, i.e., that economic development requires transportation support for both labour and freight, while tourists are potential air passengers, and both factors directly stimulate the aviation demand and hence the emissions. Notably, the Belt and Road Initiative begun in 2013 has led to flourishing airports along the route, such as Xi'an Xianyang International Airport (XIY), Lanzhou Zhongchuan International Airport (LHW), and Urumchi Diwopu International Airport (URC).

3.2. Environmental contribution

The contribution of China's aircrafts to the air quality was simulated by the CAMx model and presented by incremental concentrations (in $\mu g/m^3$) and incremental rates (%) due to aviation emissions. Fig. 4 displays the spatial distribution of the contributions, and Fig. 5 shows the average speciated contributions.

Comparing the 2016 and 2020 scenarios reveals that China's aviation emissions are projected to contribute much more to diminishment of the ambient air quality in future years. In particular, the spatial impact of aviation emissions (shown in Fig. 4) is predicted to have a greater spatial extent and exhibit higher values in 2020 (in the right column). The simulation results for the contribution averaged across mainland China (Fig. 5) indicate that aircraft emissions will enhance the concentrations (and incremental rates) of NOx, SO_2 and $PM_{2.5}$ by approximately 0.3055 $\mu g/m^3$ (1.9166% of the total NOx), 0.0178 $\mu g/m^3$ (0.2425% of the total SO_2) and 0.0452 $\mu g/m^3$ (0.1396% of the total

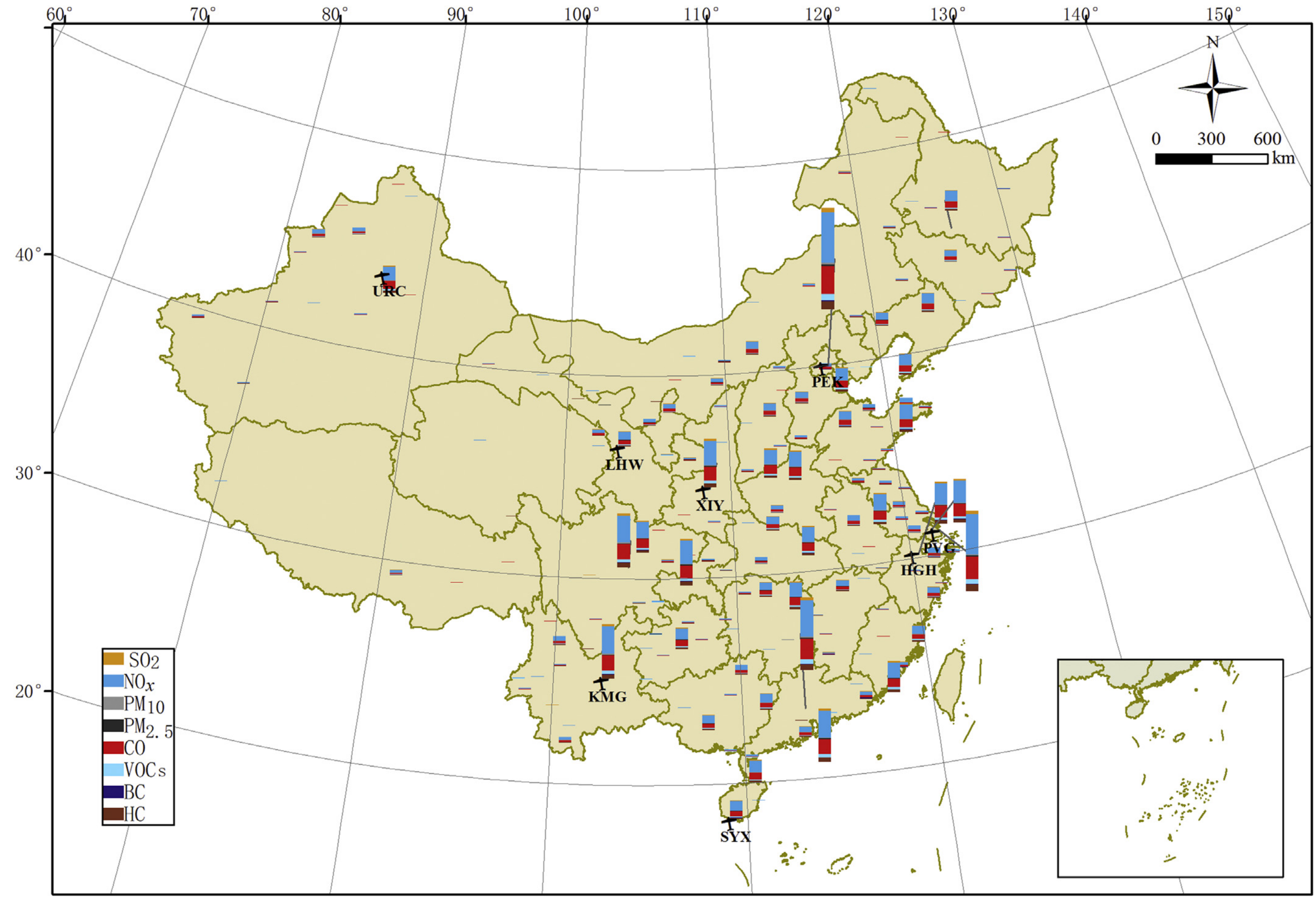


Fig. 3. Estimated aviation emissions at 217 airports in China in 2016.

$PM_{2.5}$) in 2020, respectively, which are approximately 1.4014 (1.3908), 1.4016 (1.5251) and 1.3823 (1.4201) times the corresponding concentrations (and incremental rates) in 2016. Such a substantial increase in future contributions is closely related to the unavoidable growth of the aviation demand and, hence, the activity levels expected in China's 13th Five-Year Plan. For instance, the Belt and Road Initiative has greatly increased the aviation demands in the airports near the Belt and Road, thereby increasing their aviation emissions and environmental impact (Jia, 2017), such as XIY along the Silk Road (see the high $PM_{2.5}$ increase near Xian in Fig. 4). Against this background, energy conservation and technological innovations to reduce emission factors become effective methods to curb aviation emissions and the associated environmental impacts (Kurniawan and Khardi, 2011). Promising measures are as follows: replacing the auxiliary power units with airport ground power, which could reduce the emission factors by approximately 0.6% (Kesgin, 2006); applying a multi-fuel (e.g., liquid natural gas and kerosene) hybrid engine, which could reduce the NOx emission factor by over 80% (Yin et al., 2018); and introducing a dual combustion chamber, which could reduce the PM emission factor by approximately 60% (Grewe et al., 2017).

Among emission species, NOx from China's airports is simulated to impact air quality the most in terms of the highest average contribution (see Fig. 5), whereas $PM_{2.5}$ might generate the most extensive influence in terms of the widest distribution (Fig. 4). On one hand, the average contribution of aircraft emissions to NOx is estimated to be approximately 0.2180 $\mu g/m^3$ (1.3781%) in 2016, which is far above the figures for SO_2 and $PM_{2.5}$ (i.e., 0.0127 $\mu g/m^3$ (0.1590%) and 0.0327 $\mu g/m^3$ (0.1396%), respectively). The hidden reason might be that NOx dominates China's aircraft emissions in terms of the amount (discussed in Section 3.1), thereby enhancing the corresponding concentration to the largest extent. On the other hand, even with a relatively small average contribution, $PM_{2.5}$ from aircrafts influenced the broadest geographic area, even beyond China's borders. According to Fig. 4, the areas of the total grids with average incremental contributions above 0 $\mu g/m^3$ reached 9.65, 4.81, and 10.28 million km^2 for NOx, SO_2 and $PM_{2.5}$, respectively, in 2016.

The spatial distribution of the environmental impact (see Fig. 4) seems to be quite similar to that of the estimated emissions (Fig. 3), being highly intensive at some similar airports. Fig. 6 presents the top 20 airports with the largest contributions, which are consistent with the results of Fig. 4 in that emission-intense airports are the greatest contributors to air quality. Two conclusions can be drawn regarding the underlying factors. On one hand, airports serving metropolitan areas with a high level of economic development might highly impact the ambient air quality. For example, the outstanding airports generating the largest environmental impacts include Guangzhou Baiyun International Airport (CAN) for Guangzhou (e.g., enhancing the NOx concentration by approximately 6.66% in 2016), PVG for Shanghai (6.44%) and PEK (3.79%) for Beijing. For further analysis, Fig. 8 plots the incremental contributions (in $\mu g/m^3$) due to aviation emissions against the gross domestic product (GDP) (in RMB yuan) for each province or municipality. A linear regression is conducted on the relationship between GDP and aviation impacts, with the corresponding results listed in Table 4. The regression coefficient (in Columns 2, 6 and 10 of Table 4) indicates a positive impact of GDP on aviation impacts, and *t*- and *F*-statistics statistically support this relationship at a confidence level of 95%. The hidden reason might be that economic growth would largely enhance transportation demand (including aviation

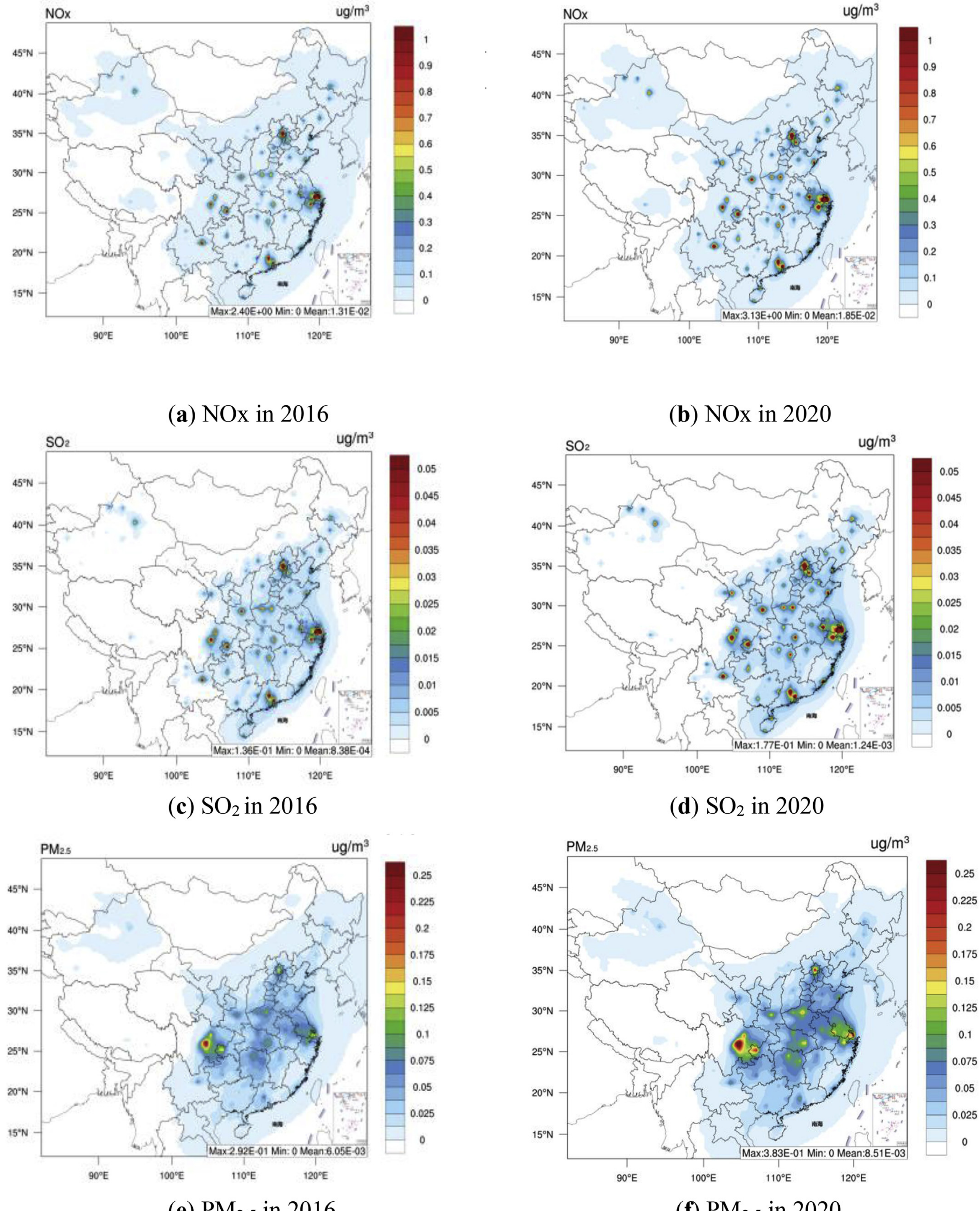
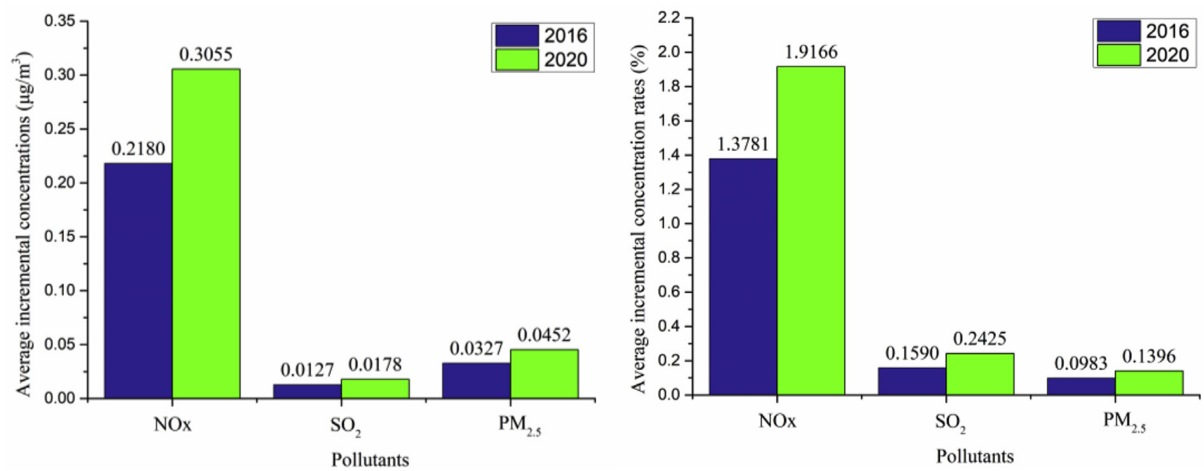
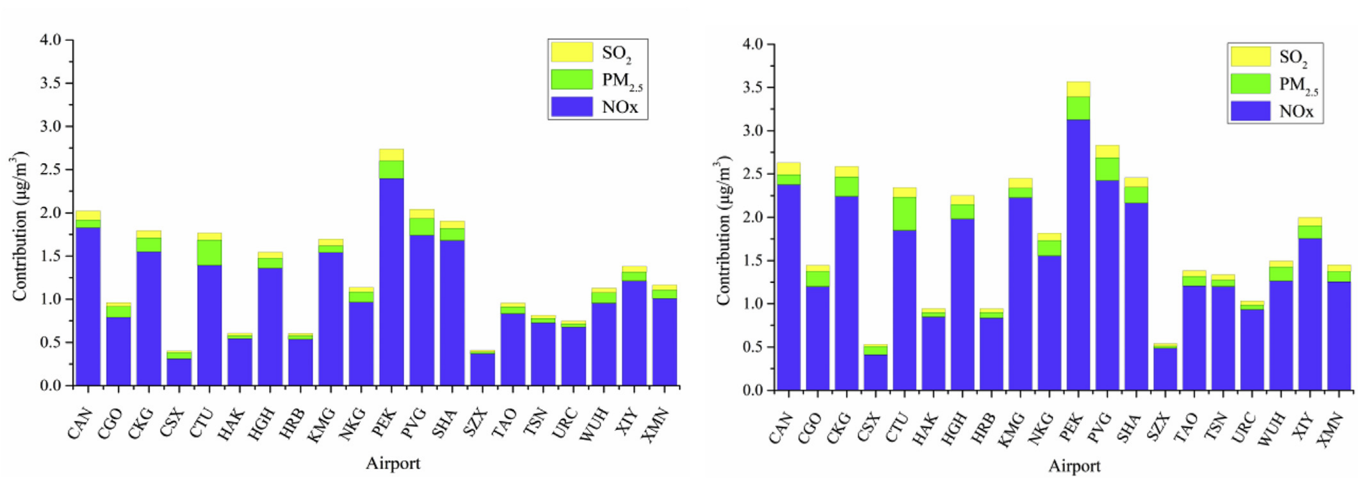


Fig. 4. Spatial distribution of the contribution of China's aviation emissions to NOx (**a** and **b**), SO_2 (**c** and **d**) and $PM_{2.5}$ (**e** and **f**) in terms of incremental concentrations (μg/m^3).



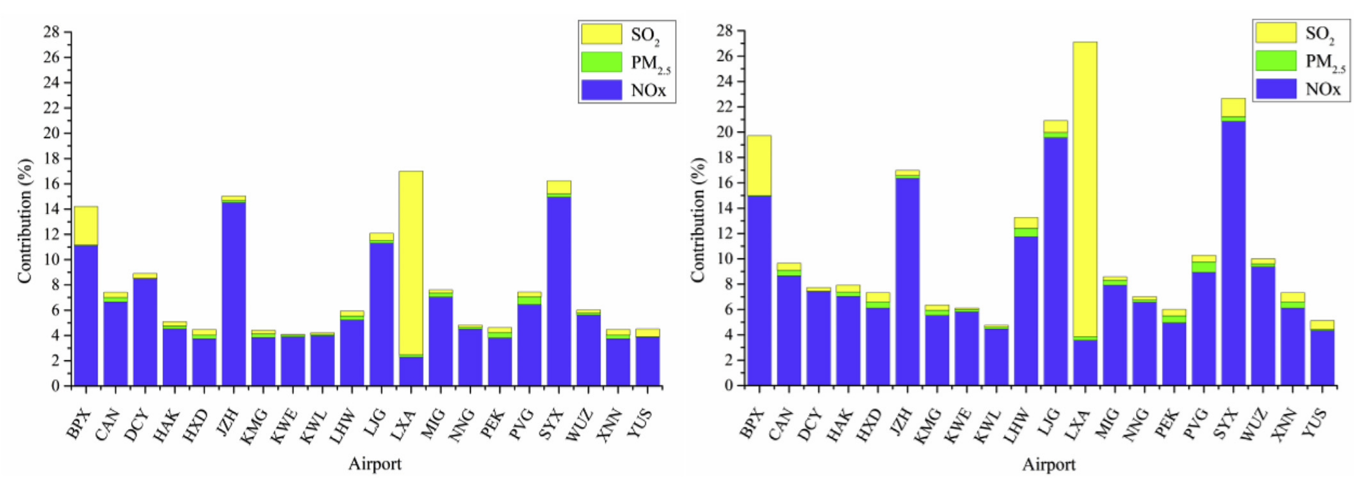
(**a**) Average incremental concentrations (μg/m³) (**b**) Average incremental concentration rates (%)

Fig. 5. Average contributions of China's aviation emissions to NOx, SO_2 and $PM_{2.5}$ in terms of incremental concentration (**a**) and incremental rates (**b**).



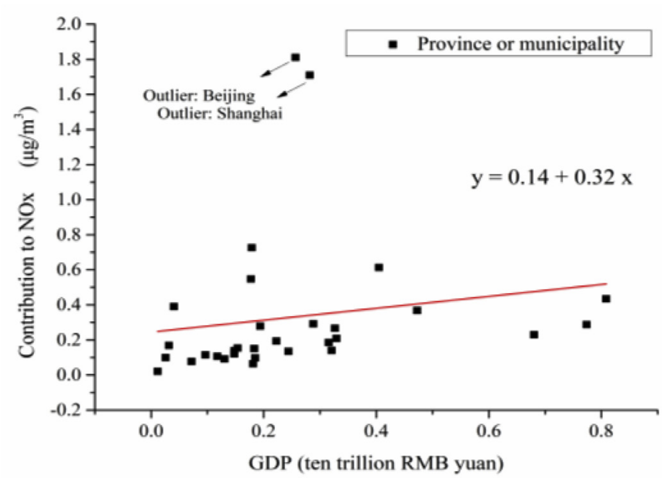
(**a**) 2016 (**b**) 2020

Fig. 6. The top 20 contributors to ambient air quality for 2016 (**a**) and 2020 (**b**) in terms of incremental concentrations (μg/m³).

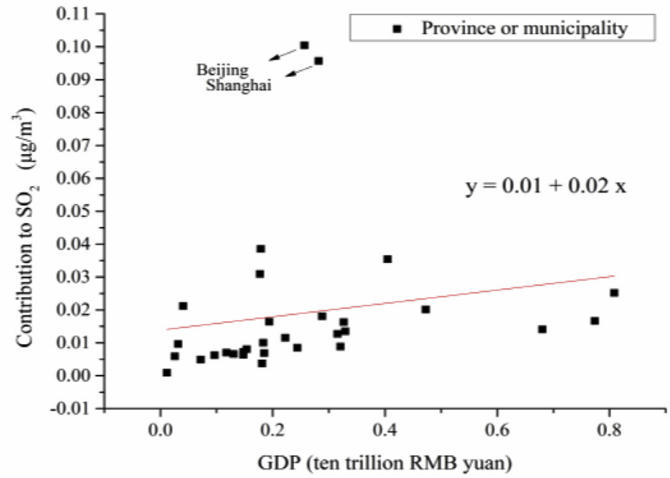


(**a**) 2016 (**b**) 2020

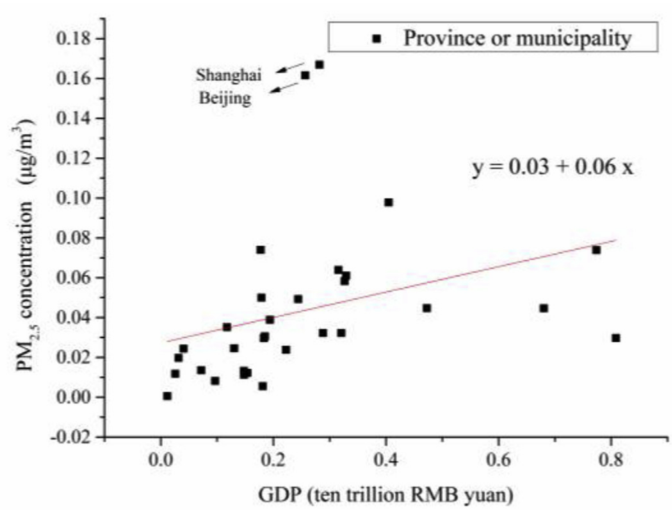
Fig. 7. The top 20 contributors to ambient air quality for 2016 (**a**) and 2020 (**b**) in terms of incremental rates (%).



(**a**) NOx



(**b**) SO_2



(**c**) $PM_{2.5}$

Fig. 8. Aviation emissions' contribution (μg/m^3) to NOx (**a**), SO_2 (**b**) and $PM_{2.5}$ (**c**) and GDP for 31 provinces or municipalities (black squares) of mainland China in 2016.

Table 4
Results of linear regression analyses on the relationship of GDP and aviation environmental impacts.

Variable	Model 1 (Y is NO_X; Fig. 8(a))				Model 2 (Y is SO_2; Fig. 8(b))				Model 3 (Y is $PM_{2.5}$; Fig. 8(c))			
	Coeff.	t-stat.	p-value	Std.	Coeff.	t-stat.	p-value	Std.	Coeff.	t-stat.	p-value	Std.
GDP	0.32**	2.29**	0.03	0.14	0.02**	2.58**	0.02	0.01	0.06***	3.63***	0.00	0.02
N	28				28				28			
F-stat.	5.26**				6.66**				13.19***			

Notes: the two outliers, Beijing and Shanghai, are not considered in the regression analysis; *** and ** denote significance at 1% and 5%, respectively.

demand) (Tsui et al., 2018), and the growth in aviation demand would lead to an increase in aviation emissions and the associated environmental impacts (Song and Shon, 2012; Hsu et al., 2014). It is worth noting that Beijing and Shanghai are highlighted as two super-polluting sources of aviation emissions, making disproportional contributions to the environmental conditions. The hidden reason might be their extremely large volume of aviation services, accounting for 12.87 and 22.87% of the total air freight and 9.29 and 6.46% of China's total air passengers, respectively, in 2016.

On the other hand, the tourism industry has become another leading driver of China's aviation emissions and air quality contributions. According to Fig. 7, the airports with the greatest environmental impacts are SYX, serving the famous tourist city of Sanya; Jiuzhai Huanglong Airport (JZH), serving Jiuzhai; Lijiang Sanyi International Airport (LJG), serving Lijiang; Qamdo Bangda Airport (BPX), serving Changdu; and Daocheng Yading Airport (DCY), serving Daocheng. With large traffic flows, these airports enhanced the ambient concentration of NOx, for example, by approximately 14.94, 14.51, 11.30, 11.10 and 8.48% in 2016, respectively. Considering the current boom in tourism, aircrafts near tourist cities have become important sources of air pollutants, which should not be ignored.

4. Conclusions

In this study, an overall, detailed inventory of China's aircraft emissions, as well as the corresponding contributions to air quality, is generated. Unlike existing related studies focusing on certain airports, this study is the first attempt to consider all civil airports in mainland China, covering a total of 217 samples. First, aviation emissions (NOx, SO_2, CO, HC, $PM_{2.5}$, PM_{10}, VOCs and BC) at each airport are estimated for both recent (2000–2016) and future (2020) scenarios. Second, the corresponding contribution to air quality is simulated by the CAMx model. Insightful results can be obtained as follows. Concerning temporal evolution, China's aviation emissions and the associated contributions to air quality have followed and will continue to follow an upward trend. Among pollutant species, NOx dominated China's aircraft emissions in terms of both emission amount and environmental impact, while $PM_{2.5}$ generated an extensive influence. In terms of spatial distribution, the air quality contributions are highly concentrated at emission-intense airports, which serve either economic zones with a high level of economic development and/or tourist spots attracting a large number of tourists.

Many topics require further investigation in future research. First, due to data availability, the Tier 1 method, based on the general emission factors per LTO cycle, is used. However, a more detailed emission estimation for different aircraft operational modes is also an important task. Second, investigating the public health impact of China's aviation emissions would be an insightful extension to this study. Third, in addition to LTO activities, the upper-layer cruise above 3 km altitude also significantly influences air quality in the boundary layer (Barrett et al., 2010; Lee et al., 2013) and could also be considered in aviation emission estimations. Third, it is necessary to validate the estimated emissions against other observations from independent sources. Fourth, thoroughly comparing aviation emissions and those from other sources is also an important task to identify the pollutants from aviation that are a major source of anthropogenic air pollutants. Finally, in the future-year estimation, important factors, e.g., mitigation strategies, technology improvements and policy reforms, could be included. We will investigate these insightful issues in the near future.

Declarations of interest

There is no known conflict of interest associated with this publication, and there has been no significant financial support for this work that could have influenced its outcome.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2019.01.005.

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