# Uncovering temporal-spatial drivers of vehicular $NO_x$ emissions in China

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## Highlights

- China's $NO_x$ emissions from provincial vehicles were estimated during 2005-2015.
- A new temporal-spatial decomposition model was built to identify emission drivers.
- Road vehicle carrying capacity drove both temporal change and spatial difference.
- Regional emission intensity and road economic growth affected spatial difference.
- Economic development played a crucial role in the temporal change.

Abstract

The increasing vehicle numbers in China have raised issues on effective mitigation of the vehicular $NO_x$ emissions recently. Notably, temporally growing and spatial agglomeration of high vehicular $NO_x$ emissions make an essential challenge to the mitigation strategy-makers. However, so far, there have been few studies to give insight into the socioeconomic drivers like the spatial imbalance of socioeconomic development, vehicle structure and road infrastructure to help governors. To fill the above gap, this study explores drivers of temporal change and spatial differences by building a temporal-spatial decomposition model and accounting for national and regional $NO_x$ emissions from vehicles in China from 2005 to 2015. Results show that, of all the driving forces in this study, only road vehicle carrying capacity ($\Delta N_{VI}$) acts as a primary driving force for both temporal growing and spatial agglomeration of vehicular $NO_x$ emissions in China. Regional vehicle emission intensity ($\Delta N_{NI}$) and road economic growth ($\Delta N_{EI}$) only mainly contributed to spatial agglomeration. While economic development ($\Delta N_G$) played a crucial role in the temporal growing of vehicular $NO_x$ emissions in China. These findings indicate that the future mitigation policy should fully cover the comprehensive socioeconomic factors, which would be useful for China and other developing countries when aiming to improve the performance of their current vehicle emissions policy system.

**Keywords**:

Vehicular $NO_x$ emissions; Temporal-spatial decomposition; Spatial differences; Agglomeration; China

# 1. Introduction

Rapid economic development and urbanization have led to dramatic growth in energy consumption and the number of automobiles in many developing countries, including China. Consequently, emissions of air pollutants have increased significantly in recent years (Zhu et al., 2013; Hao et al., 2014; Wang et al., 2017b), which has led to severe regional air pollution. Among air pollutants, emissions of nitrogen oxides ($NO_x$) are of particular concern. $NO_x$ contributes substantially to local air pollution and regional environmental risks such as acid rain, eutrophication, tropospheric ozone, haze, and loss of biodiversity (Hao et al., 2002; Peel et al., 2012; Cheng et al., 2016); it also increases health risks across regions with dense populations (Boningari and Smirniotis, 2016). As well as particulate matter with an aerodynamic diameter less than 2.5 μm (PM2.5), China has devoted increasing attention to $NO_x$ emissions reduction. In China's 12$^{th}$ and 13$^{th}$ Five-Year Plans (2010–2015 and 2016–2020), the government incorporated $NO_x$ reduction targets into the total emission control system and implemented these targets for $NO_x$ emissions control into each province. Therefore, $NO_x$ reduction has become an important political goal for energy policy and air quality management in China (Wang et al., 2014; Ding et al., 2017).

Emissions of $NO_x$（NO and $NO_2$）are from both natural processes and anthropogenic emission (Lee et al., 1997). On a global scale, nearly half of the total $NO_x$ is derived from human activities, which could rapidly increase due to economic growth (Lamsal et al., 2011). Meanwhile, $NO_x$ emissions from vehicles have gradually become a major contributor over pasts (Anenberg et al., 2017; Wild et al., 2017; Ramos et al., 2018), alongside industrial emissions. In particular, the number of vehicles in China should be focused on, as this has grown from 43.29 million in 2005 to 260.03 million in 2015 (MEP, 2016) due to the fast-growing population and expanding urbanization over the past decade. Meanwhile, the contribution of $NO_x$ emissions from vehicles rose to 31% of total Chinese emissions in 2015, reaching 5.85 million tons (MEP, 2015). Specifically, in well-developed urban areas characterized by vehicles agglomeration, $NO_x$ emissions from vehicles have become the principal source of urban $NO_x$ emissions (Liu et al., 2017a), leading to severe air pollution in those areas. Therefore, identifying the drivers and impact mechanisms of vehicular $NO_x$ emissions is key to taking effective measures to reduce $NO_x$ emissions.

Despite the increasing issue of $NO_x$ emissions from vehicles, most previous studies have only focused on $NO_x$ emissions inventories. Lang et al. (2014) estimated on-road vehicular emissions in China from 1999–2011 based on the COPERT model. Jing et al. (2016) developed a vehicle emission inventory with a high temporal-spatial resolution for the Beijing urban area based on a bottom-up methodology. Liu et al. (2018) improved the accuracy and temporal-spatial resolution of a vehicle emission inventory in a medium-sized city, Foshan, with a strip road network. Yang et al. (2018) established vehicle emission inventories for five major air pollutants in the Beijing-Tianjin-Hebei (BTH) region and carried out a policy scenario analysis based on the newly developed inventories. Lv et al. (2019) estimated the vehicle emissions in Yunnan province for 2003-2015 with the COPERT IV model. All of the above studies could help us to understand the vehicular emission characteristics in China. However, most of the studies were carried out in: (1) limited region, some of them were focused on local or developed areas, such as the Beijing–Tianjin–Hebei (BTH), Yangtze River Delta (YRD) or Pearl River Delta (PRD) region. Considering the continuous sharp growth of vehicle population and the progressive implementation of more and more stringent emission standards (from State I to State V) during the recent decade, the vehicular emissions and its characteristics in China should be further estimated and analyzed. (2) limited research perspective, these studies only involved estimating vehicle emissions, they did not explore further the driving forces behind these changes.

Nevertheless, socioeconomic factors have been identified as driving forces, which are essential to track and evaluate emissions performance (Wang et al., 2017a). Generally, in addition to econometric techniques (Jiang et al., 2016; Wang et al., 2019a) and computable general equilibrium (CGE) models (Zhang et al., 2018), the decomposition method is popular and also helpful in finding drivers. A critical advantage of decomposition analysis is that it can distribute a temporal change or spatial difference in an aggregate indicator into components related to several driving factors. The two most widely used are index decomposition analysis

(IDA) and structural decomposition analysis (SDA) (Wang et al., 2017a). Several previous studies have used decomposition analysis to explain the observed change in aggregate $NO_x$ generation from energy consumption (He et al., 2019) and power generation (Wang et al., 2018; Wang et al., 2019b). However, there are only a few studies on transportation or vehicle $CO_2$ (Wang et al., 2011; Liu et al., 2015; Luo et al., 2016; Liang et al., 2017), and this lack an exploration of the driving mechanisms behind $NO_x$ emissions from on-road vehicles.

Moreover, the above situation is similar to current regulatory policies related to vehicle emission reduction. The previous studies are mostly about technical constraints (e.g., fuel quality, technology efficiency) and rarely involve socioeconomic factors such as economic growth, road infrastructure construction, urbanization, and population agglomeration (Yang et al., 2015). In addition, regional disparities in vehicular $NO_x$ emissions have become an increasing issue (Xu and Masui 2009, Huang and Todd 2010, Li and DaCosta 2013). However, previous studies did not investigate the drivers of these geographical differences and congregation of people in certain areas. Notably, the nexus issue of economic growth and road infrastructure, which are deeply affected by urbanization, did not receive as much focus as other impact factors (Lang et al., 2012; Gu et al., 2013; Lang et al., 2014; Lang et al., 2016; Sun et al., 2016).

In summary, there are at least two knowledge gaps to be bridged. First, how did driving forces including economic growth, population clustering, and road infrastructure construction affect the temporal change in $NO_x$ emissions from the provincial on-road vehicle population? Second, what factors cause the geographical differences and clustering of $NO_x$-related vehicle emissions and whether they have a similar impact mechanism as the drivers of temporal change. To bridge the gaps, by estimating the national and regional $NO_x$ emissions from vehicles in China from 2005 to 2015, the temporal change and spatial distribution of $NO_x$ emissions from on-road vehicles in China were first shown. Then a conceptual model of the connections between vehicles, the economy, infrastructure, and population was established. Finally, the temporal-spatial decomposition method was applied to identify the dominant drivers of temporal changes and spatial differences in vehicular $NO_x$ emissions in China.

The structure of this study is as follows. Section 2 presents the vehicular $NO_x$ emissions calculation method and the temporal-spatial decomposition method used in this paper. Section 3 reveals the results of the estimated vehicular $NO_x$ emissions in China. Section 4 discusses the drivers of temporal changes and spatial differences in vehicular $NO_x$ emissions. Section 5 presents the conclusions and provides policy implications.

# *2.* Methodology

## *2.1 Estimation of vehicular $NO_x$ emissions*

In this study, $NO_x$ emissions from vehicles in 31 provinces in China from 2005 to 2015 were estimated based on emission factors and vehicle kilometers travelled (VKT) using Equation 1 (Lang et al., 2016; Liu et al., 2018):

$$N_{i,t} = \sum_j (V_{i,j,t} \times EF_{i,j,t} \times VKT_{i,j,t}) \times 10^{-6} \tag{1}$$

where

$\boldsymbol{i}$: A given municipality or province in China (except for Hong Kong, Macao, and Taiwan due to data availability);

$\boldsymbol{j}$: A given vehicle type, including freight and passenger vehicles of different sizes, fuel types and emission standards. Detailed categories are shown in Table A.1 in the Supplementary information;

$\boldsymbol{t}$ : A given year of vehicular $NO_x$ emissions estimation;

$\boldsymbol{N_{i,t}}$ : $NO_x$ emissions from vehicles in year *t* for area *i* (*t*);

$\boldsymbol{V_{i,j,t}}$ : Vehicle number of type *j* in year t for area *i*;

$\boldsymbol{EF_{i,j,t}}$ : Emission factor for vehicles of type *j* in year *t* for area *i,* (g/km);

$\boldsymbol{VKT_{i,j,t}}$: Annual average vehicle kilometers travelled by vehicles of type *j* in year t for area *i*, (km).

In Equation 1, the vehicular emission factor is a comprehensive index to measure the average vehicle emission contribution level, which is estimated using the National Emission Inventory Guidebook for On-road Vehicles (MEP, 2014). The guidebook provides data on China V standard vehicles as well as vehicles corresponding to the government vehicle registration types, which can be used to carry out a more accurate calculations (Yang et al., 2018). In this study, emission factors of vehicles of type *i* were adjusted using Equation 2 according to the change in conditions in different regions.

$$EF_{i,j,t} = BEF_j \times \varphi_{i,t} \times \gamma_{i,t} \times \lambda_{j,t} \times \theta_{i,j,t} \quad (2)$$

where

$\boldsymbol{BEF_j}$ : The comprehensive basic emission factor for a vehicle of type *j*;

$\boldsymbol{\varphi_{i,t}}$ : The environmental correction factor of area *i* in year *t*;

$\boldsymbol{\gamma_{i,t}}$ : The road traffic condition correction factor of area *i* in year *t*;

$\boldsymbol{\lambda_{j,t}}$ : The deterioration correction factor of vehicles of type *j* in year *t*;

$\boldsymbol{\theta_{i,j,t}}$ : Other use condition correction factors of vehicles of type *j* in year *t* for area *i*.

*BEF* is based on the 2014 conditional scenario (MEP, 2014) and contains the following assumptions: average cumulative VKT were under typical urban driving conditions (30 km/h) for all vehicles; meteorological condition (15°C, relative humidity of 50%); fuel quality (fuel with a sulfur content of 50 ppm and 350 ppm for gasoline and diesel fuel, respectively, gasoline without ethanol blending); and load factor (50% for a diesel vehicle under the typical working condition). Detailed information of the environmental correction factor is presented in Tables A.2–A.4 (Supplementary information).

## *2.2 The conceptual model*

This study aims to introduce a conceptual model to explore how socioeconomic factors affect vehicular $NO_x$ emissions in China and its sub regions (Fig. 1). According to Fig. 1, some subsystems, including the vehicle, road, and socioeconomic systems, are closely interconnected into a comprehensive overall system. In this context, vehicular $NO_x$ emissions are affected and driven by all areas of this connected system. Some studies (Lang et al., 2014; Liu et al., 2017b) have demonstrated a linear relationship between vehicular $NO_x$ emissions and GDP. Additionally, the population size (social system) and road miles (road system) could also push up vehicle $NO_x$ emissions because of their impact on the growth of the provincial vehicle population. Meanwhile, economic growth could be driven by improved road infrastructure, which would then lead to more investment in road infrastructure, further increasing the amount of road miles.

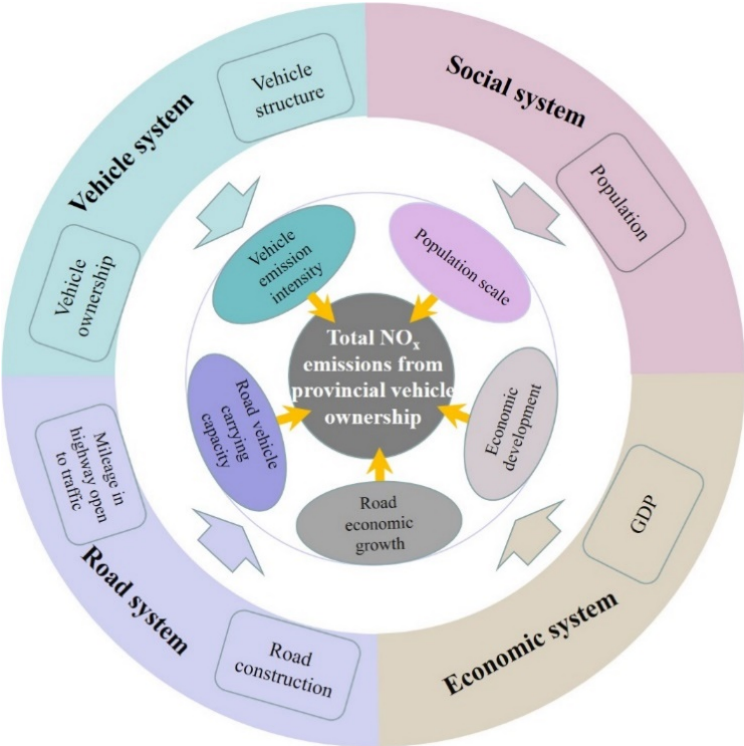


**Fig. 1.** Conceptual model of a comprehensive system connecting vehicles, roads, society, and the economy.

### *2.3 Temporal-spatial decomposition method*

From the conceptual model above, it is necessary to pull out several important drivers to further quantify the size of their effect. Then how socioeconomic factors affect temporal changes and spatial differences in vehicular $NO_x$ emissions in China can be explored. Here, a temporal-spatial decomposition model of vehicular $NO_x$ emissions was rebuilt using the LMDI (Logarithmic Mean Divisia Index) method, which is widely used due to its full breakdown of variables, clear explanation, and zero residual errors (Ang et al., 1998; Ang 1996, 2004). As the most popular index decomposition approach, LMDI performs well in the case with large variations in variable values and possesses the capacity to conduct comparative analysis within time series or across objects (Jiang et al., 2017). Previous studies were reviewed (Wang et al., 2011; Luo et al., 2016; Liang et al., 2017) to present the formula of national and provincial $NO_x$ emissions from vehicle populations shown in Equation 3. The variables involved in Equation 1 are defined in Table 1.

$$N = \sum_i N_i = \sum_i N_i/V_i \times V_i/T_i \times T_i/GDP_i \times GDP_i/P_i \times P_i$$

$$= \sum_i NI_i \times VI_i \times EI_i \times G_i \times P_i \tag{3}$$

**Table 1**

Definitions and units of the variables in Equation 1.

| Variables | Definition (units) |
|---|---|
| **N** | Total $NO_x$ emissions from vehicle population in China (t =1000 kg) |
| $\boldsymbol{N_i}$ | $NO_x$ emissions from vehicles of area *i* in China (t) |
| $\boldsymbol{V_i}$ | Total vehicle population of area *i* (vehicles) |
| $\boldsymbol{T_i}$ | Total length of highways of area *i* (km) |
| $\boldsymbol{GDP_i}$ | Gross Domestic Product (GDP) of area *i* (billion yuan) |
| $\boldsymbol{P_i}$ | Population of area *i* (ten thousand persons) |
| $\boldsymbol{NI_i}$ | $NO_x$ emissions per vehicle of area *i* (t/vehicle) |
| $\boldsymbol{VI_i}$ | Vehicle population per length of highways of area *i* (vehicles/km) |
| $\boldsymbol{EI_i}$ | Road construction mileage supported by GDP per capita of area *i* (km/billion yuan) |
| $\boldsymbol{G_i}$ | GDP per capita of area *i* (billion yuan/ ten thousand persons) |

### 2.3.1 Temporal decomposition analysis

Based on the additive LMDI method, changes to vehicular $NO_x$ emissions between the target year T and the base year 0 could be estimated by Equation 4, and effects of various driving forces on regional emissions between the target year T and the base year 0 for region *i* could be estimated using Equations 4a–e. The variables involved in Equation 4 are defined in Table 2. Moreover, the factor correlation analysis was conducted to analyze the correlation between vehicular $NO_x$ emissions and each of decomposition factors (Fig. 2).

$$\Delta N_i^{(T-0)} = N_i^T - N_i^0 = \Delta N_{i,NI}^{(T-0)} + \Delta N_{i,VI}^{(T-0)} + \Delta N_{i,EI}^{(T-0)} + \Delta N_{i,G}^{(T-0)} + \Delta N_{i,P}^{(T-0)} \tag{4}$$

$$\Delta N_{i,NI}^{(T-0)} = \sum_i L\left(N_i^T, N_i^0\right) ln\left(\frac{NI_i^T}{NI_i^0}\right) \tag{4a}$$

$$\Delta N_{i,VI}^{(T-0)} = \sum_i L\left(N_i^T, N_i^0\right) ln\left(\frac{VI_i^T}{VI_i^0}\right) \tag{4b}$$

$$\Delta N_{i,EI}^{(T-0)} = \sum_i L\left(N_i^T, N_i^0\right) ln\left(\frac{EI_i^T}{EI_i^0}\right) \tag{4c}$$

$$\Delta N_{i,G}^{(T-0)} = \sum_i L\left(N_i^T, N_i^0\right) ln\left(\frac{G_i^T}{G_i^0}\right) \tag{4d}$$

$$\Delta N_{i,P}^{(T-0)} = \sum_i L\left(N_i^T, N_i^0\right) ln\left(\frac{P_i^T}{P_i^0}\right) \tag{4e}$$

where $L\left(N_i^T, N_i^0\right) = \frac{N_i^T - N_i^0}{lnN_i^T - lnN_i^0}$. The decade from 2005 to 2015, over two five-year plans in China, was selected to analyze the temporal change of $NO_x$ emissions from vehicles. The base year is 2005 while the target year is 2010 during 2005-2010. And the base year is 2010 while the target year is 2015 during 2010-2015.

**Table 2**

Definitions of variables in Equations 4 and 5.

| Variable | Definition |
|---|---|
| $\Delta \boldsymbol{N}$ | The change of total vehicular $NO_x$ emissions from vehicle population in China. |
| $\Delta \boldsymbol{N_{NI}}$ | **Vehicle emission intensity effect**, the effect of regional vehicular emission standards, improvement of fuel quality, adjustment of vehicle structure, and other measures on provincial vehicular $NO_x$ emissions. |
| $\Delta \boldsymbol{N_{VI}}$ | **Road vehicle carrying capacity effect**, the effect of changes in vehicle population and road infrastructure construction on vehicular $NO_x$ emissions. |
| $\Delta \boldsymbol{N_{EI}}$ | **Road economic growth effect**, the effect of increasing economic growth driven by road infrastructure construction on vehicular $NO_x$ emissions. |
| $\Delta \boldsymbol{N_{G}}$ | **Economic development effect**, the effect of regional economic growth on vehicular $NO_x$ emissions. |
| $\Delta \boldsymbol{N_{P}}$ | **Population scale effect**, the effect of population migration and growth on vehicular $NO_x$ emissions. |

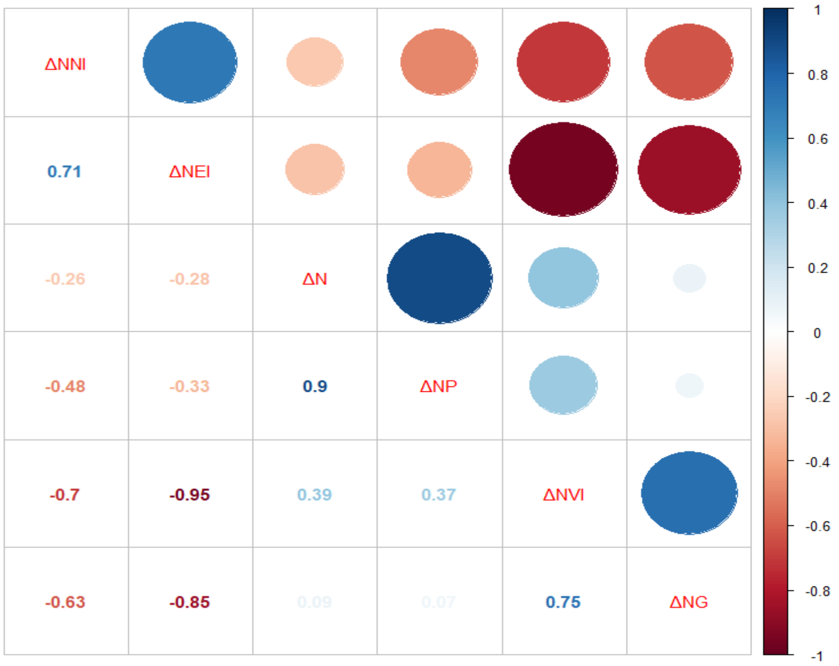


**Fig. 2.** Factor correlation analysis of vehicular NOx emissions

### 2.3.2 Spatial decomposition analysis

After the analysis of temporal change, a further spatial analysis was performed to identify the drivers of the geographical differences in provincial vehicular $NO_x$ emissions in China using data from a specific year, in this case 2005, 2010, and 2015 ( Su et al., 2016). Within this framework, each province was compared with the arithmetic average of all the provinces, or the provincial national average (Li et al., 2017). Then the spatial difference in vehicular $NO_x$ emissions was decomposed into five driving forces, according to Equation 3. The difference in vehicular $NO_x$ emissions between the province ($i$) and the provincial national average ($*$), denoted as $\Delta N^{(R_i-R^*)}$ was obtained by Equation 5:

$$\Delta N^{(R_i-R^*)} = N^{R_i} - N^{R^*} = \Delta N_{NI}^{(R_i-R^*)} + \Delta N_{VI}^{(R_i-R^*)} + \Delta N_{EI}^{(R_i-R^*)} + \Delta N_{G}^{(R_i-R^*)} + \Delta N_{P}^{(R_i-R^*)} \quad (5)$$

The effects of five forces that influence the difference in vehicular $NO_x$ emissions between the province ($i$) and the provincial national average ($*$) were calculated using Equations 5a-e. The variables in Equation 5 and its sub-equations are defined in Table 2.

$$\Delta N_{NI}^{(R_i-R^*)} = \sum_i L\left(N^{R_i}, N^{R^*}\right)\ln\left(\frac{NI^{R_i}}{NI^{R^*}}\right) \quad (5a)$$

$$\Delta N_{VI}^{(R_i-R^*)} = \sum_i L\left(N^{R_i}, N^{R^*}\right)\ln\left(\frac{VI^{R_i}}{VI^{R^*}}\right) \quad (5b)$$

$$\Delta N_{EI}^{(R_i-R^*)} = \sum_i L\left(N^{R_i}, N^{R^*}\right)\ln\left(\frac{EI^{R_i}}{EI^{R^*}}\right) \quad (5c)$$

$$\Delta N_{G}^{(R_i-R^*)} = \sum_i L\left(N^{R_i}, N^{R^*}\right)\ln\left(\frac{G^{R_i}}{G^{R^*}}\right) \quad (5d)$$

$$\Delta N_{P}^{(R_i-R^*)} = \sum_i L\left(N^{R_i}, N^{R^*}\right)\ln\left(\frac{P^{R_i}}{P^{R^*}}\right) \quad (5e)$$

where $\left(N^{R_i}, N^{R^*}\right) = \frac{N^{R_i}-N^{R^*}}{lnN^{R_i}-lnN^{R^*}}$ . This analysis covers 22 provinces, 5 autonomous regions, and 4 direct-controlled municipalities in China. Moreover, 2005, 2010, and 2015 were chosen as typical years to explore the drivers on spatial differences in line with the temporal decomposition analysis in this study.

### *2.4 Data sources*

According to the conceptual model described above, and considering data availability and accuracy, provincial-level registered vehicle population data were used to estimate $NO_x$ emissions attributed to vehicles in each province and then discussed the socioeconomic drivers.

To estimate vehicular $NO_x$ emissions, data was used that reflects the level of vehicle activity as it varied by region and year. Number of vehicles, temperature, humidity, and altitude for each province were obtained from the China statistical yearbook (NBS, 2006-2016). Other inputs, such as vehicle kilometers travelled (VKT) for different vehicle types were derived from the National Emission Inventory Guidebook for On-road Vehicles and adjusted based on previous research (Song et al., 2016; Lang et al., 2016; Sun et al., 2016). Both the implementation timetable for emissions standards for different vehicle types and annual data on the sulfur content of vehicle fuels in each province were collected from the China Vehicle Emission Control Annual Report (MEP, 2016).

The input data used in the spatial-temporal LMDI method, including the total length of highways, Gross Domestic Product (GDP), and provincial population were taken from the China Statistical Yearbook (NBS, 2006-2016).

# 3. Results and Discussion

## 3.1 Trends of vehicular $NO_x$ emissions from 2005 to 2015

Fig. 3 shows the estimated result of national vehicular $NO_x$ emissions in China from 2005 to 2015. Significantly, the trend in vehicular $NO_x$ emissions exhibits a nonlinear change with time. From 2005 to 2008, $NO_x$ emissions from vehicles only show a moderate increase ( from $3250\times 10^3$t to $3510\times10^3$t), partly because of a slow increase in the vehicle population and widespread implementation of the State II emissions standards. However, from 2008 to 2010 the rapid development of the economy led to a sharp increase in the vehicle population as well as vehicular $NO_x$ emissions (from $3510\times10^3$t to $5000\times10^3$t ). Since 2011, total $NO_x$ emissions from vehicles have remained at approximately $660\times10^3$t with a slight downward trend in recent years, which may be due to state control of vehicle population growth and the implementation of cleaner emissions standards. The following discussion in section 4.1 will further analyze the socioeconomic factors behind the mechanism for emissions changes.

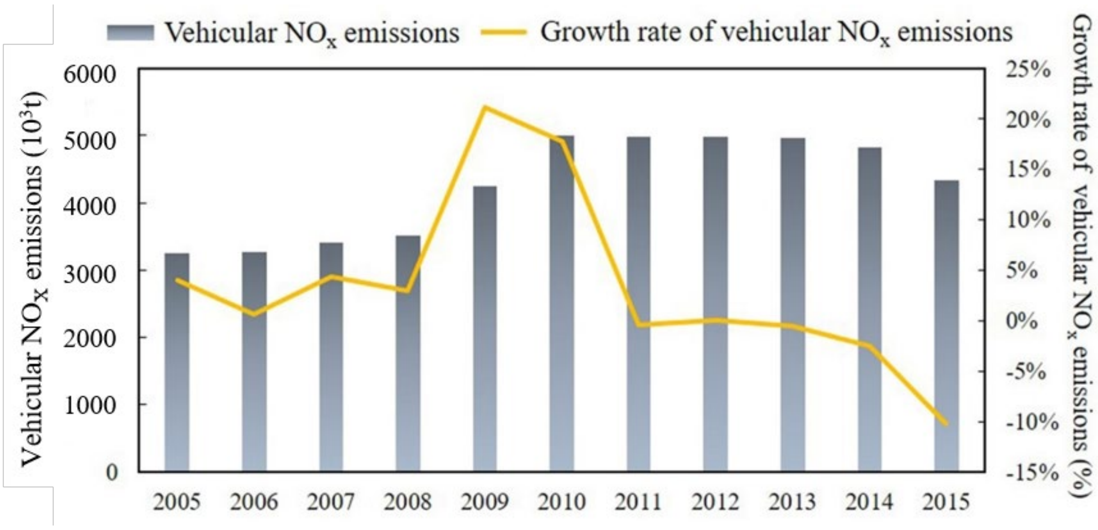


**Fig. 3.** National vehicular $NO_x$ emissions from 2005 to 2015

## 3.2 Spatial distribution and agglomeration of vehicular $NO_x$ emissions

Spatial autocorrelation models are popular to characterize spatial distribution characteristics.

Moran's I which measures spatial autocorrelation (Moran, 1948) can be further classified into Global Moran's I and Local Moran's I (Anselin and Griffith, 1988). In this study, we use Global Moran's I to estimate the degree of spatial dependence and heterogeneity of vehicular $NO_X$ emissions among 31 provinces in China from the year 2005 to 2015. As shown in Table 3, the Moran's I value was more than zero for each year, which indicating that there was a spatial autocorrelation of vehicular $NO_x$ emissions. P-value and Z-score, as indicators to measure whether there is statistical significance of Moran index, could help us to make judgment of random hypothesis. Table 4 shows the critical P-values and critical Z-scores at different confidence levels. If the Z-score is greater than the critical value of the normal distribution function at the 0.05 level of 1.96, it indicates that the attribute value of the research object has a significant correlation in the spatial distribution. Although the spatial correlation in 2005 is not obvious, the p-value of 2010 and 2015 had a significance level of 1% (Table 3), which means that the null hypothesis can be rejected. It also indicated that spatial agglomeration becomes more and more obvious from 2005 to 2015. In terms of Z-score, the index value for 2010 and 2015 was over 1.65, suggesting that there was a positive spatial autocorrelation of High-high and Low-low in terms of vehicular $NO_x$ emissions.

**Table 3**

Moran's I of vehicular $NO_x$ emissions in China.

| Year | Moran’s I | Z-score | P-value |
|---|---|---|---|
| 2005 | 0.0565 | 0.7718 | 0.2020 |
| 2010 | 0.2166 | 2.1571 | 0.0250 |
| 2015 | 0.2182 | 2.1804 | 0.0270 |

**Table 4**

Critical p-value and critical z-score under different confidence levels.

| Confidence level | Z-score | P-value |
|---|---|---|
| 90% | < -1.65 or > 1.65 | < 0.10 |
| 95% | < -1.96 or > 1.96 | < 0.05 |
| 99% | < -2.58 or > 2.58 | < 0.01 |

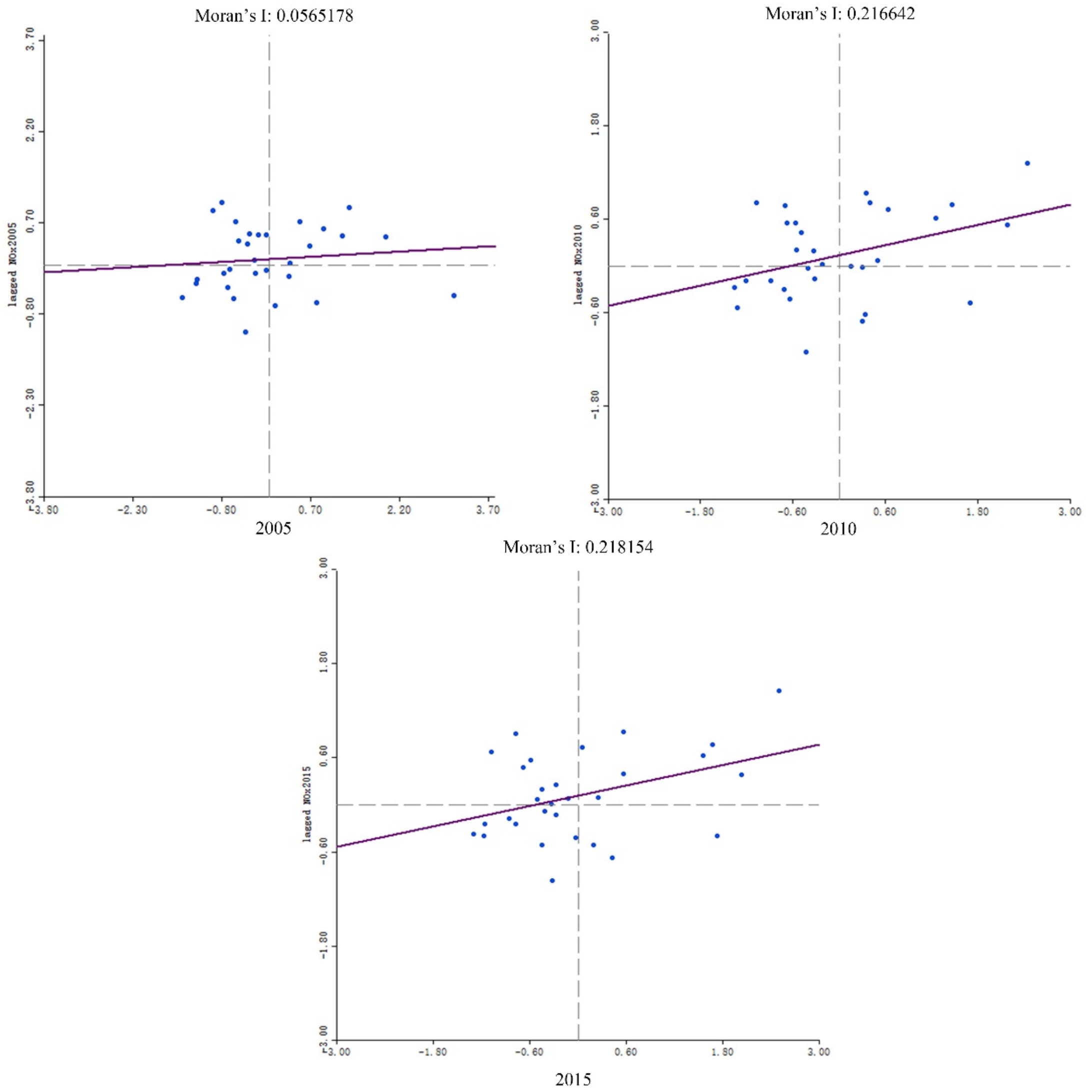


**Fig. 4.** Moran scatter plot of vehicular NOx emissions in 30 provinces in China

As shown in Fig. 4, this study examined the Moran scatter plots of 30 provinces and municipalities in China (Hainan was excluded due to no spatial neighbors). Combining the Moran scatter plots for three years, it can be found that the areas with high vehicular $NO_X$ emissions between itself and the surrounding areas (High-High) are mainly concentrated in eastern regions such as Shandong, Hebei, Henan, Jiangsu and Anhui. This is also hotspots for $NO_X$ emissions from vehicles in China. On the contrary, Low-Low areas mainly concentrated in underdeveloped areas such as Gansu, Ningxia, Qinghai, Guizhou and Tibet.

Fig. 5 shows the spatial distributions of provincial vehicular $NO_x$ emissions in 2005, 2010, and

2015. Significant spatial agglomeration was found in China. Notably, the Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Pearl River Delta (PRD) are hot spots with higher contributions to emissions. These three regions contribute approximately 40% (40.03%, 37.36%,36.99% in 2005, 2010, 2015, respectively) of the national vehicular $NO_x$ emissions, but only account for 4.4% of China’s geographical area. Fast economic growth and urbanization, a rapid increase in the vehicle population, and improved road infrastructure have an essential impact on increased vehicular $NO_x$ emissions in these three regions.

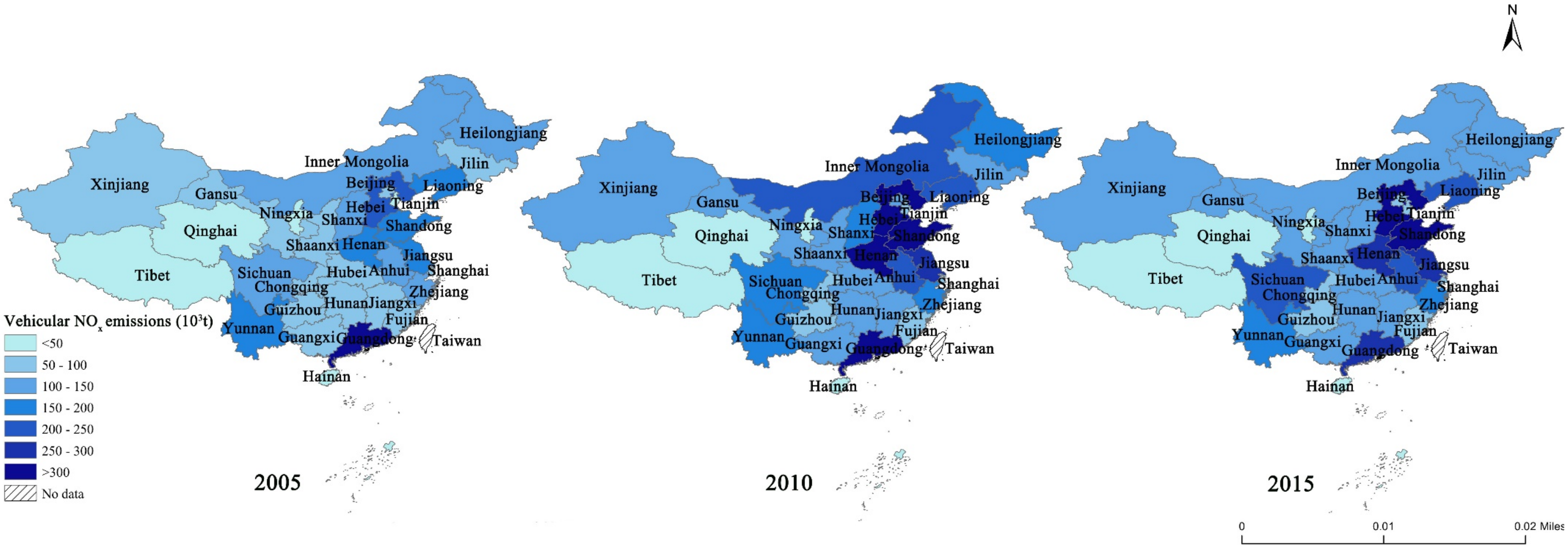


**Fig. 5.** Vehicular NO$_x$ emissions for 31 provinces in China

(Note: no data was available for Hong Kong, Macao, and Taiwan in this study)

### *3.3 Drivers of temporal changes in vehicular $NO_x$ emissions*

#### 3.3.1 Drivers on national vehicle $NO_x$ emissions

Fig. 6 shows the temporal decomposition results at the national level from 2005 to 2015. Overall, under the combined effect of five influencing factors, vehicular $NO_x$ emissions trended upwards in period 1 (2005–2010) but decreased in the following period (2010–2015). It was found that the road vehicle carrying capacity ($\Delta N_{VI}$), economic development ($\Delta N_G$), and population-scale effects ($\Delta N_P$) substantially drove the growth of national vehicular $NO_x$ emissions in China from 2005 to 2015. In contrast, the vehicle emission intensity ($\Delta N_{NI}$) and road economic growth effects ($\Delta N_{EI}$) inhibited the growth of $NO_x$ emissions from vehicles over time.

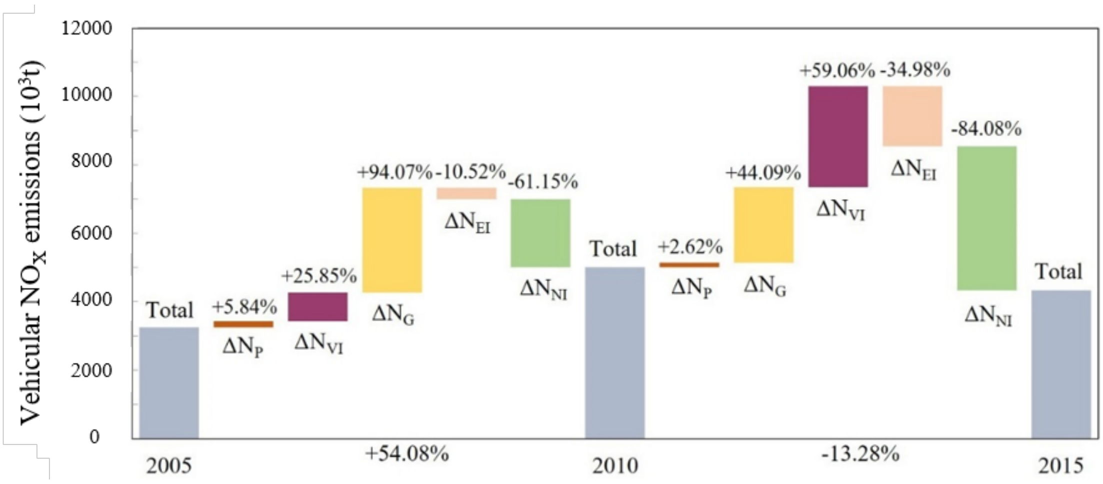


**Fig. 6.** Contributions from five influencing factors of national vehicular NOx emissions in China.

The contributions of the influencing factors to vehicular $NO_x$ emissions were further contrasted (Fig. 6). In the first period (2005-2010), it was found that, of all driving forces, $\Delta N_G$ was the most critical factor driving vehicular $NO_x$ emissions to increase $3060 \times 10^3$t (with a contribution rate of +94.07%), while $\Delta N_{VI}$ and $\Delta N_P$ only accounted for $840 \times 10^3$t (+25.85%) and $190 \times 10^3$t (+5.84%), respectively. Interestingly, in the following period (2010-2015), due to the rapid growth and high-intensity use of vehicles, $\Delta N_{VI}$ substituted $\Delta N_G$ and became the crucial factor in increasing vehicular $NO_x$ emissions about $2960 \times 10^3$t. In contrast, $\Delta N_{NI}$ and $\Delta N_{EI}$ drove emission reduction during this time.

### 3.3.2 Drivers on province $NO_x$ emissions

In this section, the temporal vehicular $NO_x$ emissions changes of each province in China were decomposed as shown in Fig. 7. It was found that $NO_x$ emissions from vehicles increased in all provinces in period 1 (2005-2010) and 29 provinces (all except Gansu and Tibet) then showed reduced emissions in period 2 (2010-2015). This indicates that most provincial emission levels react similarly to the national level under the combined effect of the five drivers ($\Delta N_{VI}$, $\Delta N_G$ and $\Delta N_P$ play positive roles for vehicular $NO_x$ emissions growth, whereas $\Delta N_{NI}$ and $\Delta N_{EI}$ reduce emissions). Although the driving mechanism is similar among the provinces, the significance of the drivers shows spatial diversity across the provinces. Next, how these five factors affect the emissions of different provinces will be analyzed.

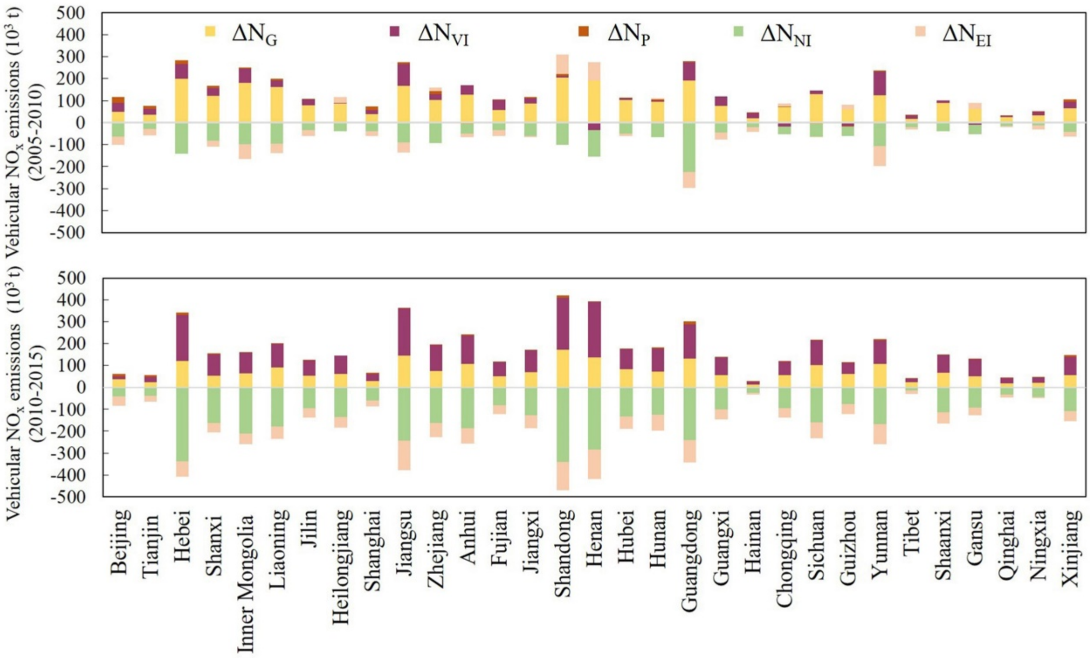


**Fig. 7.** Decomposition results of vehicular $NO_x$ emissions in 31 provinces in China

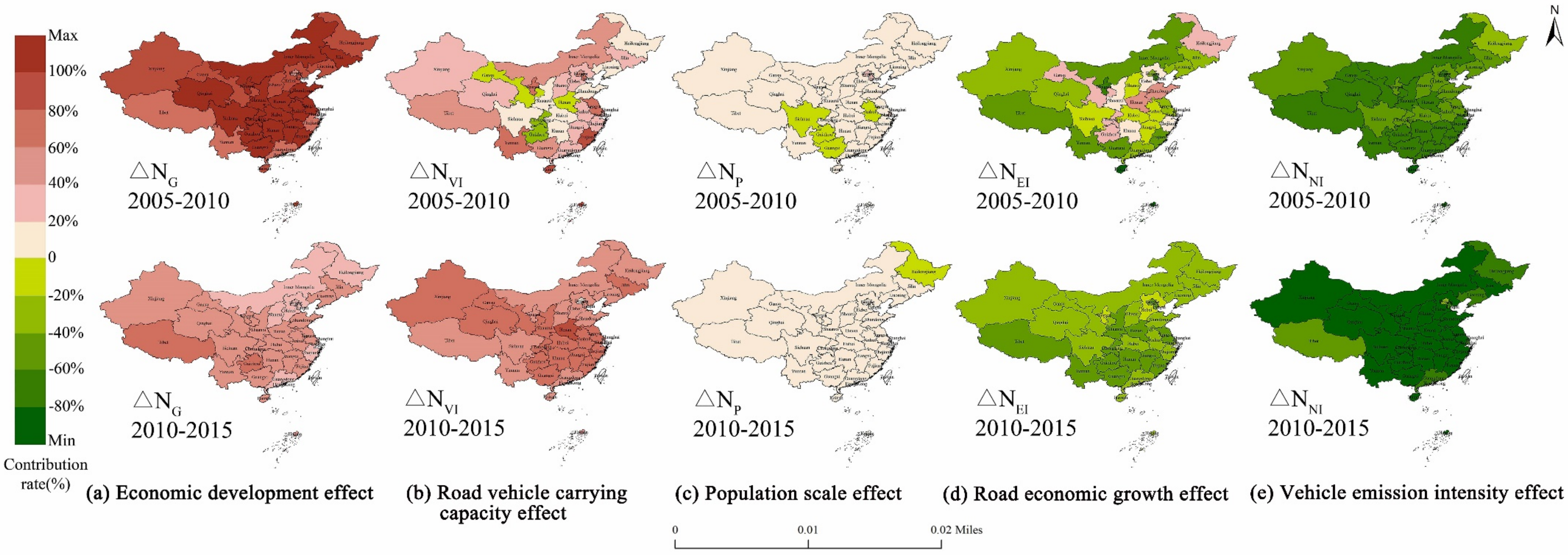


**Fig. 8.** The contribution rate of five influencing factors in 31 provinces.

(Note: red and green colors represent an increase and decrease of vehicular $NO_x$ emissions during the study periods, respectively.)

(1) Economic development effect ($\Delta N_G$)

Of all the drivers, Economic development ($\Delta N_G$) was the most positive factor on vehicular $NO_x$ emissions for 2005-2010 (Fig. 8). The contribution rate was approximately 50% to 120%. The significant contribution of $\Delta N_G$ can be predominantly attributed to increasing resident income per capita and growing travel demand, which is often accompanied by an increase in the number of vehicles (Liang et al., 2017). Nevertheless, in the following stage from 2010 to 2015, it was found that the effect of $\Delta N_G$ weakened gradually, which differs from previous studies (Wang et al., 2011; Liu et al., 2015; Luo et al., 2016). Decoupling index $I_D$ is applied to quantitatively measure the relationship between economic growth and vehicular $NO_x$ emissions. As shown in Table 5, decoupling index $I_D$ of Vehicular $NO_x$ emissions and GDP per capita were 0.28 in 2005-2010 and 0.46 in 2010-2015, respectively. This result can be shown as a gradual decoupling between economic growth and $NO_x$ emissions from vehicles during the period of China' s 12th Five-Year Plan，especially in several economically developed regions like Beijing, Tianjin, Shanghai, Zhejiang, Fujian, etc. (see Fig. 9). This also indicates that vehicular $NO_x$ emissions in China are no longer as increasing with economic growth, possibly due to its more advanced economic development.

**Table 5**

Decoupling between vehicular from 1997 to 2008

| Period | Year | Vehicular NOx emissions(ton) | GDP per capita (Yuan/people） | Decoupling indicator | Rate of change of decoupling indicator | Decoupling index $I_D$ |
|---|---|---|---|---|---|---|
| 2005-2010 | 2005 | 3248671.09 | 15375.90 | 211.28 | 0.72 | 0.28 |
| | 2010 | 5005621.88 | 437041.99 | 152.77 | | |
| 2010-2015 | 2015 | 4340943.84 | 722767.87 | 82.33 | 0.54 | 0.46 |

Note: the valve range of $I_D$ is [0,1], if $I_D$>0, it means the decoupling phenomenon occurs. The larger the value, the more significant the decoupling phenomenon is (Wang et al., 2012).

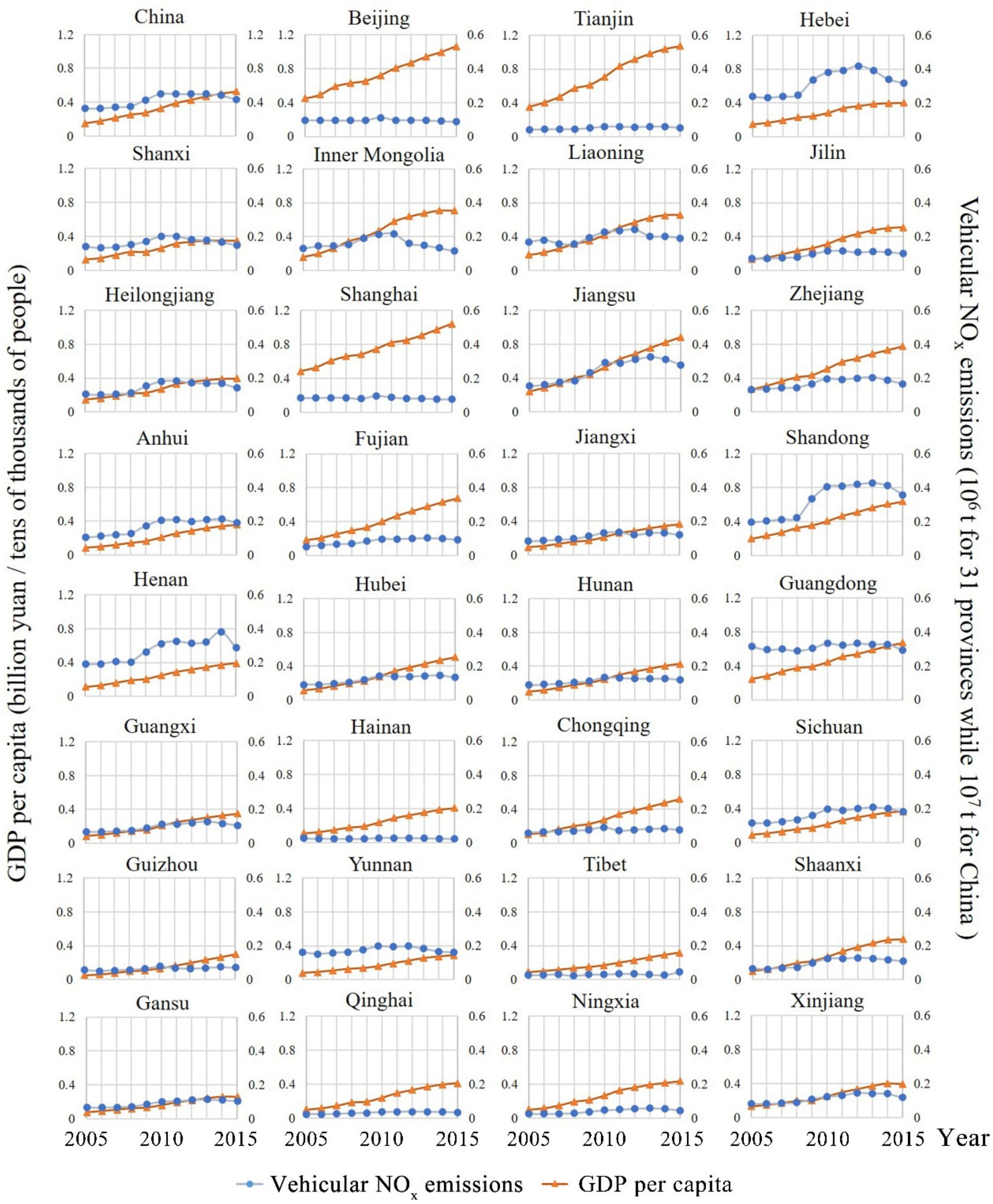


**Fig. 9.** The change in vehicular $NO_x$ emissions and GDP in China and 31 provinces from 2005 to 2015.

(2) Road vehicle carrying capacity effect ($\Delta N_{VI}$)

Road vehicle carrying capacity effect ($\Delta N_{VI}$) is another critical driver on promoting the growth of vehicular $NO_x$ emissions across most provinces. It was found that the rapid change of Road vehicle carrying capacity has replaced $\Delta N_G$ as the dominant factor responsible for increasing vehicular $NO_x$ emissions since 2010. Especially, stronger $\Delta N_{VI}$ effects were found in the Beijing-

Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Pearl River Delta (PRD) regions than in other regions from 2005 to 2010. Also, in the second stage (2010-2015), the role of $\Delta N_{VI}$ in non-hotspot regions showed a similar positive effect as in eastern China.

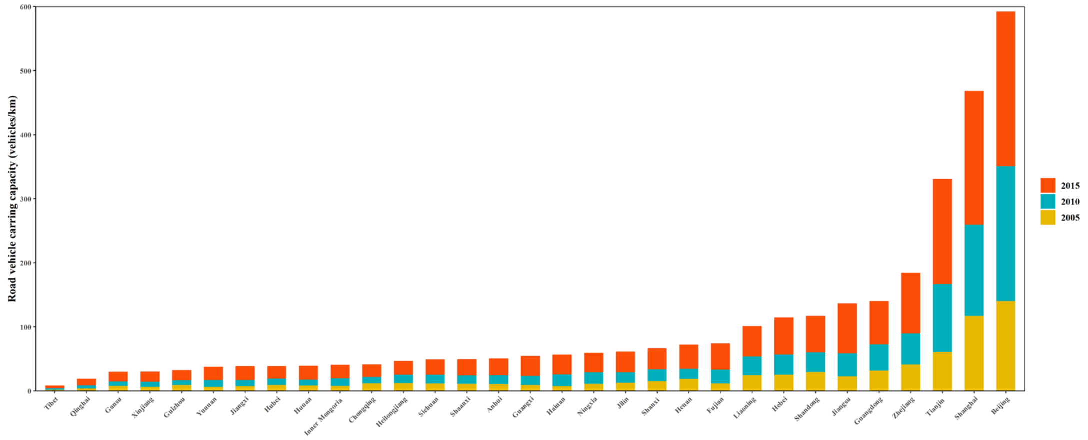


**Fig. 10.** Road vehicle carrying capacity of 31 provinces in 2005, 2010, and 2015.

We further explored the reasons for this result and found that this effect in the Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Pearl River Delta (PRD) regions are related to increasing on-road vehicles and traffic pressure. With the rapid economic development and improvement in the resident income, vehicle ownership has surged dramatically, especially in some big cities. As shown in Fig. 10, the $\Delta N_{VI}$ of Beijing, Tianjin, and Shanghai has almost reached the maximum road capacity (270 vehicles/km). High road vehicle carrying capacity mostly means high $NO_x$ emissions. However, $\Delta N_{VI}$ in central and western regions like Hainan and Ningxia slightly contributed to the change in vehicular $NO_x$ emissions. The reason is that it is still far from the carrying capacity of developed provinces, although road vehicle carrying capacity also increased from 2005 to 2015 (such as Hainan from 7.63 to 30.80, Ningxia from 11.42 to 30.05). Nevertheless, considering the potential for economic growth and urbanization in these provinces, policy-makers should raise issues on its gradual contribution to increasing vehicular $NO_x$ emissions.

(3) Population scale effect ($\Delta N_P$)

Of all the drivers, the change of population-scale ($\Delta N_P$) plays the smallest effect size (Fig. 11). Overall, it contributed to an increase of only 5–20%. Nonetheless, some provinces, including Beijing, Hebei, Jiangsu, Shanghai, Guangdong, and Zhejiang, show more noticeable contribution growth (approximately $8\times10^3$ t to $14\times10^3$ t) than other regions from 2005 to 2010.This result could be explained mostly by increasing population migration from surrounding regions because of high urbanization, which leads to the rapidly growing number of vehicles and related $NO_x$ emissions.

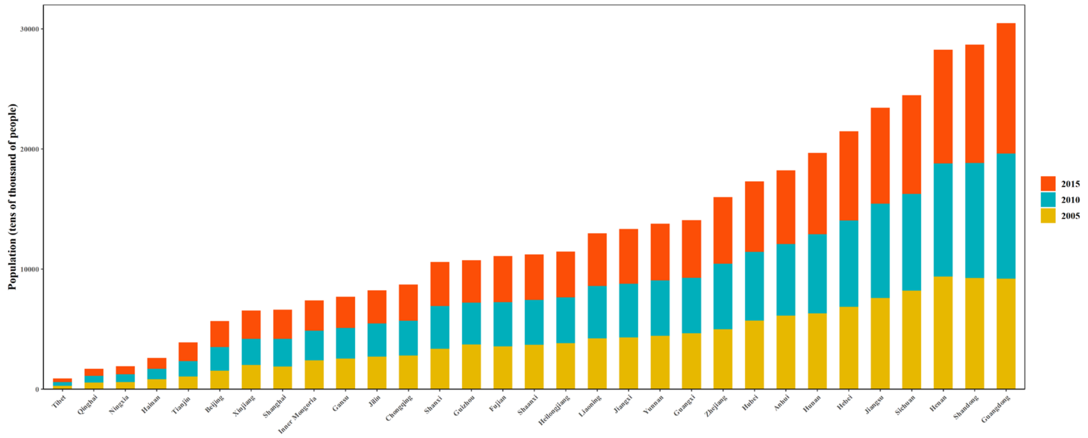


**Fig. 11.** The change in population of 31 provinces in 2005, 2010, and 2015.

(4) Road economic growth effect ($\Delta N_{EI}$)

Road economic growth effect ($\Delta N_{EI}$) reflects the change in regional road infrastructure induced by economic development, which indirectly affects $NO_x$ emissions from vehicles. According to the decomposition results, it was found, of all the drivers, the effect of $\Delta N_{EI}$ acts as the role with the biggest impact on spatial difference during 2005-2010. Also, it was observed that $\Delta N_{EI}$ positively affects the increasing emissions only in Shandong, Henan, Hebei, Heilongjiang, Gansu, Guizhou, Zhejiang, Hunan and Ningxia. These results indicate that the increased GDP required more road infrastructure than other provinces, which also caused more vehicle $NO_x$ emissions. Especially, Shandong and Henan seemed to have the biggest driving force on economic development. In comparison, Shanghai, Guangdong, and Beijing negatively contribute to $NO_x$ emissions from vehicles. However, during the second stage, $\Delta N_{EI}$ started acting as an inhibitor of $NO_x$ emissions from vehicles across all provinces due to the decline of road mileage per GDP across the country (Fig. 12). As a result, this study revealed that the role of $\Delta N_{EI}$ is somewhat complicated due to the connection between road infrastructure construction, economic growth, and vehicle population. The economic growth induced by increasing highway mileages could play positive or negative effect on $NO_x$ emissions from vehicles, which mainly depend on the economic development level of regions.

So, we hope that mitigation policy-makers should carefully evaluate the effect of economic growth on NOx emissions.

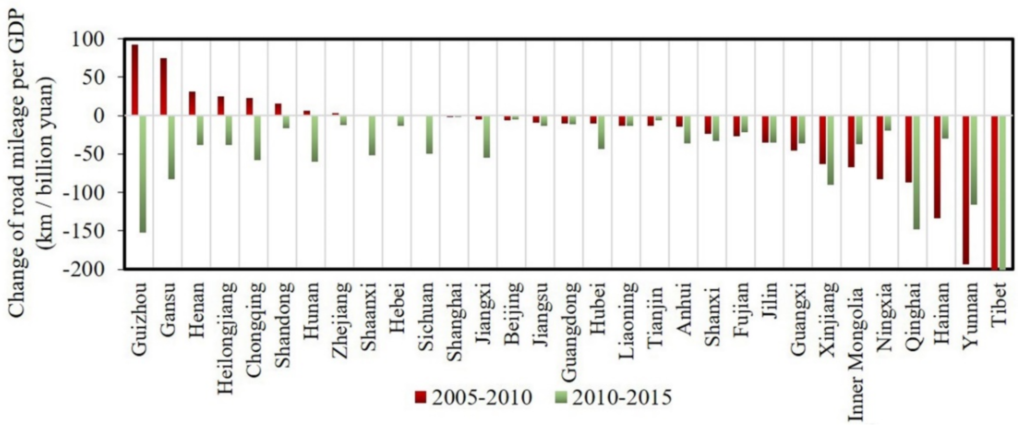


**Fig. 12.** The change in regional road intensity induced by economic development.

(5) Vehicle emission intensity effect ($\Delta N_{NI}$)

Here, the regional vehicle emission intensity comprehensively involves changes in vehicular emission standards, vehicular fuel quality, and vehicle structure on $NO_x$ emissions, and represents the average emission level of one registered vehicle in a province. As shown in Fig. 8, the most remarkable result to emerge from the decomposition model was that vehicle emission intensity effect ($\Delta N_{NI}$) is a pivotal factor in reducing vehicular $NO_x$ emissions across all provinces from 2005 to 2015. Notably, according to decomposition results, the effect of $\Delta N_{NI}$ shows the obvious spatial-differences from 2000 to 2005. The influenced provinces are mainly located in hot spot regions such as Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD), and the Pearl River Delta (PRD). We also found that, in the following stage, with the implementation of State IV across most provinces in China since 2013 (Fig. 13), $\Delta N_{NI}$ has changed into a significant positive effect on controlling national $NO_x$ emissions. Our findings also underline the importance of stringent emission standards (Fig. 13) and the improvement of fuel quality over the past ten years (Wu et al., 2017). The primary cause for this spatial distribution is due to the stringent emission standards of megacities such as Beijing, Tianjin, and Shanghai.

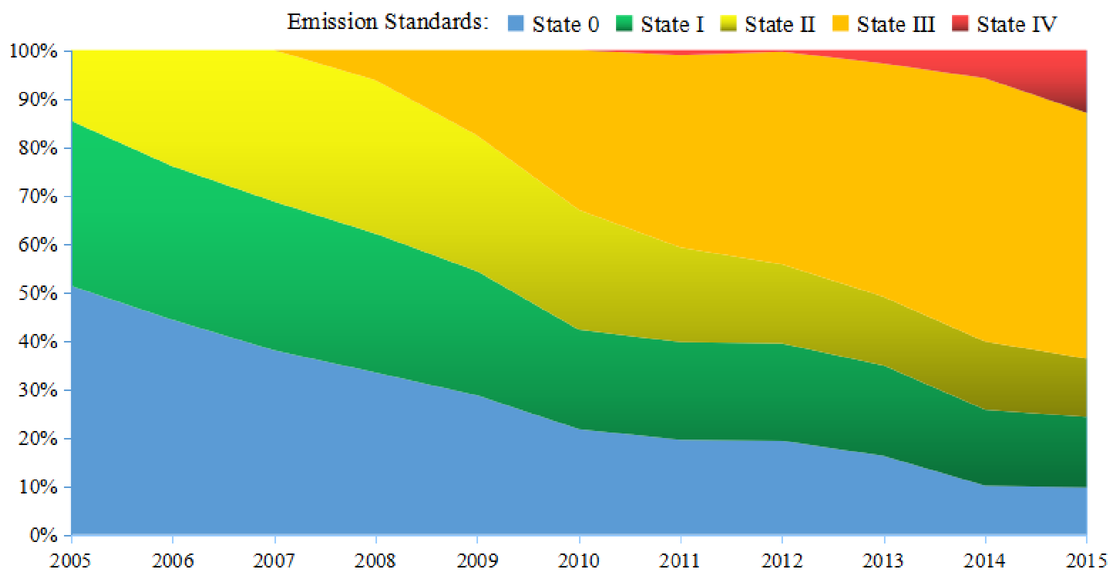


**Fig. 13.** The proportion of vehicles in China with different emission standards.

(The implementation timetable of vehicular emission standards in China is presented in Table A.5 in Supplementary information.)

## *3.4 Drivers of spatial differences in vehicular $NO_x$ emissions*

### 3.4.1 Mapping spatial differences in vehicular $NO_x$ emissions

China has a huge geographical area and features the imbalance of socio-economic development. Therefore, studying the drivers of vehicular $NO_X$ emissions at the provincial level from a spatial perspective is useful for regional emission reduction. Based on the estimated results of provincial $NO_x$ emissions, we observed significant regional disparity since 2005 (Fig. 14). It was found that differences between provinces were widening as overall $NO_x$ emissions from vehicles rose, which had led to the important challenge of reducing national vehicular $NO_x$ emissions.

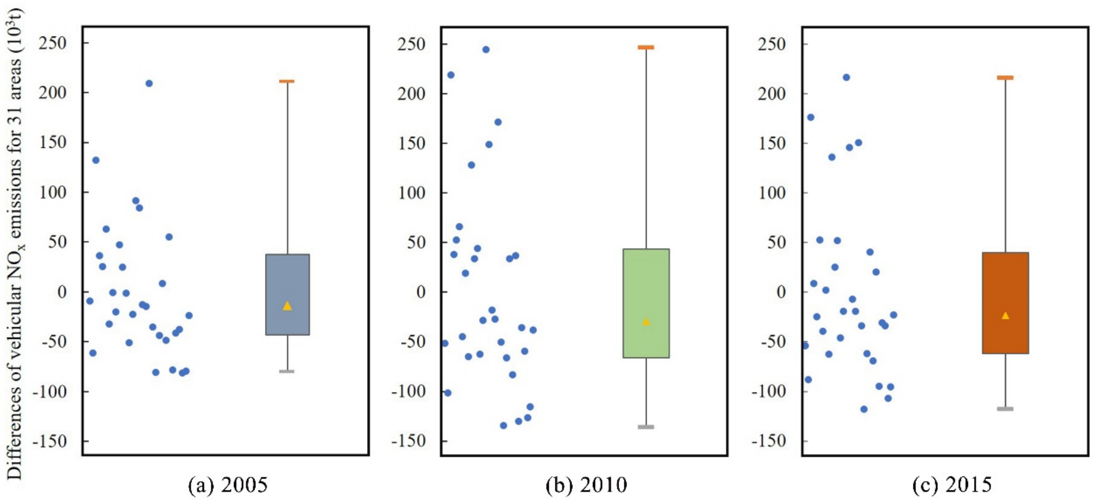


**Fig. 14.** Spatial differences in provincial vehicular $NO_x$ emissions.

(Each dot represents each region)

Based on the above concerns, this study further mapped the changes in spatial differences from 2005 to 2015. As shown in Fig. 15, it was observed that vehicular $NO_x$ emissions in China are clustered in certain areas. The provinces which have the biggest difference from the national average are mainly located in hot spot regions including Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD), and the Pearl River Delta (PRD). Shandong, Henan, Liaoning, and Yunnan also emitted more than 50% above the national average. The remaining provinces, especially Qinghai, Hainan, Ningxia, and Tibet, emitted approximately 75% less than the average level. The critical drivers of spatial differences will be further analyzed between different provinces in vehicular $NO_x$ emissions in section 4.2.2.

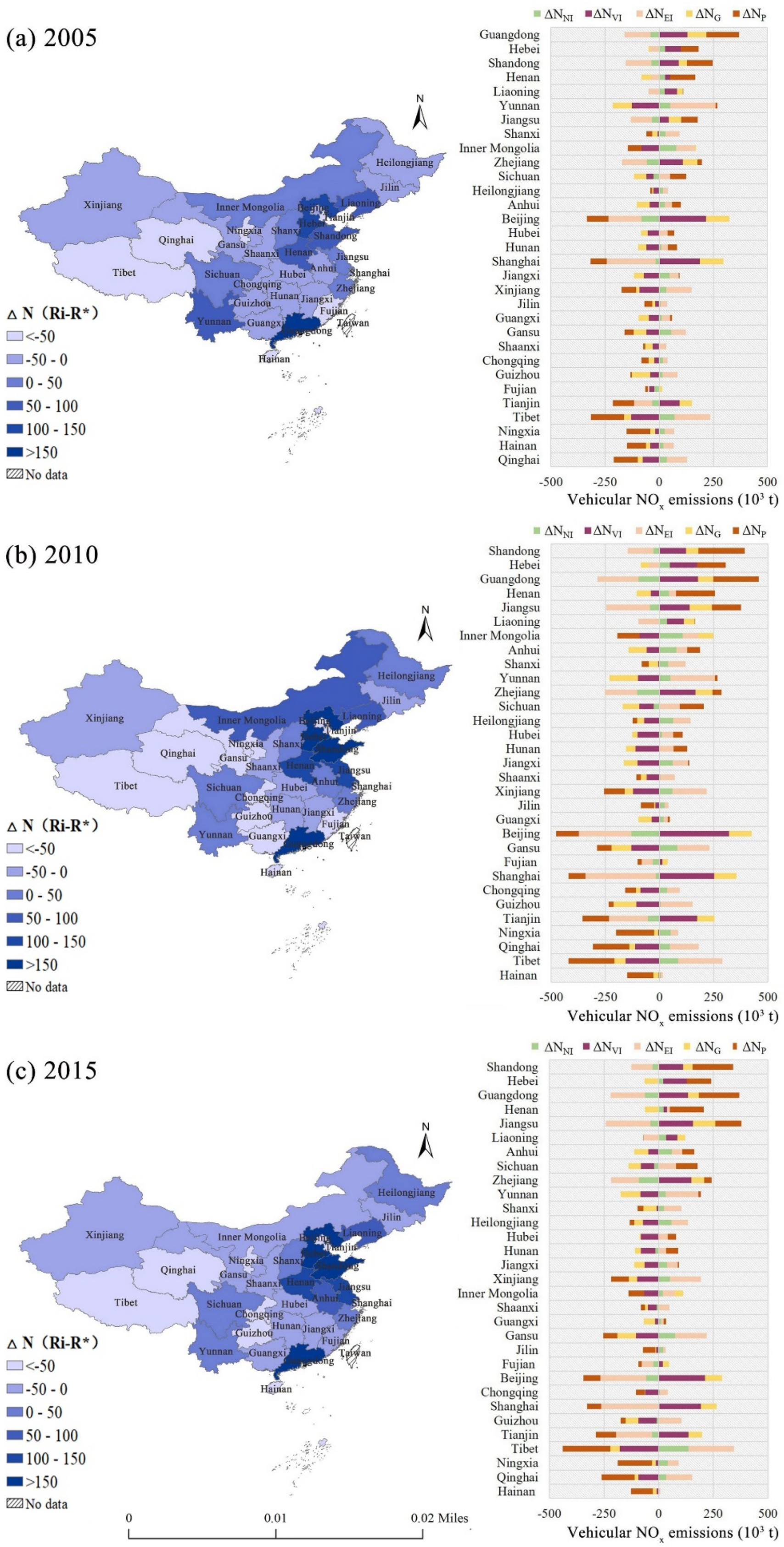


**Fig. 15.** Spatial diversity of the drivers of vehicular NOx emissions in China ($10^3$ t).

### 3.4.2 Identifying the key drivers of spatial differences in vehicular $NO_x$ emissions

Here, the aim is to identify the factors causing this regional disparity and spatial agglomeration, which would help policymakers to reduce national and local $NO_x$ emissions from vehicles. We applied the multi-regional (M-R) spatial decomposition method to build a fresh temporal-spatial model. We hope it could find and quantify the key drivers of the spatial difference.

This study decomposed the spatial differences into the five factors: $\Delta N_{NI}$, $\Delta N_{VI}$, $\Delta N_{EI}$, $\Delta N_{G}$, and $\Delta N_{P}$ and estimated each effect using Equations 5a–e. Moreover, in order to find the key drivers, a key-driver list of all provinces was made by ranking the 31 regions according to their spatial differences in vehicular $NO_x$ emissions. The ranked results are shown in Fig. 16. Those with the most significant contribution rates were named as the key factors which affect emissions, differentiating them from less important ones. Further, joint drivers were identified by values which differ by less than 50% of the contributions of the key drivers. The joint and key drivers contribute to spatial differences and agglomeration of vehicular $NO_x$ emissions. Considering the synergistic effect between drivers, joint drivers were classified with key drivers into the following types: population-driven, economic development-driven, vehicle-driven, and road infrastructure-driven.

| Provinces | 2005 | | | | | | 2010 | | | | | | 2015 | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | Nationwide Ranking | Contribution rate of each factor | | | | | Nationwide Ranking | Contribution rate of each factor | | | | | Nationwide Ranking | Contribution rate of each factor | | | | |
| | $\Delta N_{tot}$ | $\Delta N_{NI}$ | $\Delta N_{VI}$ | $\Delta N_{EI}$ | $\Delta N_{G}$ | $\Delta N_{P}$ | $\Delta N_{tot}$ | $\Delta N_{NI}$ | $\Delta N_{VI}$ | $\Delta N_{EI}$ | $\Delta N_{G}$ | $\Delta N_{P}$ | $\Delta N_{tot}$ | $\Delta N_{NI}$ | $\Delta N_{VI}$ | $\Delta N_{EI}$ | $\Delta N_{G}$ | $\Delta N_{P}$ |
| Beijing | 14 | 8.69 | -22.98 | 16.10 | -11.32 | 10.50 | 21 | 2.52 | -6.26 | 4.74 | -2.06 | 2.05 | 23 | 1.03 | -3.94 | 3.88 | -1.43 | 1.46 |
| Tianjin | 27 | 0.53 | -1.53 | 1.37 | -0.95 | 1.58 | 27 | 0.53 | -1.72 | 1.76 | -0.78 | 1.21 | 27 | 0.34 | -1.56 | 1.87 | -0.72 | 1.06 |
| Hebei | 2 | 0.20 | 0.55 | -0.32 | -0.05 | 0.61 | 2 | 0.22 | 0.58 | -0.22 | -0.17 | 0.60 | 2 | 0.12 | 0.61 | -0.03 | -0.33 | 0.64 |
| Shanxi | 8 | 0.80 | -0.17 | 1.80 | -0.71 | -0.72 | 9 | 1.06 | -0.15 | 2.10 | -1.14 | -0.87 | 11 | 2.85 | -1.08 | 9.26 | -6.90 | -3.13 |
| Inner Mongolia | 9 | 3.09 | -3.19 | 3.37 | 0.24 | -2.52 | 7 | 2.04 | -1.75 | 1.38 | 1.29 | -1.96 | 17 | -0.75 | 2.64 | -2.27 | -1.54 | 2.92 |
| Liaoning | 5 | 0.40 | 0.92 | -0.76 | 0.41 | 0.04 | 6 | 0.53 | 1.18 | -1.49 | 0.74 | 0.05 | 6 | 0.67 | 0.97 | -1.29 | 0.68 | -0.03 |
| Jilin | 20 | -0.17 | 0.60 | -0.95 | 0.39 | 1.14 | 19 | -0.53 | 0.43 | -0.40 | 0.12 | 1.38 | 21 | -0.55 | 0.29 | -0.27 | 0.10 | 1.43 |
| Heilongjiang | 12 | -22.96 | 34.36 | -30.86 | 8.91 | 11.56 | 13 | 3.31 | -3.75 | 4.20 | -1.72 | -1.04 | 12 | 30.33 | -36.66 | 39.15 | -20.97 | -10.85 |
| Shanghai | 17 | 0.79 | -9.27 | 11.17 | -5.34 | 3.66 | 24 | 0.26 | -3.89 | 5.02 | -1.60 | 1.22 | 25 | -0.08 | -3.01 | 4.21 | -1.15 | 1.02 |
| Jiangsu | 7 | -0.71 | 0.94 | -2.07 | 1.21 | 1.63 | 5 | -0.34 | 1.08 | -1.59 | 0.81 | 1.03 | 5 | -0.27 | 1.16 | -1.51 | 0.75 | 0.87 |
| Zhejiang | 10 | -2.27 | 4.43 | -4.67 | 2.64 | 0.87 | 11 | -3.03 | 4.86 | -4.37 | 2.30 | 1.23 | 9 | -3.55 | 5.88 | -4.98 | 2.29 | 1.34 |
| Anhui | 13 | -21.69 | 36.35 | -28.63 | 48.97 | -34.00 | 8 | 1.76 | -1.36 | 1.15 | -1.90 | 1.35 | 7 | 1.16 | -0.91 | 0.93 | -1.22 | 1.04 |
| Fujian | 26 | 0.43 | 0.47 | 0.14 | -0.28 | 0.23 | 23 | 0.50 | -0.22 | 0.81 | -0.40 | 0.31 | 22 | 0.53 | -0.40 | 1.15 | -0.63 | 0.36 |
| Jiangxi | 18 | -2.12 | 3.13 | -1.89 | 2.05 | -0.16 | 16 | -2.11 | 3.54 | -2.48 | 2.24 | -0.19 | 15 | -1.92 | 3.31 | -2.61 | 2.43 | -0.21 |
| Shandong | 3 | -0.40 | 1.00 | -1.30 | 0.42 | 1.28 | 1 | -0.12 | 0.50 | -0.48 | 0.24 | 0.87 | 1 | -0.13 | 0.51 | -0.44 | 0.21 | 0.86 |
| Henan | 4 | 0.33 | 0.26 | -0.44 | -0.52 | 1.38 | 4 | 0.29 | -0.27 | 0.22 | -0.44 | 1.20 | 4 | 0.16 | 0.09 | 0.09 | -0.42 | 1.07 |
| Hubei | 15 | -0.26 | 4.14 | -2.72 | 2.25 | -2.42 | 14 | -0.65 | 5.58 | -2.88 | 1.36 | -2.41 | 13 | -0.04 | 11.77 | -6.01 | 0.86 | -5.58 |
| Hunan | 16 | -0.65 | 3.94 | -2.15 | 2.63 | -2.77 | 15 | 0.05 | 4.04 | -2.39 | 1.61 | -2.31 | 14 | 0.79 | 3.43 | -1.75 | 1.45 | -2.91 |
| Guangdong | 1 | -0.19 | 0.63 | -0.58 | 0.42 | 0.73 | 3 | -0.57 | 1.04 | -1.10 | 0.41 | 1.23 | 3 | -0.41 | 0.89 | -1.04 | 0.33 | 1.23 |
| Guangxi | 21 | -0.33 | 1.32 | -1.07 | 1.36 | -0.28 | 20 | -0.37 | 0.72 | -0.40 | 1.23 | -0.19 | 19 | -0.33 | 0.52 | -0.37 | 1.48 | -0.29 |
| Hainan | 30 | -0.24 | 0.51 | -0.61 | 0.24 | 1.10 | 31 | -0.05 | 0.03 | -0.06 | 0.18 | 0.90 | 31 | 0.00 | 0.07 | -0.07 | 0.14 | 0.86 |
| Chongqing | 24 | -0.41 | 0.52 | -0.45 | 0.62 | 0.72 | 25 | -0.51 | 1.32 | -0.90 | 0.33 | 0.76 | 24 | -0.09 | 1.01 | -0.59 | 0.02 | 0.66 |
| Sichuan | 11 | -2.98 | -3.73 | 5.87 | -6.78 | 8.63 | 12 | -0.81 | -1.97 | 2.74 | -2.24 | 3.28 | 8 | -0.50 | -1.49 | 1.99 | -1.43 | 2.43 |
| Guizhou | 25 | -0.31 | 0.86 | -1.41 | 1.69 | 0.17 | 26 | -0.07 | 1.29 | -1.77 | 1.25 | 0.29 | 26 | 0.14 | 1.20 | -1.51 | 0.84 | 0.33 |
| Yunnan | 6 | 0.92 | -2.27 | 3.78 | -1.60 | 0.17 | 10 | 1.34 | -2.68 | 5.59 | -3.58 | 0.33 | 10 | 1.59 | -4.08 | 7.50 | -4.53 | 0.52 |
| Tibet | 28 | -0.91 | 1.66 | -2.09 | 0.39 | 1.95 | 30 | -0.66 | 1.20 | -1.57 | 0.40 | 1.63 | 28 | -1.43 | 1.88 | -2.19 | 0.45 | 2.30 |
| Shaanxi | 23 | 0.05 | 0.69 | -0.78 | 0.81 | 0.23 | 17 | -0.13 | 1.65 | -1.85 | 0.76 | 0.57 | 18 | 0.27 | 1.30 | -1.60 | 0.42 | 0.62 |
| Gansu | 22 | -1.50 | 1.58 | -1.77 | 1.59 | 1.11 | 22 | -1.38 | 2.20 | -2.51 | 1.55 | 1.14 | 20 | -2.22 | 3.03 | -4.24 | 2.52 | 1.91 |
| Qinghai | 31 | -0.42 | 0.93 | -1.16 | 0.29 | 1.36 | 29 | -0.37 | 0.90 | -1.05 | 0.20 | 1.33 | 30 | -0.32 | 0.86 | -1.11 | 0.17 | 1.40 |
| Ningxia | 29 | -0.32 | 0.24 | -0.55 | 0.29 | 1.35 | 28 | -0.45 | 0.05 | -0.30 | 0.16 | 1.53 | 29 | -0.45 | 0.14 | -0.52 | 0.17 | 1.66 |
| Xinjiang | 19 | -1.39 | 3.80 | -4.90 | 0.67 | 2.82 | 18 | -1.56 | 3.18 | -4.14 | 1.02 | 2.50 | 16 | -2.26 | 4.31 | -6.16 | 1.61 | 3.50 |

**Fig. 16.** Key and joint drivers of spatial differences in vehicular $NO_x$ emissions[1]

[1] : Orange regions indicate higher $NO_x$ emissions from vehicles than the national average while yellow regions indicate lower than average emissions. Dark blue drivers are the key drivers of the spatial differences of vehicular $NO_x$ emissions while light blue indicates joint drivers, with a contribution rate of ( $\frac{\Delta N_{ecah\ factor}}{\Delta N_{tot}}$ ).

We found that the population-driven factor influenced most provinces. Henan, Shandong, Guangdong, Hebei, and Sichuan not only feature the largest population in China but also intense population agglomeration. They both show a population-driving effect on the difference from other provinces. Within the provinces with population-driven effect, we also found that $\Delta N_P$ often is along with $\Delta N_{VI}$ and $\Delta N_{EI}$ to play a significant impact on making the spatial differences. These results can be observed in Guangdong in the Pearl River Delta, and Hebei and Shandong in Beijing-Tianjin-Hebei, where the key driver $\Delta N_P$ combines with the joint driver $\Delta N_{VI}$ to make the difference. Moreover, $\Delta N_P$ of Sichuan, together with $\Delta N_{EI}$, lead to spatial differences of vehicular $NO_x$ emissions with other provinces.

In contrast to the population factor, road infrastructure factor shows the complicated effect on making the spatial difference. $\Delta N_{VI}$ refers to the relationship among the changing vehicle population, road infrastructure construction and emission growth. In some provinces, including Hunan, Hubei, Zhejiang, and Shanxi, $\Delta N_{VI}$ crucially causing spatial differences. $\Delta N_{EI}$ results indicate a complicated relationship between road infrastructure construction, regional economic growth, and emission growth. Shanxi is close to the Beijing-Tianjin-Hebei region and it is one of China's major coal production provinces. We observed that most of the coal carriers are heavy-duty diesel vehicles, which account for 74% of total vehicular $NO_x$ emissions, with only 15% of the vehicle population (Fig. 17). The linkage between the number of coal carriers and economic growth induces a higher $\Delta N_{NI}$ contribution to emissions than other factors.

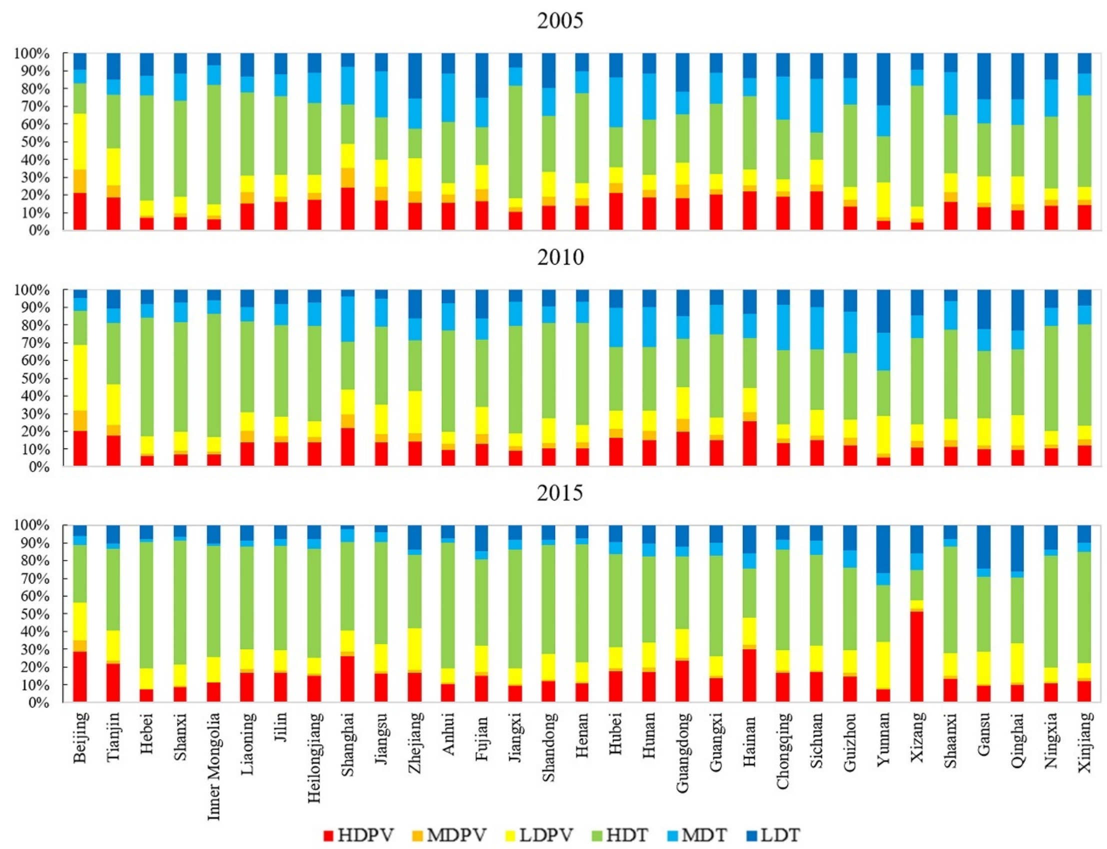


**Fig. 17.** The proportion of vehicle types in all 31 provinces in 2005, 2010, and 2015[2]

According to the results shown in Fig. 18, we found that Vehicle-driven effects ($\Delta N_{NI}$) only showed a minor and declining influence on making a spatial difference. Vehicle-driven effects ($\Delta N_{NI}$) were mainly from local regulations on vehicular $NO_x$ emissions, such as stringent vehicular emission standards, improvement in local vehicular fuel quality, and other control measures. Moreover, this role of Vehicle-driven effects ($\Delta N_{NI}$) is closely related to the declining proportion of trucks amongst total vehicles (Fig. 17). It was found that $\Delta N_{NI}$ had a positive effect on the spatial differences of emission in Beijing, Shanghai, and Guangdong. These results underlined that stringent regulation in developed megacities still be important, and it would help decrease the disparities in regional emissions.

Moreover, we found that economic development effect ($\Delta N_G$) had a key impact on the growing spatial differences in vehicular $NO_x$ emissions between provinces. Interestingly, it was found that

[2] LDPV: light-duty passenger vehicle; MDPV: medium-duty passenger vehicle; HDPV: heavy-duty passenger vehicle; LDT: light-duty truck; MDT: medium-duty truck; HDT: heavy-duty truck;

economic development effect ($\Delta N_G$) usually works with joint drivers to make a spatial difference. Here, economic development effect ($\Delta N_G$) links two factors to show the complicated connection between the economy and emissions. On the one hand, a high level of economic development requires large vehicles to support its activities; on the other hand, rapid economic growth usually brings an increased need for road infrastructure construction. We found that, in some hot spot regions (Jiangsu and Zhejiang) with a high level of economic activity and vehicle population, economic development effect ($\Delta N_G$) played the crucial role in growing the spatial differences.

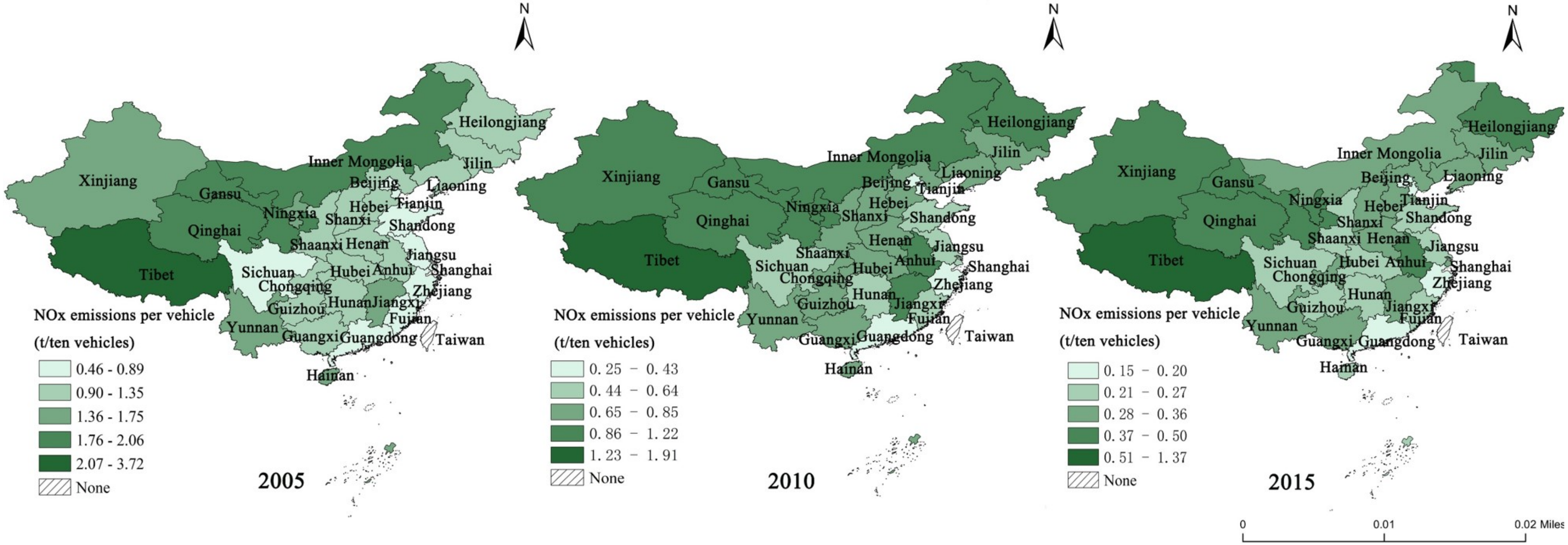


**Fig. 18.** $NO_x$ emissions per vehicle for all 31 provinces in 2005, 2010, and 2015

### *3.5 Uncertainty analysis*

Note that although the main purpose of this study is to explore emission trends and their driving forces on NOx emissions from on-road vehicles in China from a temporal-spatial perspective, the uncertainties in emission estimation in this study present a need for future research. To aid in this effort, a table (Table 6) was made to compare previous studies on vehicular NOx emissions with the estimation results in this study for uncertainty analysis.

Based on comparison results, the reasons for uncertainty in the estimation of total vehicular NOx emissions were mainly from uncertainties in vehicle emission factors (see Equation 1), annual VKT, and vehicle population. Vehicle emissions factors were the leading factor (Zhang et al., 2014), which is key to estimating emissions. Some previous studies have been conducted based on the COPERT or Multi-resolution emission inventory for China (MEIC) models (Lang et al., 2014; Sun et al., 2016; Liu et al., 2016; Zheng et al., 2018). Based on the present study and the National Emission Inventory Guidebook for On-road Vehicles (MEP, 2014), the localized vehicle emissions factors were estimated using the various emissions standards in each province of China. Moreover, each parameter in the estimation equation was obtained from official sources.

However, based on the calculation process, the uncertainty in emission factors was observed in Equation 1, where the estimation equation of emission factor was established by multiplication of five factors. So, the quality of the data used for each factor will contribute to uncertainties. For example, BEF is based on the 2014 scenario and adjusted according to the other factors ($\varphi$, $\gamma$, $\lambda$ and $\theta$). However, average annual values do not cover extreme conditions of temperature, humidity, traffic speed, and other factors, which should be considered in the uncertainty analysis. Meanwhile, we should not ignore the fact that there are many substandard oil products in China, which leads to the improper emission factors based on qualified oil products (Tang et al., 2015). We have corrected the impact of the vehicle's use conditions (such as load factor, oil quality, etc.) by $\theta$ (MEP, 2014). As for VKT, due to the lack of official province-statistics, the data used in this study were obtained from the National Emission Inventory Guidebook for On-road Vehicles and adjusted based on previous studies. Therefore, the uncertainty from VKT was assumed to be lognormal with the coefficients of variation (CVs, the standard deviation divided by the mean) of 30% (Lang et al., 2016), even though only the most reliable data were used for this study.

**Table 6**

Comparison of vehicular $NO_x$ emissions estimates with other studies.

| Study | Method & Data | Region | Year or Period | Emissions（$10^4$t） or emission change (%) | Results in this study | Uncertainty |
|---|---|---|---|---|---|---|
| **Lang et al. (2014)** | COPERT IV model | China | 2005-2010 | 67% | 54% | 13% |
| **Sun et al. (2016)** | COPERT IV model | Shandong | 2014 | 51.38 | 41.11 | 25% |
| **Zhang et al. (2017)** | Guidebook of China | Tianjin | 2013 | 6.74 | 6.02 | 10% |
| **Yang et al. (2018)** | Guidebook of China | Beijing | 2014 | 8.34 | 8.98 | 7% |
| | | Tianjin | 2014 | 6.97 | 5.94 | 17% |
| | | Hebei | 2014 | 39.16 | 33.89 | 15% |
| **Tang et al. (2016)** | | China | 2006 | 45.94 | 32.67 | 28.9% |
| | | | 2010 | 51.68 | 50.06 | 3.2% |
| **Zheng et al. (2018)** | MEIC | China | 2012-2015 | -6 % | -12% | / |
| **Liu et al. (2016)** | OMI | China | 2005-2011 | 53%(OMI); 42%(MEIC) | 53.4% | 0.4-11.4% |
| | MEIC | China | 2011-2015 | -32%(OMI); -21%(MEIC) | -12.9% | 8.1- 19.1% |
| **De, B. Foy et al. (2016)** | OMI | Beijing | 2010-2014 | -24.7% | -18.4% | 6.3% |
| | | Shanghai | 2010-2014 | -13.9% | -18.9% | 5% |
| | | Chongqing | 2010-2014 | -12.8% | -9.8% | 3% |

# 4. Policy implications

These findings could provide meaningful policy implications, not only for China, but for many other developing countries. One of these is the monitoring indicator of regional vehicle emission intensity which are influenced not only by emissions standards and fuel quality but also the widespread impact of vehicle numbers and structure of every province. Considering the gradual changes in vehicle emission intensity, here we suggest put regional vehicle emission intensity into the current regional vehicle emission policy system. We believe that it would help the government better manage the impact of vehicle types. The prioritizing regulations on heavy-duty diesel vehicles would effectively reduce $\Delta N_{NI}$ and $NO_x$ emissions from vehicles.

This study also suggests that policy-makers should evaluate the linkages between economic growth, urban population agglomeration, and substantial road infrastructure construction. Rapid population agglomeration dramatically increased the demand for construction of road infrastructure and the number of vehicles. This would cause spatial agglomeration of vehicular $NO_x$ emissions in more economically developed and densely populated regions. Therefore, critical continuous area and regional policies are crucial to controlling vehicle $NO_x$ emissions. Also, it is necessary to limit the spatial transfer of high-emission vehicles, coordinate the elimination and treatment of high-emission vehicles, adjust the transportation structure, and promote efficient green freight organization.

Moreover, cooperation and differentiated emission-reduction measures should be considered to control NOx emissions from vehicles of China's regions from the perspective of both equity and efficiency. More attention should be paid to central and western regions regarding China's emission-reduction. These regions with higher vehicle emission intensity have developed fuel quality and vehicle structure, and thus have great potential of emission-reduction through optimizing vehicle structure, improving fuel quality and emission standard. More importantly, marginal abatement cost in these regions is much lower than that of the relatively developed eastern region. Total abatement cost of China as a whole would decrease if Chinese government transfer the focus of emission-reduction from developed eastern regions to less developed central and western regions.

On the other hand, the population as well as vehicle ownership of developed regions are becoming oversaturated. Population scale, economic development and road vehicle carrying capacity are main reasons for the high $NO_x$ emissions from vehicles in these areas. If eastern developed regions choose to provide less developed regions with technical support, funds and management for emission-reduction, not only improves the emission-reduction efficiency of less developed regions, but also promotes the development of local economy. The rapid development of less developed regions would push a large number of population migration and vehicle transfer, which could relieve the pressure of traffic emissions in developed regions indirectly. China would achieve a better emission-reduction and mitigate the economic loss.

# 5. Concluding remarks and future prospects

## *5.1 Conclusion*

In this study, vehicular $NO_x$ emissions in China were estimated from 2005 to 2015 and their temporal and spatial trends were also explored. We observed that there is an increasing difference in emissions among regions. Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD), and the Pearl River Delta (PRD) are high-emission regions which also face more severe human health risks than in non-hotspot regions such as Central and West China.

So, the drivers were explored using a temporal-spatial decomposition model. It was found that both economic development ($\Delta N_G$) and road vehicle carrying capacity ($\Delta N_{VI}$) are the main factors in driving the growth of provincial vehicular $NO_x$ emissions. The most dominant factor $\Delta N_G$ has changed into $\Delta N_{VI}$ since 2010. Specifically, Regional vehicle emission intensity ($\Delta N_{NI}$) and road economic growth ($\Delta N_{EI}$) contributed to reducing $NO_x$ emissions from vehicles but increased emission differences between regions. On the contrary, economic development ($\Delta N_G$), as well as population scale ($\Delta N_p$) played crucial roles in reducing the spatial agglomeration of vehicular $NO_x$ emissions in China, but promoted the emission growing during 2005 to 2015.

## *5.2 Future prospects*

Registered vehicle populations were acquired from the official statistical yearbooks, in which all the data were summarized directly from the registered vehicle population (except motorcycles) in local government. As a result, the uncertainty in the vehicle population is small. However, this study did not consider the registered vehicle fluidity across provinces. The estimated vehicle $NO_x$ emissions only reflect aggregated $NO_x$ emissions from the registered vehicle population in each province. So, the estimated results in this study are not exactly equal to the real emissions from vehicles running in each province. Based on this, the results were compared with satellite monitoring data from the Ozone Monitoring Instrument (OMI). A good agreement was found between the estimated emission trends in this study and OMI observations (Liu et al., 2016; Cai et al., 2018;).

Moreover, this study applied provincial data other than city-level $NO_x$ emissions to explain the socioeconomic drivers on provincial vehicle $NO_x$ emissions. So, the estimated results are not suitable to explain city-level air quality related to $NO_x$ emissions. The province is a core local government in China, which has the responsibility to plan and manage economic growth, road infrastructure projects, and population urbanization. So, when talking about the driving forces on vehicle $NO_x$ emissions, provincial data was considered an appropriate alternative to explore the impact mechanisms. However, due to increasing concerns about air pollution in core cities, using city-level data would be useful when considering the impact of immigration and urbanization on vehicular $NO_x$ emissions in future.


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