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Spatiotemporal dynamics of CO_2 emissions from central heating supply in the North China Plain over 2012–2016 due to natural gas usage

Yuanzheng Cui[a], Weishi Zhang[b,c,d,*], Can Wang[d,e], David G. Streets[f], Ying Xu[g], Mingxi Du[h], Jintai Lin[h,*]

[a] Institute of Land and Urban-rural Development, Zhejiang University of Finance and Economics, Hangzhou 310018, China
[b] School of Geographic and Environmental Sciences, Tianjin Normal University, Tianjin 300387, China
[c] Research Center of Environment and Sustainable Development of the China Civil Aviation, Civil Aviation University of China, Tianjin 300300, China
[d] State Key Joint Laboratory of Environment Simulation and Pollution Control (SKLESPC), and School of Environment, Tsinghua University, Beijing 100084, China
[e] Ministry of Education Key Laboratory for Earth System Modeling, and Department of Earth System Science, Tsinghua University, Beijing, China
[f] Energy Systems Division, Argonne National Laboratory, Argonne, Illinois 60439, United States
[g] Department of Geography and Resource Management, the Chinese University of Hong Kong, Hong Kong
[h] Laboratory for Climate and Ocean-Atmosphere Studies, Department of Atmospheric and Oceanic Sciences, School of Physics, Peking University, Beijing 100871, China

HIGHLIGHTS

- Spatiotemporal changes of central heating CO_2 emissions at city level are shown.
- A high-resolution gridded inventory of heating-related CO_2 emissions is built.
- The satellite nighttime light data is used to downscale the city level emissions.
- Differences in CO_2 emissions between urban and non-urban areas are discussed.

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ABSTRACT

Energy consumption from central heating has rapidly increased in the cities of the North China Plain (NCP). The increasing use of natural gas in the central heating supply system may have altered the spatial and temporal patterns of CO_2 emissions from central heating, yet the quantitative impacts are poorly understood. Here we detect the spatio-temporal dynamics of CO_2 emissions of central heating from 2012 to 2016 at the prefectural-city level in the NCP region, by using the satellite NPP-VIIRS nighttime light data and a panel regression model to estimate CO_2 emissions on a $5 \times 5\,km^2$ grid. We find that despite a slight decrease (2%) in 2014 under the “Natural Gas Utilization Policy”, CO_2 emissions continued to grow. Between 2012 and 2016, CO_2 emissions from central heating in the NCP increased from 106 to 121 Tg, although CO_2 emissions declined by 12% in Beijing due to the increasing contribution of natural gas boilers. The gridded CO_2 emissions map shows that over 2012–2016 coal burning is the main driving force of CO_2 emissions in both urban and non-urban regions, despite the increasing fraction of gas-based heating. Our results contribute to city-level policymaking on carbon reduction and climate change mitigation. The high-resolution gridded CO_2 emissions can also be applied in physical models to facilitate carbon cycle studies.

1. Introduction

China is the largest emitter of anthropogenic carbon dioxide (CO_2) in the world, and in 2015 China’s total CO_2 emissions reached approximately 9265 teragrams (Tg) [1], which contributes about 30% of global emissions in 2015 [2]. In accordance with the Paris Agreement, China has promised to peak its CO_2 emissions by 2030, among other actions. A prerequisite of achieving these mitigation goals is detailed accounting and verification of emissions from different sectors. In the past, the greatest emphasis has been placed on coal-fired power plants, because they emit the most CO_2 and their emissions are well-known [1,3,4]. However, another important consumer of coal and emitter of

* Corresponding authors at: Research Center of Environment and Sustainable Development of the China Civil Aviation, Civil Aviation University of China, Tianjin 300300, China (W. Zhang).
E-mail addresses: zhangweishi@link.cuhk.edu.hk (W. Zhang), linjt@pku.edu.cn (J. Lin).

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Nomenclature

CO_2	carbon dioxide
NCP	North China Plain
NTL	nighttime light
Tg	Teragrams
NDRC	the National Development and Reform Commission of China
GHGs	greenhouse gases
TPPs	thermal power plants
IPCC	the Intergovernmental Panel on Climate Change
MOUHRD	the Ministry of Housing and Urban-Rural Development of the People's Republic of China
DMSP-OLS	Defense Meteorological Satellite Program’s Operational Linescan System
NOAA/NGDC	National Oceanic and Atmospheric Administration’s National Geophysical Data Center
VIIRS	Visible Infrared Imaging Radiometer Suite
NPP	National Polar-orbiting Partnership
AIC	Akaike info criterion

CO_2 is the residential heating supply.

This study focuses on CO_2 emissions from the central heating supply system, namely the heating supply by central generation technologies that is distributed to end-users, during the cold season (120–180 days annually) in the cities of northern China [5]. Over the last five decades, central/district heating has been widely used in many regions. Russia has the oldest but relatively inefficient central heating system in the world [6]. The Scandinavian countries have the best technologies of using sustainable heating sources in their centralized heating system network since 1970s [7]. By 2015, Poland and Germany owned the largest district heating grids in Central and Western Europe [8]. China has very fast development of the central heating supply network since 1998 [9]. Up to 2016, approximately 87% of the central heating in China was produced by coal burning [10], which makes central heating supply in China both energy and carbon intensive. However, this contributing sector is much more poorly characterized: the quantities of coal and other fuels burned is not well known. Statistics on residential energy use are unreliable, leading to unpredictive uncertainties on the estimation of China’s total CO_2 emission [11]. Coal burning from central heating supply also means a substantial amount of air pollutant emissions in the vicinity of residential dwellings [12,13], threatening the public health. In January and February 2010, residential heating and cooking in Beijing-Tianjin-Hebei contributed to 28–44% of ambient $PM_{2.5}$ concentrations in the regions [14].

The North China Plain region (NCP, including Beijing-Tianjin-Hebei, Henan, and Shandong provinces) is one of the most densely populated regions in the world, and the total CO_2 emissions of NCP accounted for 25% of China’s total emissions in 2015 [1]. CO_2 emissions for the central heating sector in the NCP was approximately 149 Tg in 2015, which was approximately equivalent to the total CO_2 emissions in the Netherlands (156 Tg) [15,16]. To save energy and reduce air pollution from residential heating, the Chinese government has launched the clean heating policy in the “2 + 26” cities, 24 of which are located in the NCP. The policy is expected to be implemented in the whole country at a later stage. Replacing coal with gas represents a major part of such a policy; for example, in 2012 the National Development and Reform Commission of China (NDRC) launched the “Natural Gas Utilization Policy” [17]. From 2000 to 2016, China’s total natural gas consumption increased about seven times [10]. The development of gas has also been beneficial for controlling CO_2 emissions from central heating, because the CO_2 emission factor of gas boilers is approximately half of that of coal-based boilers [3]. The effect of increasing penetration of natural gas boilers, together with increasing energy demands [10], has meant complex changes in the spatial and temporal pattern of CO_2 emissions. However, the quantitative information about such changes is poorly understood, prohibiting a detailed understanding of the carbon reduction co-benefit of natural gas development on the city and smaller scales.

Understanding of emissions at the city and gridded levels is critical for spatially targeted carbon accounting and mitigation policymaking [18]. Previous studies of emissions of CO_2 and other greenhouse gases (GHGs) mostly focused on national- or provincial-level emissions [4,19,20,21], and most of the city-level emissions provided only total emissions [22] or some selected sectors [23–25]. Few studies have specifically studied GHGs emissions from residential heating supply, particularly on the city-level and as a gridded dataset. Kennedy et al. [26] calculated emissions from seven sectors, although they did not separate the heating supply from power and heating generation. Shan et al. [18] estimated CO_2 emissions for 182 Chinese cities, and then decomposed the results into 46 socioeconomic sectors, including the heating supply sector by using the ‘energy balance tables’ in the China energy statistical system. Their research covered about half of the cities located in the NCP and did not analyze the heating supply sector in detail. Liu et al. [27] calculated the energy-related GHG emissions from four megacities in China, and they found that emissions from heat supply contributed to about 9% of total emissions in Beijing and Tianjin during 1995–2009. However, Liu et al. did not separate central heating from the total of industrial heat supply and residential central heating. Pang et al. [28] measured the emission reduction effects achieved by the use of gas instead of coal for CO_2 and six major air pollutants in 15 heating cities of China in 2010, but they did not show the spatial and interannual dynamics of the emission changes. Du et al. [15] calculated the CO_2 emissions from central heating on a provincial basis, and they found that the emissions in 15 provinces increased from 189 to 319 Tg CO_2 between 2006 and 2015, and that higher CO_2 emissions were generated in regions with larger central heating coverage and heating area.

Satellite-based nighttime light (NTL) intensity data have been used as a proxy to estimate the CO_2 emissions on a regional scale [29], in the absence of direct data to establish a high-resolution gridded inventory. Doll and Pachauri [30] employed the DMSP-OLS NTL data to map the total CO_2 emission distribution at the national level and found that the NTL intensity in more than 90% of countries were well matched with their CO_2 emissions. Also, Ghosh et al. [31] and Oda and Maksyutov [32] built a global fossil-fuel CO_2 emission inventory based on the NTL data. For China, Meng et al. [33] developed a top-down method to map the CO_2 emission distribution at an urban scale. Meanwhile, the relationship between economic development indicators and NTL-based CO_2 emissions in Chinese cities has been studied [34]. Su et al. [35] proposed a normalized method to calculate CO_2 emissions at a city level in China from 1992 to 2010. Shi et al. [36] analyzed the spatio-temporal dynamics of CO_2 emissions in China on the national, regional and urban agglomeration scales. Zhang et al. [37] applied the DMSP-OLS and NPP-VIIRS nighttime light data to estimate the CO_2 emissions from energy consumption in China at the provincial and prefectural-city levels.

Spatially gridded satellite NTL data, aided by panel regression models, can offer a feasible way to estimating the CO_2 emissions from central heating on a gridded basis. This is because gridded data of nighttime light can reflect the exact locations and extents of human settlements [32], offering a useful tool to estimate population density, urban population, and urban built-up area [29,38–40]. Moreover, central heating is closely related to the distribution of the urban population and urban built-up area. For example, in Beijing there were over 5,000 coal-fired and 1,000 gas-fired space heating boilers surrounding the populated areas in 2014 [41]. Despite their usefulness, satellite NTL data have not been used to estimate CO_2 emissions from central heating and their changes driven by the energy structure upgrade, i.e., from coal to gas.

To estimate CO_2 emissions from coal usage and the replacement by gas of central heating supply, we use gridded satellite NTL data, together with a panel regression model, to estimate annual CO_2 emissions from central heating in the NCP over 2012–2016 at high spatial resolution ($5 \times 5\,km^2$). As such, we aim to assess the spatiotemporal dynamics of CO_2 emissions from central heating due to the recent changes in energy structure from coal to gas in the NCP region, and contrast the changes in urban and non-urban areas. We first build a bottom-up emission inventory of CO_2 emissions for central heating on the prefecture-city level in the NCP region. We then use the NTL data to project the city-level emissions data on a $5 \times 5\,km^2$ grid. Finally, we analyze the effects of coal-to-gas transformation on the spatial and temporal patterns of CO_2 emissions. Our results contribute to cover the current research gaps on estimating the gridded carbon emissions from central heating, improving the understanding of the changing fuel structure, and reducing the uncertainties in CO_2 emissions in China and other developing countries. The high-resolution gridded CO_2 emissions can also be applied in the physical models to facilitate carbon cycle studies [32,42].

2. Methodology and data

2.1. Study area

The North China Plain contributes about 25% of the total population of China [43]. Fig. 1 shows the North China Plain, which contains Beijing, Tianjin, Hebei (together called JJJ, consuming about 12% of energy in China [43]), Henan, and Shandong (the two most highly populated provinces in northern China). Coal consumption in the above mentioned five provinces together accounts for approximately 24% of the total national coal consumption during 2012–2016 [44]. Most areas in these provinces are located in the north of the Qin Mountain-Huai River line that distinguishes the northern areas with accessible central heating from the southern areas without (Fig. 1, green triangles and blue line). We selected 46 prefecture-level cities and two province-level municipalities (Beijing and Tianjin) in the NCP. Zhoukou and Xinyang in Henan Province, which sit on the Qin Mountain-Huai River boundary, were excluded due to lack of central heating supply. We separated urban from non-urban areas in Fig. 1, according to the maps of urban and non-urban area which are provided by the Beijing City Lab Database [45].

2.2. Method to estimate CO_2 emissions from central heating based on NTL data

Central heating is supplied by three main methods: coal-fired boilers for heating, coal-fired heat and electricity cogeneration thermal power plants (TPPs), and gas-fired boilers for heating [10]. Hereafter the first two methods are combined as coal-based supply for simplicity.

Fig. 2 shows the four main steps used to estimate the spatiotemporal dynamics of CO_2 emissions from the central heating supply system in the NCP region. First, CO_2 emissions from central heating at the prefecture-city level of five provincial regions in the NCP over 2012–2016 were calculated based on a bottom-up approach. Three types of CO_2 emissions from central heating supply system were included: coal-fired boilers, gas-fired boilers and TPPs. Second, the prefectural-city level nighttime light intensity during the heating period was summed from the gridded monthly mean NPP-VIIRS nighttime light data. Third, a panel regression model was used to link the NTL data to heating-related CO_2 emissions at the prefecture-city level, and then to allocate the prefectural-level CO_2 emissions on the high-resolution grid by using NTL as a proxy at each grid cell. Finally, the spatiotemporal dynamics of gridded CO_2 emissions from central heating over 2012–2016 were analyzed.

2.2.1. Calculating CO_2 emissions from central heating based on a bottom-up method

CO_2 emissions from central heating are calculated for the coal-based and gas-based heating systems separately. Our calculation followed the method used by the Intergovernmental Panel on Climate Change (IPCC) [46]. The annual CO_2 emissions from different boilers (f) in year t, denoted by $EM_{f,t}$, were estimated as the product of the annual central heating related energy consumption ($EC_{f,t}$) and the CO_2 emission factor (EF_f). Thus, the total CO_2 emissions from central heating in year t were estimated as follows:

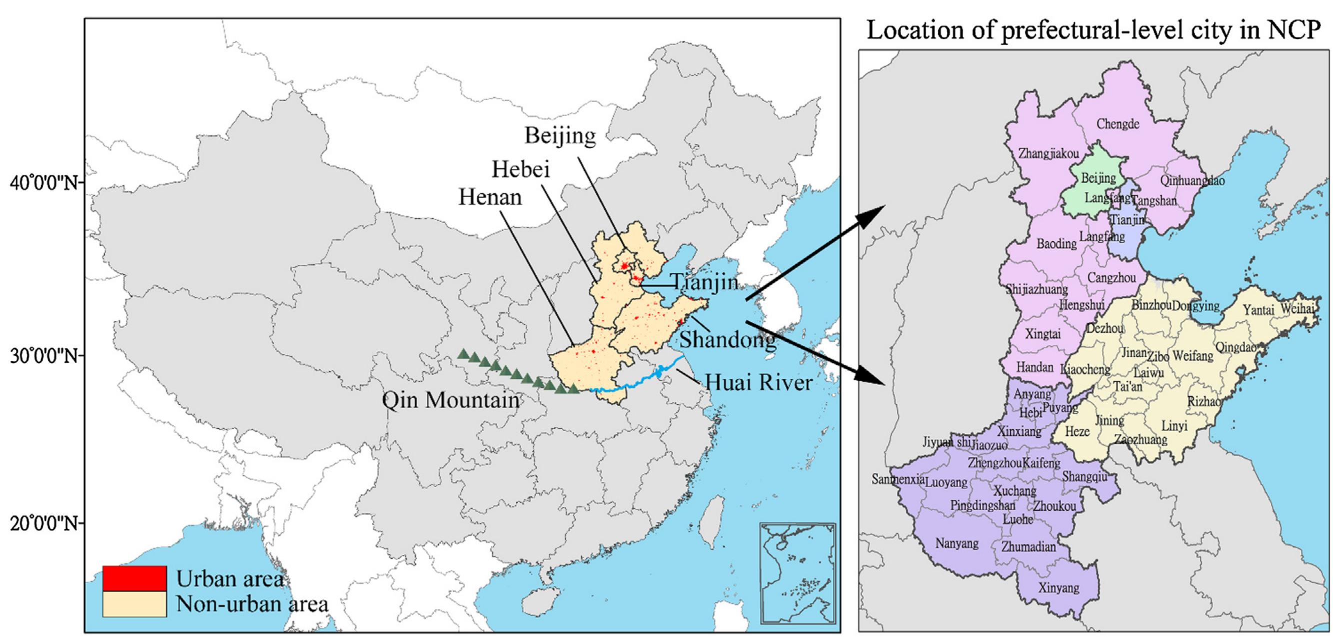

Fig. 1. Provinces (left) and prefectural-level cities (right) studied here. The left panel also separates the urban (in red) and non-urban areas (in light yellow). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

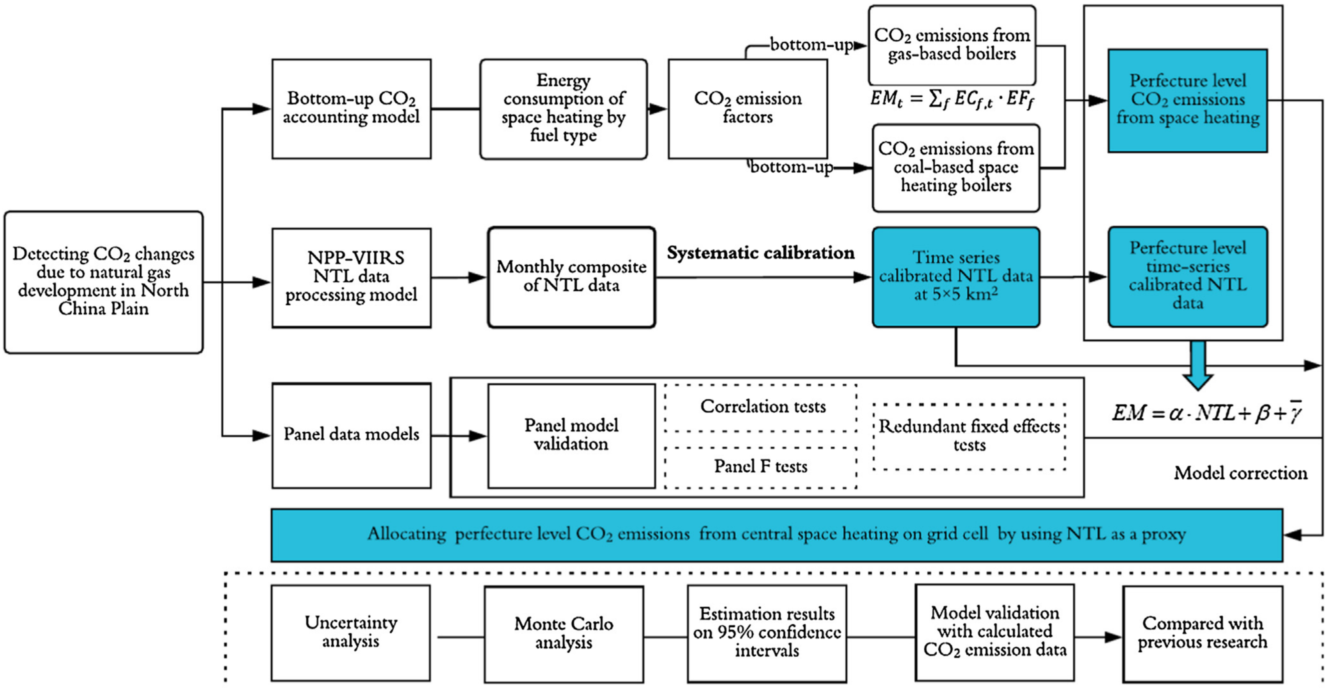

Fig. 2. Framework to estimate CO_2 emissions and changes due to gas development.

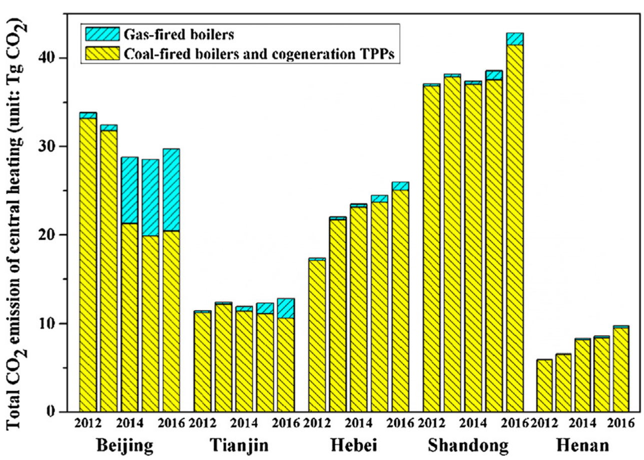

Fig. 3. Total CO_2 emissions ($TgCO_2$) from central heating at the provincial level by energy type from 2012 to 2016.

$$EM_t = \sum_f EC_{f,t} \cdot EF_f \tag{1}$$

CO_2 emission factors for different boiler types were taken from Liu et al. [3], which suggested 96.51 gCO_2/MJ for raw coal and 56.17 gCO_2/MJ for natural gas. The same values were used by Du et al. [15]. The annual coal consumption data (unit: MJ) for coal-based boilers (including heating only and cogeneration TPP) from 2012 to 2016 on a prefecture city level were collected from the “China Urban Construction Statistical Yearbook” [10] published by the Ministry of Housing and Urban-Rural Development of the People's Republic of China (MOUHRD). The natural gas consumption data for gas-based boilers on a prefecture city level were collected from the “China Urban-rural Construction Statistical Yearbook” [47] published by the MOUHRD.

2.2.2. Nighttime light data

Gridded nighttime light intensity reflects the general intensity of human activities, and it has been widely used to estimate population, built-up area, economic development, energy consumption, and CO_2 emissions [48–50]. In many previous studies, the gridded NTL data were taken from annual datasets of the Defense Meteorological Satellite Program’s Operational Linescan System (DMSP-OLS) archived by the National Oceanic and Atmospheric Administration’s National Geophysical Data Center (NOAA/NGDC) of the United States with the spatial resolution of 1 km. In this study, we used a much-improved gridded NTL dataset on a monthly basis over 2012–2016 based on the day/night band of the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (NPP) satellite. Compared to the previous DMSP-OLS NTL data, the NPP-VIIRS NTL data have a finer spatial resolution (15 arc-second, about 500 m) and much less saturation problem due to the wider radiometric detection range [51]. Additionally, the monthly NPP-VIIRS NTL dataset allows the extraction of seasonal information about human activities.

The NPP-VIIRS monthly NTL data over 2012–2016 (unit: nano-W cm^{-2} sr^{-1}) are available from NOAA/NGDC (https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html). We only used the wintertime (November to March) NTL data, to be consistent with the heating period. For our purposes, only lights from cities, towns, and other sites with persistent lighting were used. We removed episodic events (fires, gas flares, volcanoes or aurora) from the NTL dataset using two additional datasets that have been specifically calibrated to remove such events, including the official 1-year NPP-VIIRS NTL composite dataset for 2015 and the DMSP-OLS yearly composite data for 2012–2013 (available at https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html) [52]. After excluding the episodic events, there still existed a few outliers that are probably caused by the stable lights from ship light in the coastal, and from fires of oil or gas wells in the study area in the NTL intensity data to be removed [51]. Thus we used the maximum intensity in the megacity of Beijing and Shanghai for each year as the threshold, above which the intensity in any location (satellite pixel) was assumed to be unrealistic and was adjusted to the largest intensity value from its eight immediate neighbor pixels. Subsequently, the (500 m resolution) gridded NTL dataset was re-mapped to the Albers Equal Area Conic projection. To obtain the city-level intensity, we summed up all grid cells of NTL data within the administrative boundaries of each city by ArcGIS 10.3 software. We further converted and aggregated the 500 m resolution

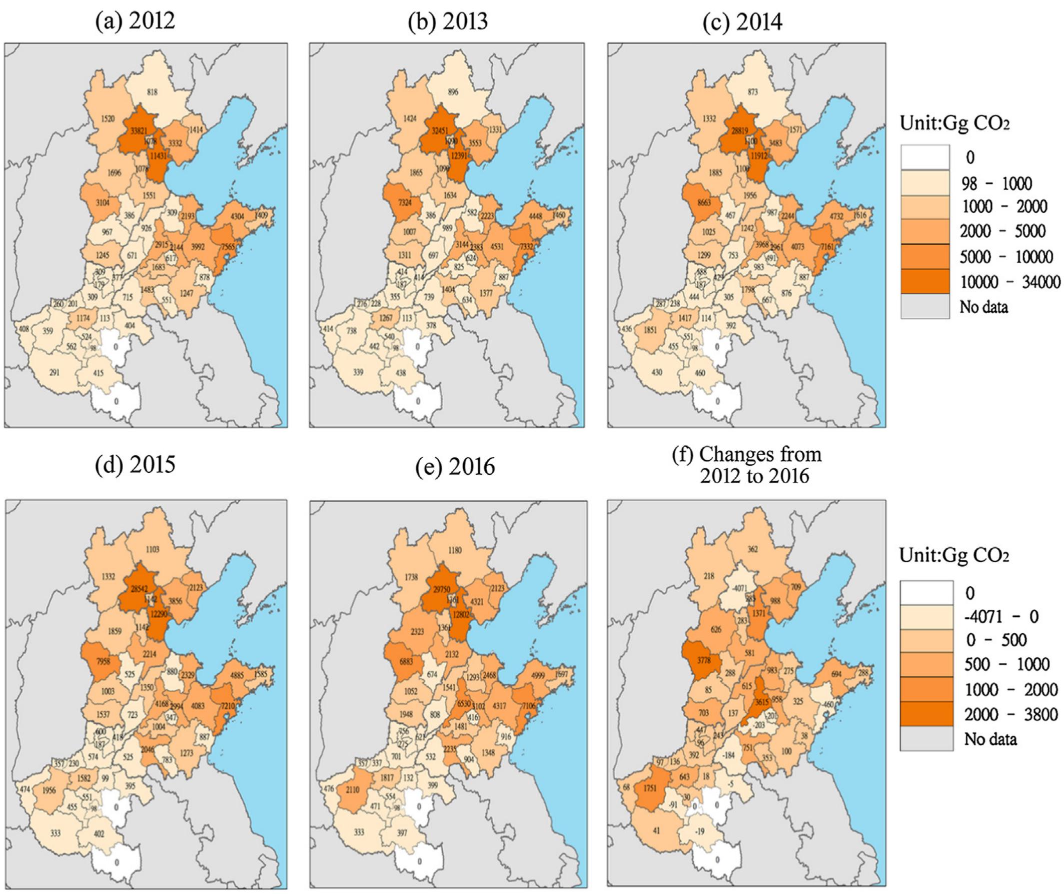

Fig. 4. City-level CO_2 emissions from central heating in different years (a–e), as well as (f) the change from 2012 to 2016 (f). Two cities, Xinyang and Zhoukou, sit on the Qin Mountain-Huai River boundary with no central heating; their emissions are shown as zero in all panels.

Table 1
Results of the panel regression model with city fixed effects.

	Coefficient	Std. Error	*t*-Statistic	p-value
Intercept	1642.315	418.901	3.921	0.000
Slope	0.014	0.006	2.134	0.034
Model adjusted R^2	0.976			
F-statistic	356.061			
Prob (F-statistic)	0.000			
Akaike info criterion	15.747			
Cross-section F (effects test)	71.238 (p = 0.000)			
Cross-section Chi-square (effects test)	627.286 (p = 0.000)			

NTL data to a $5 \times 5\,km^2$ grid, to be consistent with the resolution of the gridded CO_2 emissions.

2.2.3. Linking NTL data to energy consumption and CO_2 emissions from central heating

We used a panel regression model to estimate CO_2 emissions over 2012–2016 from the NTL data on a gridded basis. The model assumed that the NTL data are linearly correlated to CO_2 emissions on a prefecture city level, albeit with some random uncertainty, and that such a relationship can be applied to all grid cells ($5 \times 5\,km^2$) within that city. For a given city, the linear relationship between the city-level NTL data and corresponding heating-related CO_2 emissions can be established as follows:

$$y = a * NTL + b + \varepsilon \tag{2}$$

where y is the bottom-up CO_2 emissions from central heating at a city, NTL the sum of nighttime light intensity within that city, a the slope, b the intercept, and ε the random error of the regression model.

Panel regression models have been widely used to estimate CO_2 emissions, and these models perform effectively across spatial and temporal dimensions [33,36]. Since the relationship between CO_2 emissions and NTL may vary from one city to another, due to differences in the type of energy consumption and other factors, we further introduced a city-specific variable β_i to improve the regression:

$$y_{i,t} = a * NTL_{i,t} + \mathrm{b} + \beta_i + \varepsilon_{i,t} \tag{3}$$

where the subscript t denotes the year (2012–2016), i denotes the city, and β_i is essentially a city-specific adjustment to the intercept of the regression model. Note that a and b are independent of the cities and years.

The bottom-up city-level total (coal + gas) CO_2 emissions in Section 2.2.1 were used to establish the regression model. The statistical T-test rejects the null hypothesis of $a = 0$. Such a statistical relationship was then applied to all grid cells of the cities. For each year and city, we used the ratio of coal-related and gas-related emissions at the city level (from Section 2.2.1) to grid cells of that city to obtain gridded coal-related and gas-related emissions, separately, in that year.

Applying the linear model in Eq. (3) to estimate (predict) gridded CO_2 emissions means that, for a city, the total amount of emissions (from coal and gas burning) summed over the grid cells within its administrative boundaries may not be exactly equal to the bottom-up emissions calculated in Section 2.2.1. Such emission differences are generally small, as further discussed in Section 3.5. Nevertheless, for each year, we further used Eq. (4) to adjust the gridded CO_2 emissions, such that the total of gridded emissions within the boundaries of any city fully matches the emission value of that city from the bottom-up calculation:

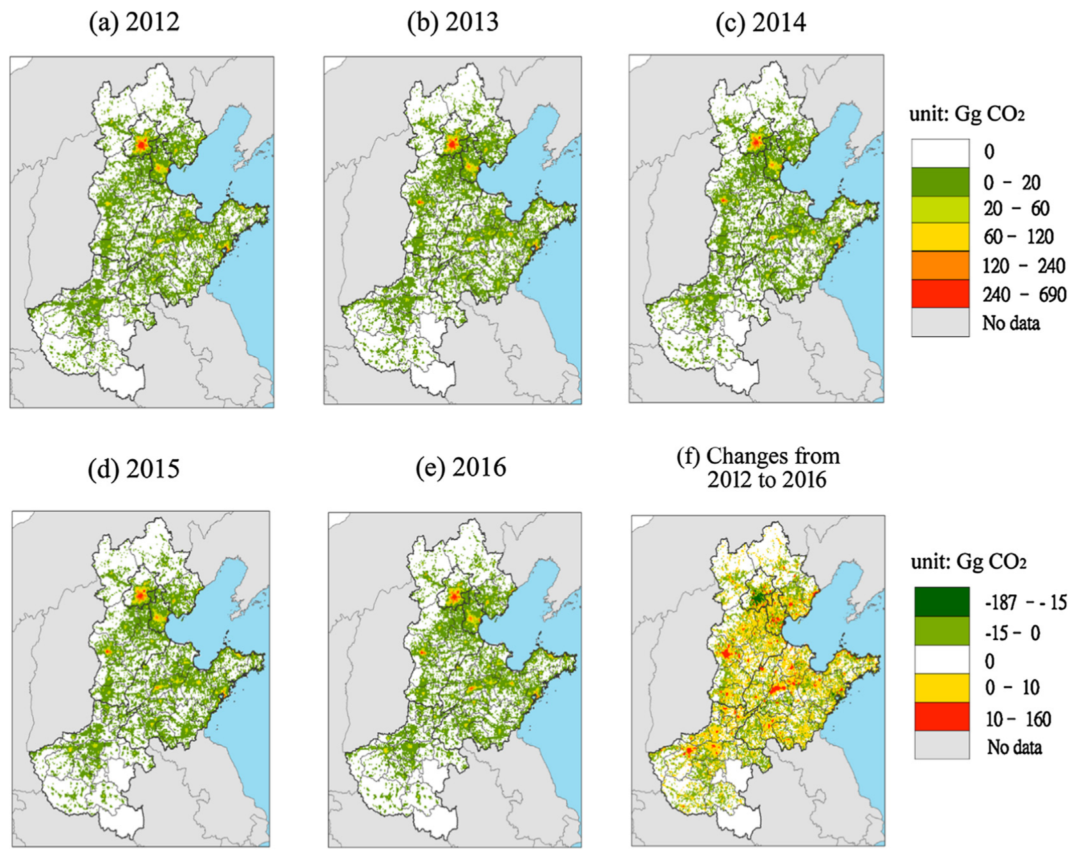

Fig. 5. Annual gridded CO_2 emissions from central heating (coal + gas) in the NCP in different years (a–e), as well as the changes from 2012 to 2016 (f).

$$EE_g = SE_g \times \left(\frac{EE_i}{SE_i}\right) \tag{4}$$

where EE_g denotes the final corrected CO_2 emissions in a specific grid cell within a city i, SE_g the predicted CO_2 emissions of that grid cell from Eq. (3), SE_i the predicted CO_2 emissions of that city from Eq. (3), and EE_i the bottom-up emissions of that city from Section 2.2.1 (i.e., *EM* in Eq. (1)).

3. Results

3.1. Bottom-up CO_2 emissions from central heating from 2012 to 2016

Fig. 3 shows CO_2 emissions from central heating in each province of the NCP, as calculated from the bottom-up approach in Section 2.2.1. Between 2012 and 2016, the total emissions in the NCP increase by 14.6%, from 106 to 121 Tg. Among the five provinces, Shandong and Beijing have the largest emissions during 2012–2016 due to their high energy consumption of about 0.38–0.45 and 0.36–0.38 × 10^9 GJ, respectively.

Fig. 3 also separates the contributions from coal-based (yellow bars) and gas-based (blue bars) heating systems. From 2012 to 2016, gas-based CO_2 emissions in the NCP grew dramatically from 1 to 14 Tg, and coal-based emissions increased slightly from 104 to 107 Tg. Meanwhile, energy consumption in the NCP by coal-based boilers grew from 10.8 to 11.1 × 10^9 GJ and by gas-based boilers from 0.3 to 2.5 × 10^9 GJ. These changes reflect the fact that many cities in the NCP region have been undergoing strategic heating supply reform, especially through the development of gas-fired central heating.

Nonetheless, coal burning still plays a dominant role in CO_2 emissions, contributing 88.5–98.6% of heating-related emissions in the NCP as a whole. Beijing has undergone the most rapid replacement of coal- by gas-based central heating, and the share of gas-related emissions in Beijing increased from 1.9% in 2012 to 31.2% in 2016 (Fig. 3). In Hebei, Shandong and Henan, gas burning contributes much less (below 10%) to total CO_2 emissions from central heating, despite their increasing shares throughout the years. In these three provinces, coal-related emissions continue to grow over the years, as driven by the increasing energy need for central heating.

Fig. 4a-e shows the city-level, bottom-up, annual CO_2 emissions from central heating from 2012 to 2016. Emissions exceed 2000 Gg in many cities in the JJJ region; and Beijing, Tianjin, Shijiazhuang (capital of Hebei) and Qingdao (in Shandong) have the highest CO_2 emissions due to their large energy consumption and coal use for central heating. Fig. 4f further shows that annual emissions increased from 2012 to 2016 in most cities, with Shijiazhuang and Jinan (capital of Shandong) having the largest emission enhancements (more than 3500 Gg). In contrast, annual emissions in Beijing decreased by 4060 Gg (about 12%) due to the implementation of the "Beijing Clean Air Action Plan 2013–2017", with strong actions since 2013 to eliminate coal-fired boilers and increase the proportion of cleaner energy-based heating supply systems.

3.2. Panel data regression results

The correlation analysis shows that the NTL data and heating-related total (coal + gas) CO_2 emissions are highly correlated at the city level across the 48 cities over 2012–2016 (R^2 = 0.796, n = 240), suggesting the appropriateness of building the panel regression model between NTL and CO_2 emissions.

Eq. (5) presents the results of the city-level panel data regression between NTL (predictor) and total CO_2 emissions (predicted). Table 1 shows that both the intercept and the slope of the regression are statistically significant at the 95% confidence interval (p-value < 0.05) with the *t-statistics* of 3.921 and 2.134. The redundant fixed effects tests for the cross-section fixed effects also show a p-value of 0.000, further

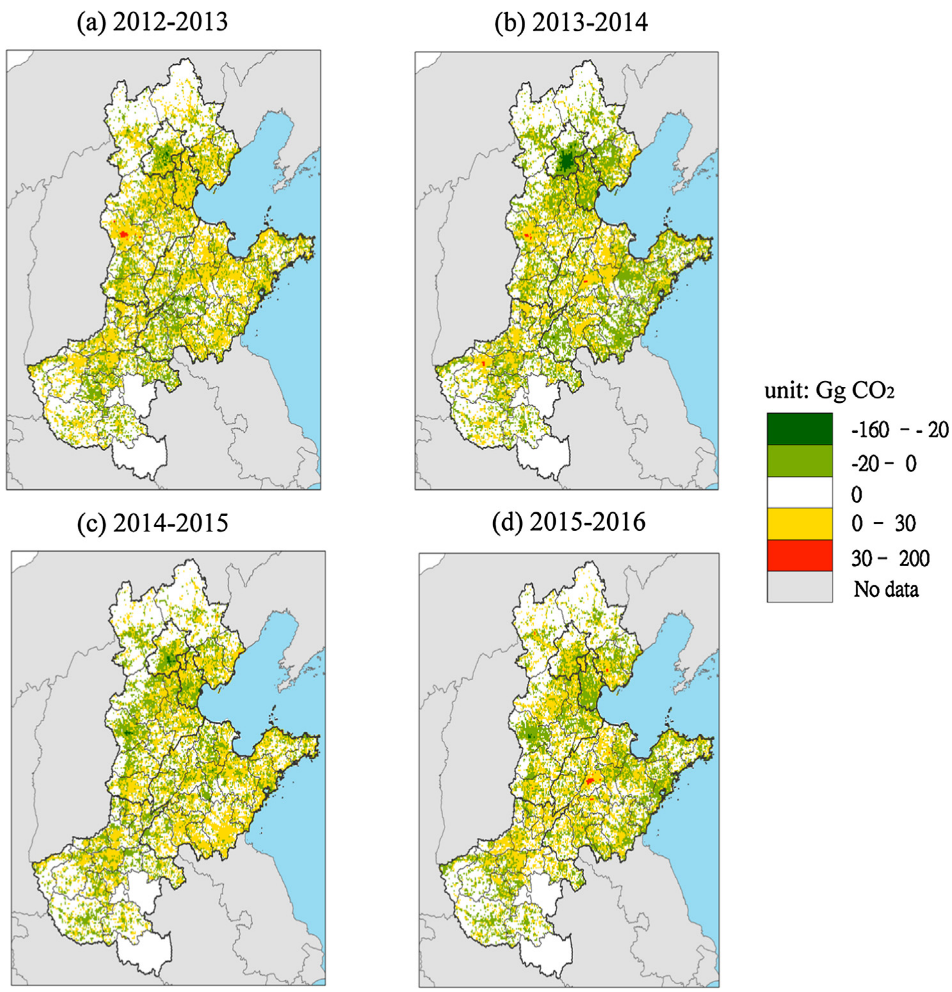

Fig. 6. The year-on-year changes in CO_2 emissions from coal-based central heating in the NCP.

validating the regression model used in this paper. The model-adjusted R^2 reaches 0.976. Other statistical results of the regression model, including the F-test and Akaike info criterion (AIC), also verify the applicability of the panel regression model.

$$\widehat{y_i} = 0.014 * NTL_i + 1642.315 + \beta_i \quad (5)$$

3.3. Spatiotemporal dynamics of gridded CO_2 emissions from central heating

3.3.1. Total gridded CO_2 emissions from coal and gas burning

Fig. 5(a)–(e) illustrates the spatial distribution of gridded annual CO_2 emissions from central heating in different years at a resolution of $5 \times 5\,km^2$. Grids with high CO_2 emissions (larger than 1.6 Gg CO_2) are found in the urban centers of large cities like Beijing, Tianjin, Shijiazhuang (capital of Hebei), Tangshan (in Hebei), Qingdao (in Shandong), and Yantai (in Shandong), due to dense urban population and extensive central heating services.

Fig. 5 shows that from 2012 to 2016, CO_2 emissions declined in the urban areas of Beijing but increased in its suburban areas. This likely reflects the migration of residents from the city center to the suburban areas to avoid the high and increasing living costs in the urban center. A similar (although weaker) spatial change occurs in the other megacity, Tianjin. In many other cities, emissions from central heating grow in both urban centers and suburban areas (in yellow and red color, accounting for more than 50% of the grid cells), because distributed space heating has been increasingly substituted by central heating over the past few years, and that heating supply has become more abundant.

3.3.2. Coal-related gridded CO_2 emissions

Fig. 6(a)–(d) shows the year-on-year changes in CO_2 emissions from the coal-based heating system (coal-fired boilers and cogeneration TPPs) on the high-resolution grid. Changes in coal use are the main driving force for changing CO_2 emissions in suburban and less developed areas. From 2012 to 2016, CO_2 emissions from coal burning increased in most areas of South Hebei, North Henan and West Shandong. From 2015 to 2016, grid cells from Jinan and Tai'An (both in Shandong) experienced notable emission enhancements (large than 30 Gg), indicating their intensive development of coal-based central heating. Large and often increasing amounts of coal-related emissions in the cities of Hebei, Shandong and Henan provinces throughout the years reflect the fact that coal is still the dominant energy source in these cities.

The green colors in Fig. 6a–d show that from 2012 to 2016, coal-related emissions declined in the urban areas of the two megacities (Beijing and Tianjin) and three provincial capital cities (Shijiazhuang, Zhengzhou and Jinan). The decline reflects the transformation from coal- to gas-based boilers, as further shown in Fig. 7. Coal-related emissions in most grid cells of cities in Qingdao, Tai'An, Laiwu (Shandong Province) and Kaifeng, Zhumadian, Shangqiu, Pingdingshan (Henan Province) decreased by 2–19% during the study period.

3.3.3. Gas-related gridded CO_2 emissions

Fig. 7 a-d presents the year-on-year changes of gridded CO_2 emissions from gas-based central heating in the NCP region. The interannual changes are relatively small, compared to the changes in coal-related emissions (Fig. 6), due to the relatively small fractions of central

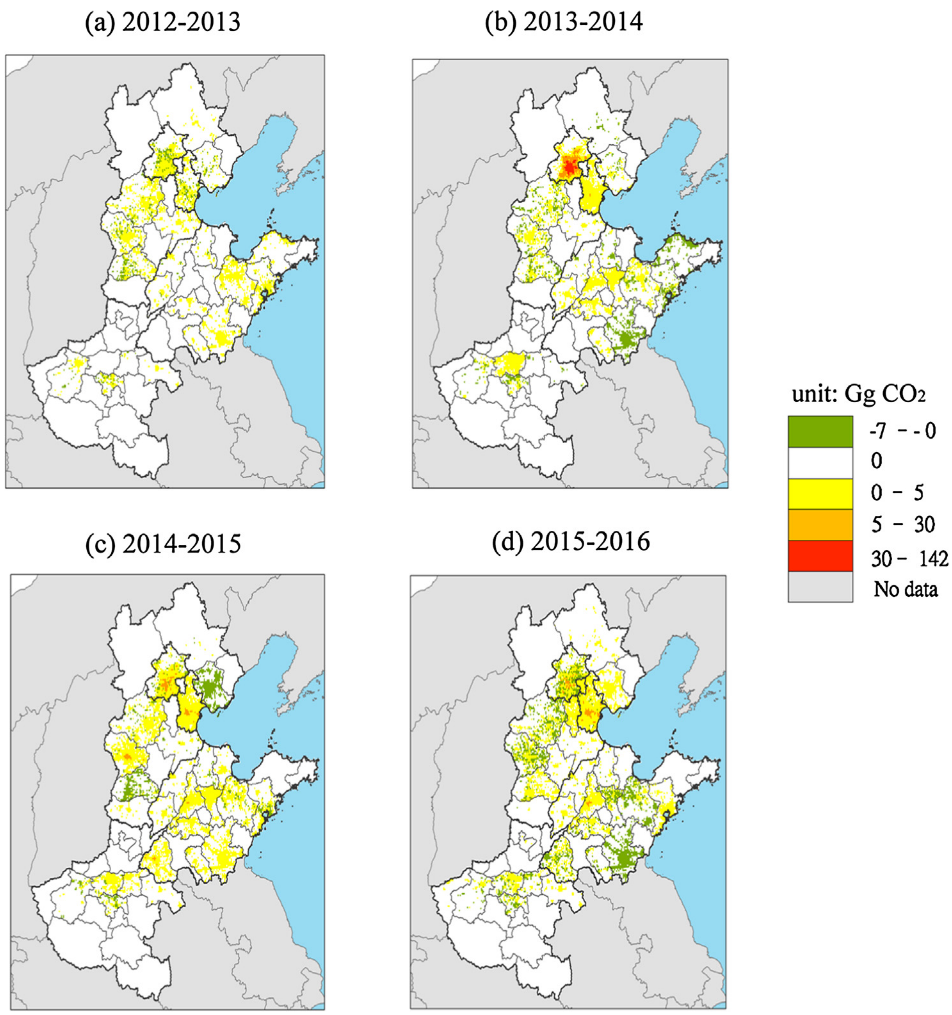

Fig. 7. The year-on-year changes in CO_2 emissions from gas-based central heating in the NCP region.

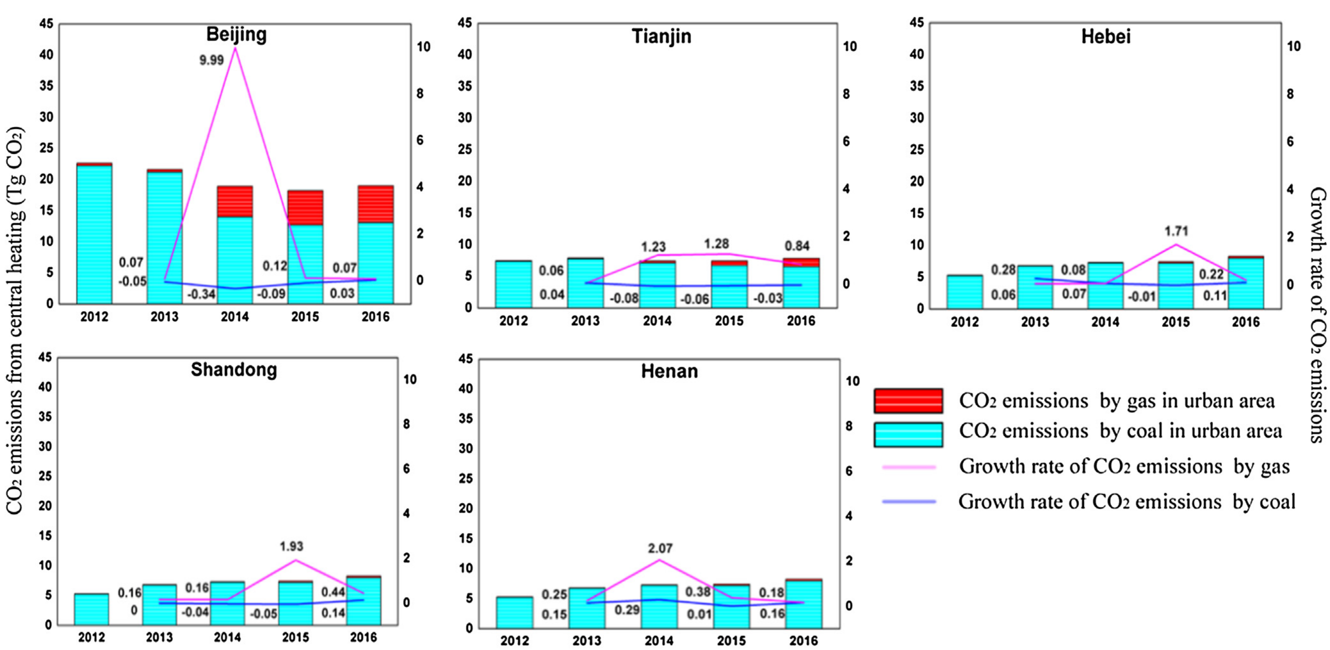

Fig. 8. Interannual changes in CO_2 emissions due to urban heating in the five provincial regions. The growth rate is defined as year-on-year change in emissions, e.g., [emissions in 2013 − emissions in 2012]/[emissiions in 2012].

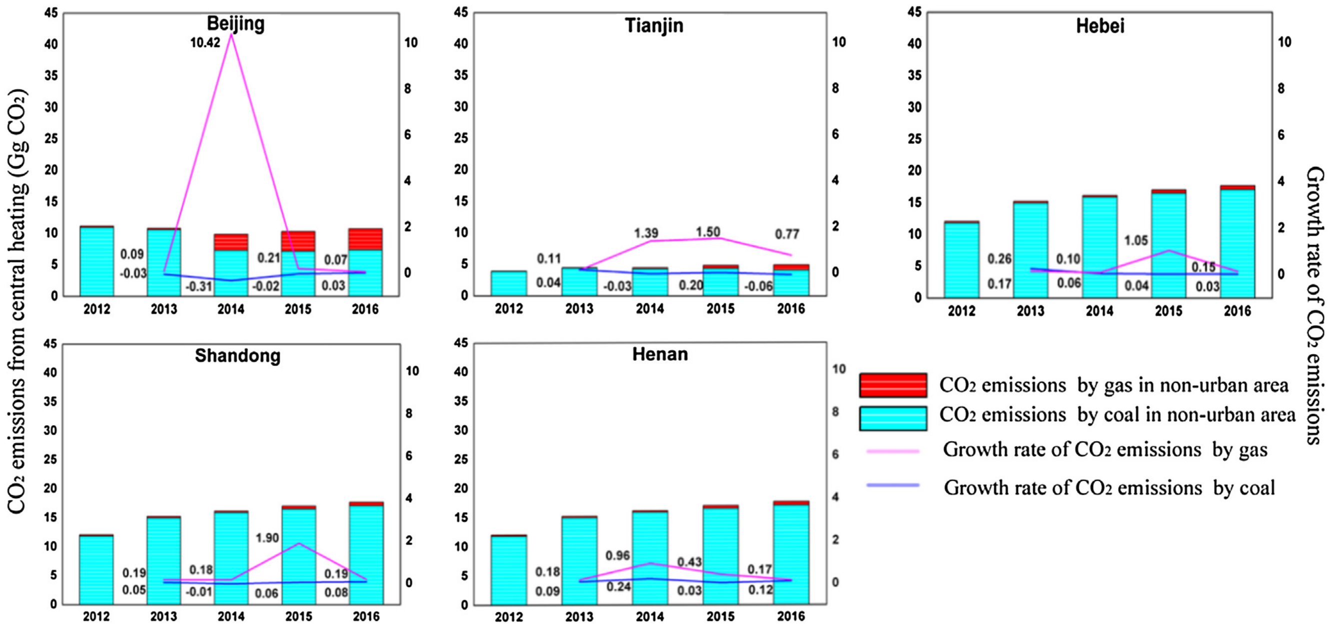

Fig. 9. Interannual changes in CO_2 emissions due to non-urban heating in the five provincial regions. The growth rate is defined as year-on-year change in emissions, e.g., [emissions in 2013 − emissions in 2012]/[emissiions in 2012].

Table 2
Comparison of emissions ($TgCO_2$) by different approaches at the provincial level.

	Our bottom-up inventory: Mean (95% CI) from Monte-Carlo simulations. Provincial emissions are summed from city-level emissions					Inventory from Du, Wang [15]
Year	2012	2013	2014	2015	2016	2015
Beijing	34(31,37)	32(30,35)	29(27,31)	29(27,31)	30(28,32)	48
Tianjin	11(11,12)	12(11,13)	12(11,13)	12(11,13)	13(12,14)	16
Hebei	17(16,19)	22(20,24)	24(22,26)	25(23,27)	26(24,28)	33
Henan	6(6,7)	7(6,7)	9(8,9)	9(8,10)	10(8,11)	13
Shandong	35(32,38)	36(33,39)	36(33,39)	37(34,40)	42(38,45)	39

heating supply from gas-fired boilers. Many cities have not used gas-based central heating, due to abundant coal reserves and the higher cost of gas-supplied heating, leading to essentially no changes in emissions (white color in Fig. 7).

The largest magnitude of change in gas-related emissions occurs in Beijing from 2013 to 2014, where the emissions increased significantly (Fig. 7b), concurrent with the large decline in coal-related emissions (Fig. 6b). The contrasting changes in gas- and coal-related emissions reflect the rapid switch from coal- to gas-based heating in the first year of implementing the "Beijing Clean Air Action Plan 2013–2017" and that Beijing is the first major city to implement the "Natural Gas Utilization Policy" in China. From 2013 to 2014, the gas-related (coal-related) emissions also increase (decline) in Tianjin (Figs. 6b and 7b). From 2015 to 2016, gas-related emissions in Beijing exhibit mixed changes among its districts, due to the influence of the shortage in gas supply [53,54]. Fig. 7 also shows that cities in other provinces, including Shijiazhuang, Jinan, Zibo, Heze and Zhengzhou also exhibit emission growth (large covered area with yellow color in Fig. 7a–d) from gas-fired boilers.

3.4. Interannual variation of CO_2 emissions: Urban versus non-urban areas

We further contrast the interannual changes in CO_2 emissions between urban (Fig. 8) and non-urban (Fig. 9) heating in each province, based on the gridded emission inventory. The results for urban heating in Fig. 8 show that from 2012 to 2016, coal-related CO_2 emissions in urban Beijing and Tianjin decreased by 41% and 11%, respectively, in contrast to the growth for urban Hebei, Henan and Shandong. In all provinces, gas-related emissions grew much faster than coal-related emissions did (red versus blue lines). Thus, from 2012 to 2016 the shares of coal-related emissions in total (coal + gas) emissions decreased largely for urban Beijing (by 30%) and urban Tianjin (by 16%) and slightly for urban heating in Hebei, Shandong and Henan (from 98–99% in 2012 to 96–97% in 2016).

The results for non-urban heating in Fig. 9 show that the coal-related emissions (blue bars) in Hebei, Shandong and Henan kept increasing from 2012 to 2016, except for a slight decrease (by −1%) in Shandong between 2013 and 2014. The gas-related emissions increased constantly, similar to the growth pattern in urban heating. The shares of coal-related emissions declined in all provinces.

Contrasting Figs. 8 and 9 shows that in Beijing and Tianjin, the total (gas + coal) CO_2 emissions are mainly from urban heating consumption (60–67%), due to the large urban population in these two cities, although the difference between urban and non-urban heating is declining throughout the years. In Hebei, Henan and Shandong provinces, CO_2 emissions are mainly from non-urban heating consumption (56–69%).

Contrasting Figs. 8 and 9 further shows that for gas-related CO_2 emissions (red bars), the contribution of urban heating was approximately 1.6–2.0 times that of non-urban heating in Beijing and Tianjin. In contrast, gas-related emissions for urban heating were only 50–80% of the emissions for non-urban heating in Hebei, Shandong and Henan. In these less developed provinces of Hebei, Shandong and Henan, non-urban households are dominant, so is their heating need.

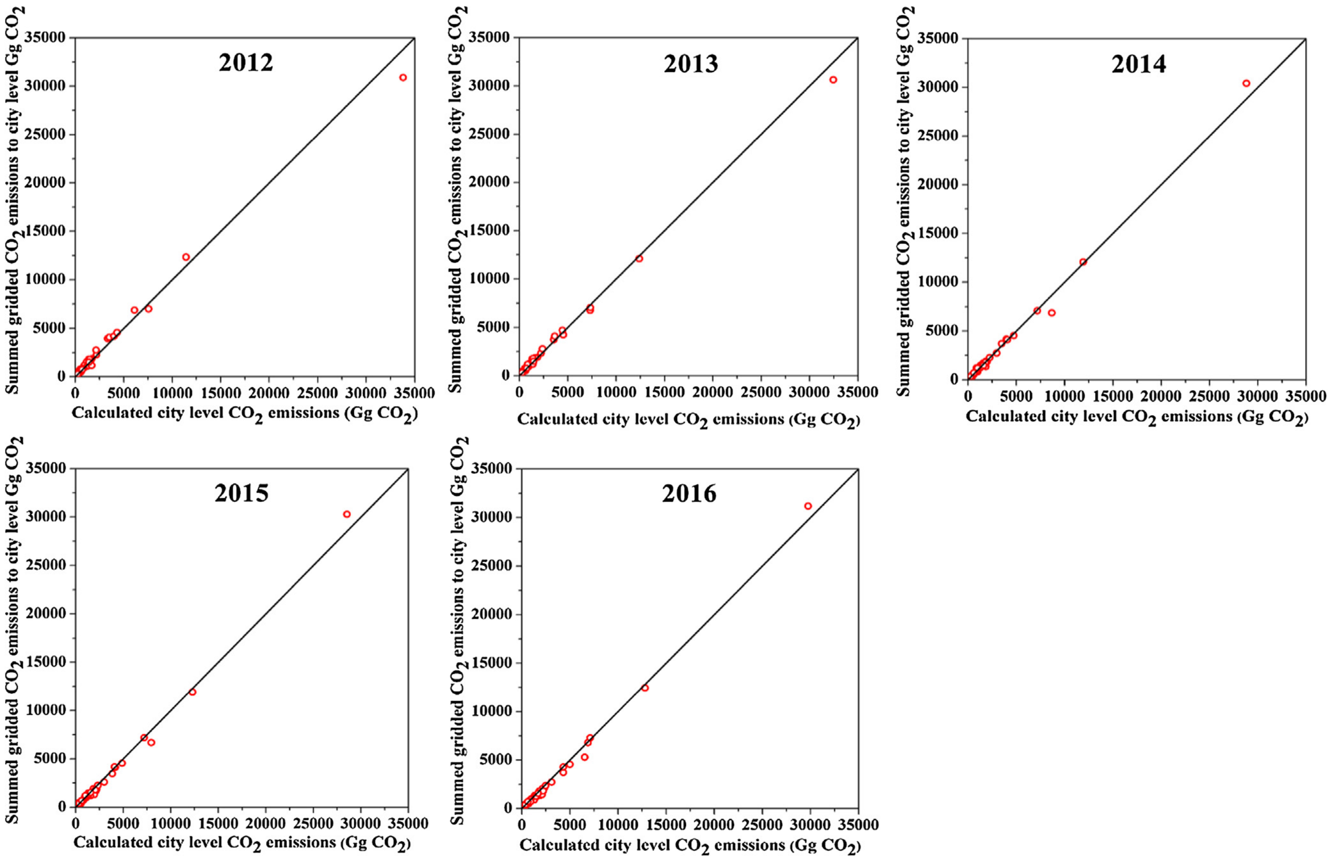

Fig.10. Scatter plots for the regression model estimated CO_2 emissions (SE_i in Eq. (4), y-axis) and bottom-up calculated CO_2 emissions (EE_i in Eq. (4), x-axis), on a city-level and annual basis.

3.5. Data validation

Uncertainties associated with the estimates in our work may arise from the calculations of CO_2 emissions from central heating at a city level and the use of nighttime light data as the proxy to establish the CO_2 emission inventories in the NCP region on a gridded basis. The CO_2 emissions from central heating are calculated through a bottom-up approach based on fuel consumption data and emission factors. The fuel consumption data are collected from the official China statistical yearbooks, which may contain an uncertainty (one standard deviation) of ± 5% for gas and ± 10% for coal [3,15]. The uncertainty for emission factors for coal-boilers and thermal power plants is ± 3% and for gas-boilers is ± 2%, which is the same value calculated by Liu et al. [3].

The Monte Carlo approach is used to assess the distribution range (95% CI) of the bottom-up calculated CO_2 emissions on the prefecture-city level, which is then aggregated to the provincial level (Table 2). At the provincial level, the Monte-Carlo simulations suggest relatively small uncertainties in Beijing (e.g., 95% CI = 29–32 Tg in 2015) and Tianjin, modest uncertainties in Hebei and Shandong, and the largest uncertainty in Henan.

Table 2 also shows that our bottom-up emissions of the five provinces in 2015 are lower than those in Du et al. [15] by 5–40%. In Du et al., the gas consumption data were not available before 2012, and so they estimated the share of gas-fired boilers based on the heat loss during the production and consumption process, which information is available from the energy balance tables of the “China Energy Statistical Yearbooks” [55]. By comparison, we directly use the gas consumption data for central heating at the prefecture city level over 2012–2016 provided by the MOHURD [10].

Satellite-based NTL data are used as a proxy to project city-level CO_2 emissions to a $5 \times 5\,km^2$ grid under the assumption that NTL data directly correlates with CO_2 emissions from central heating. NTL data are subject to uncertainties in various aspects, although we have made efforts to reduce these uncertainties. Saturated pixels in this study were processed and assigned the highest intensity values derived from Beijing and Shanghai Municipalities. Future work should be done to further improve the quality of NTL data and to adopt more methods for the data correction process [51].

The panel regression model implies that the relationship between NTL data and CO_2 emissions from central heating is linear in this study. To validate this assumption, Fig. 10 compares the regression model estimated CO_2 emissions (SE_i in Eq. (4)) and bottom-up calculated CO_2 emissions (EE_i in Eq. (4)) of 48 cities in 2012–2016. The figure shows high consistency between SE_i and EE_i, suggesting that the panel regression model has performed well at estimating city-level CO_2 emissions from central heating. This provides confidence in using NTL data as the spatial proxy to build a gridded CO_2 emission inventory, as also found in previous studies [56]. Nonetheless, applying the regression relationship to each grid cell raises an additional uncertainty, which is difficult to assess and not quantified here. Note that when aggregated to the city level, the emission uncertainty is reduced to that in the bottom-up calculation.

4. Conclusions

This work combines a bottom-up emission calculation, satellite nighttime light data and a panel regression model to study the spatio-temporal dynamics of CO_2 emissions from central heating in the North China Plain region over 2012–2016. It also examines the effects of recent developments in natural gas-based heating, on a $5 \times 5\,km^2$ grid. We find that Beijing, Tianjin, Shijiazhuang and Qingdao have the largest CO_2 emissions during 2012–2016. Most cities exhibit emission growth throughout the years because of the increasing need of energy for central heating. However, emissions in Beijing decrease by 4060 $GgCO_2$ from 2012 to 2016.

The gridded emission map shows that CO_2 emissions from central heating supply are mainly from urban consumption (60–67%) in Beijing and Tianjin, although the gap in emissions for urban versus non-urban heating narrowed from 2012 to 2016. Meanwhile, in Hebei, Henan and Shandong provinces, non-urban heating contributed to the majority of heating-related CO_2 emissions (56–69%).

Our study also separates CO_2 emissions from coal burning (including coal-fired heating systems and cogeneration thermal power plants) and the emissions from gas-fired boilers. During 2012–2016, coal still played a dominant role in the central heating supply and heating-related CO_2 emissions over the NCP. The gridded CO_2 emissions data show that from 2012 to 2016, most cities in South Hebei, North Henan and West Shandong exhibited enhancements in coal use and resulting emissions. Although many cities have increased the fraction of gas-fired boilers for central heating throughout the years, gas-based heating still plays only a minor role in both the heating supply and resulting emissions. Beijing has had the most dramatic transformation from coal- to gas-based central heating, such that in Beijing the contribution of gas-related emissions increased from 1.9% in 2012 to 31.2% in 2016.

Overall, we find that further efforts to improve the energy efficiency in central heating and/or to promote cleaner energy sources are needed to reduce CO_2 emissions. Also, although gas-fired boilers lead to less CO_2 emissions than coal-based heating (to generate the same amount of heat), the potential gas (methane) leakage must be avoided or minimized, as methane is a greenhouse gas with a higher global warming potential than CO_2 per unit mass.

Our gridded CO_2 emission data can be used as inputs to atmospheric chemical transport models or Earth System Models to study carbon flux and cycling [32,42]. Also, our integrated approach may be applied to other cities and other pollutants (e.g., NO_x and SO_2) in China and elsewhere to facilitate city-level pollution control and climate change mitigation.

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