**Province-level fossil fuel $CO_2$ emission estimates for China based on seven inventories**

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## Abstract

China pledges to reach a peak in $CO_2$ emissions by 2030 and to make its best efforts to reach this peak earlier. Previous studies have paid much attention to the total amount of China's $CO_2$ emissions, but usually only one dataset is used in each evaluation. The pledged national reduction target is administratively divided into provincial targets. Accurate interpretation of province-level carbon emissions is essential for making policies and achieving the reduction target. However, the spatiotemporal pattern of provincial emissions and the associated uncertainty are still poorly understood. Thus, an assessment of province-level $CO_2$ emissions considering local statistical data and emission factors is urgently needed. Here, we collected and analyzed 7 published emission datasets to comprehensively evaluate the spatiotemporal distribution of provincial $CO_2$ emissions. We found that the provincial emissions ranged from 20-649 Mt $CO_2$ and that the standard deviations (SDs) ranged from 8-159 Mt. Furthermore, the emissions estimated from provincial-data-based inventories were more consistent than those from the spatial disaggregation of national energy statistics, with mean SDs of 26 and 65 Mt $CO_2$ in 2012, respectively. Temporally, emissions in most provinces increased from 2000 to approximately 2012 and leveled off afterwards. The interannual variation in provincial $CO_2$ emissions was captured by provincial-data-based inventories but generally missed by national-data-based inventories. When compared with referenced inventories, the discrepancy for provincial estimates could reach -57%-162% for national-data-based inventories but were less than 45% for provincial-data-based inventories. Using comprehensive data sets, the range presented here incorporated more factors and showed potential systematic biases. Our results indicate that it is more suitable to use provincial inventories when making policies for subnational $CO_2$ reductions or when performing atmospheric $CO_2$ simulations. To reduce uncertainties in provincial emission estimates, we suggest the use of local optimized coal emission factors and validations of inventories by direct measurement data and remote sensing results.

**Keywords**: fossil fuel $CO_2$; provincial emissions; multiple inventories; climate mitigations

Abbreviations:

ODIAC: Open-Data Inventory for Anthropogenic Carbon dioxide, EDGAR: Emissions Database for Global Atmospheric Research, PKU: Peking University-$CO_2$, MEIC: Multi-resolution Emission Inventory for China, NJU: Nanjing University-$CO_2$, CHRED: China High Resolution Emission Database, CEADs: China Emission Accounts and Datasets, CDIAC: Carbon Dioxide Information Analysis Center, GDP: gross domestic production, NBS: National Bureau of Statistics of the People's Republic of China, EF: emission factor, IPCC: The Intergovernmental Panel on Climate Change.

## 1. Introduction

Anthropogenic $CO_2$ emissions from fossil fuel combustion and industrial processes are primarily responsible for global warming by increasing atmospheric $CO_2$ concentrations (Stocker et al., 2013). Over 2008-2017, the mean global fossil $CO_2$ emissions (FFCO2) were 9.4 ± 0.5 Gt C $yr^{-1}$ (Le Quéré et al., 2018). Currently, stabilizing the concentration of atmospheric $CO_2$ has become one of the most urgent challenges for humanity (Ballantyne et al., 2018). Efforts for climate change mitigation are making progress after the implementation of the Paris Agreement, which helps to regulate the total amount of $CO_2$ emitted into the atmosphere to limit warming to below 2 ℃ in the long term (Rogelj et al., 2016; Schleussner et al., 2016). China plays a crucial role in climate change mitigation due to its large contribution (~30%) to global total $CO_2$ emissions (Le Quéré et al., 2018). The Chinese government pledges to reach a peak in its emissions by 2030 and has established a set of carbon emission reduction actions in the 13th Five-Year Plan (NDRC, 2016). Therefore, an accurate assessment of China's $CO_2$ emissions is a vital step towards formulating emission reduction policies.

More efforts have been made to estimate the amount of $CO_2$ emissions at the national scale (Guan et al., 2018; Liu et al., 2013; Shan et al., 2017; Wang et al., 2014) and from key emitting sectors in China (Guo et al., 2014; Liu, F. et al., 2015; Shan et al., 2018a; Shan et al., 2016b; Zheng et al., 2014). However, large uncertainty still exists due to the discrepancy between emission factors and energy statistics used by different inventories (Berenzin et al., 2013; Hong et al., 2017; Zhao et al., 2012). The quality of energy statistics is considered the largest contributor to the accuracy of emission estimates (Guan et al., 2012). The emissions estimated from provincial energy statistics were generally higher than those from national statistics (Guan et al., 2012; Shan et al., 2016a). The difference is mainly caused by the inconsistency between national and provincial energy statistics. The energy-induced uncertainty could be attributed to the different statistical standards, inadequacies in China's statistical system and artificial factors (Hong et al., 2017; Shan et al., 2016a). Furthermore, the discrepancy in energy data could result in a substantial effect on the emission trends (Hong et al., 2017). However, we still have a limited understanding of the influence of energy statistics differences on the spatiotemporal distribution of $CO_2$ emissions.

The carbon emissions in China have significant regional heterogeneity due to differences in social conditions, economic development, urbanization level, industry structure, and trade openness among regions (Bai et al., 2014; Dong and Liang, 2014; Xu and Lin, 2016). To interpret the differentiated contributions of regions to $CO_2$ emissions, several researchers have focused on provincial-level carbon emissions in recent years (Bai et al., 2014; Du et al., 2017; Shan et al., 2016a). This analysis can improve the understanding of the spatial patterns of emissions and provide assistance in allocating different responsibilities and setting emission targets (Shao et al., 2018). To date, provincial-level $CO_2$ emission estimates have been developed on the basis of provincial or national energy statistics. Verified provincial statistics have been shown to better agree with satellite observations (Akimoto et al., 2006; Zhao et al., 2012). Emissions based on national statistics were downscaled from national totals to province-level values according to provincial fractions or spatial proxies (Asefi-Najafabady et al., 2014; Zhao et al., 2012), such as PKU-$CO_2$ (Wang et al., 2013) and the Carbon Dioxide Information Analysis Center (CDIAC). However, disaggregating national emissions to the subnational or grid level using population and nightlight maps as a proxy results in spatial biases in allocating emissions within a country (Asefi-Najafabady et al., 2014; Rayner et al., 2010), especially in China (Liu et al., 2013; Wang et al., 2013). Therefore, quantitative evaluation of emissions uncertainty caused by different energy statistics and different proxies at the subnational level is urgently needed, and the evaluation of provincial emissions will provide data that are needed for local reductions and mitigations.

This study is a first attempt to comprehensively evaluate provincial emission estimates using the most up-to-date inventories. The purposes were to estimate the magnitude and uncertainty or differences in provincial $CO_2$ emissions based on seven datasets, identify the commonalities and disparities of provincial carbon emissions in terms of spatiotemporal variations among different estimates, and thus provide support for policymakers to develop region-oriented emissions reduction policies. This study also indicated that national-level data-based inventories may not be suitable for local policy making. In the following sections, we first introduce the data and methods (Sections 2.1 and 2.2) and then present the results in the following 5 sections (Sections 3.1 - 3.5): the provincial emissions and standard deviations (SDs); temporal emissions changes from 2000 – 2018; fractions of the high emitting provinces; correlations of inventories' estimates at the provincial level; and differences between the estimates and the referenced inventories. Third, we discuss the root causes (activity data at provincial and national levels, coal emission factor and spatial proxies) that contribute to the differences and implications for inventory use and improvement (Sections 4.1 - 4.4).

## 2. Data and methods

### 2.1 Data

The evaluation of provincial-level $CO_2$ emissions was conducted from 7 published $CO_2$ emission estimates based on national and provincial energy statistics (Table S1). Specifically, the global fossil fuel and industrial processes $CO_2$ emission datasets included the year 2018 version of ODIAC (ODIAC2018), version v5.0 of EDGAR (EDGARv5.0, https://edgar.jrc.ec.europa.eu/overview.php?v=booklet2019), and version 2 of PKU-$CO_2$ (PKU-$CO_2$-v2), which are developed from the national energy statistics of the International Energy Agency (IEA). The provincial-statistics-based emission datasets were the data for the years 2007 and 2012 from CHRED, version 1.3 of MEIC (MEIC v1.3), NJU-$CO_2$ and CEADs, which used provincial energy balance sheets from China Energy Statistical Yearbook (CESY) activity data. For detailed methods and key features of the total emission estimates and spatial disaggregation, please refer to the Supplementary Materials, Tables S2 and S3, and Han et al. (2020). Data for the year 2012 were used in spatial analysis since it was the most recent year for all data sets.

The Open-source Data Inventory for Anthropogenic $CO_2$ (ODIAC) is primarily based on country-level emission estimates for three fuel types from the CDIAC and has used the BP Statistical Review of World Energy for recent years (Oda and Maksyutov, 2011; Oda et al., 2018). The Emissions Database for Global Atmospheric Research (EDGAR) was developed by the European Commission's Joint Research Centre (JRC) based on IEA national statistics for fossil fuel combustion sources and other international statistics as input activity data under the guidelines of the Intergovernmental Panel on Climate Change (IPCC) and technology-specific emission factors (Crippa et al., 2019; Janssens-Maenhout et al., 2019). PKU-$CO_2$ (PKU) was developed from the Peking University Fuel Inventories (PKU-FUEL), which used a subnational disaggregation method (SDM) based on the combustion rates for different fuel types compiled at the global/national level and emission factors, and for China, it used NBS provincial consumption fractions to spatially distribute the IEA total energy consumption amount (Wang et al., 2013). MEIC was developed by Tsinghua University using a technology-based methodology built upon more than 700 anthropogenic sources and emission factors (Li et al., 2017; Liu, F. et al., 2015; Zheng, 2018). NJU-$CO_2$ was developed at Nanjing University using a sectoral approach under the guidelines of the IPCC (Liu et al., 2013; Wang et al., 2019). CHRED was constructed by enterprise-level point sources from the First China Pollution Source Census (FCPSC) survey and used local emission factors compiled by the NCCC (Cai et al., 2019; Wang et al., 2014). The CEADs were calculated based on apparent energy consumption data and the most up-to-date emission factors using the sectoral and reference approaches under the guidelines of the IPCC (Guan et al., 2018; Shan et al., 2016a).

Considering the differences in national and provincial energy statistics, the 7 inventories were classified into two groups: one includes ODIAC, EDGAR, and PKU, and the other includes MEIC, NJU, CHRED, and CEADs. CHRED is based on the most comprehensive enterprise-level data (1.5 million enterprises) from a national pollution source census and regular pollution reporting systems in China (Cai et al., 2019; Wang et al., 2014). The CEADs are based on apparent energy consumption data and local optimized emission factors that are similar to China's fossil fuel quality based on 602 coal samples and 4243 coal mines (Liu, Z. et al., 2015). Therefore, $CO_2$ emissions calculated from CHRED and CEADs were used as a reference to evaluate the estimates from other emission datasets.

### 2.2 Methods

These inventories were first extracted by provincial mask (in shapefile format) from the National Geomatics Center of China using ArcGIS 10.02 software (ESRI, 2012). To allocate the carbon emissions with ArcGIS when a grid spans more than two provinces, we first change the grid data into polygon (shapefile) format, calculate the area fraction of the irregular shape that falls within a certain province, and apply this fraction to the total emissions of this polygon; this result is assumed to be the emissions allocated to this province. This method produces a difference of 4% with respect to the NJU products, which provide both tabular data and gridded data. Emission intensity was calculated as $CO_2$ emissions divided by the gross domestic product (GDP) (billion USD), which was derived from the National Bureau of Statistics of the People's Republic of China (NBS). The GDP data were adjusted by a purchasing power parity (PPP) conversion factor, defined as the number of local currency units required to buy the same amounts of goods and services in the local market that a US dollar would buy in the United States in the reference year 2010

(Wang et al., 2019). Correlation relationships (R) were conducted using the Python Scipy package (Virtanen, 2020) between inventories, and figures were plotted using the matplotlib package (Hunter, 2007) and ArcGIS.

# 3. Results

## 3.1 Provincial $CO_2$ emissions derived from national and provincial energy statistics

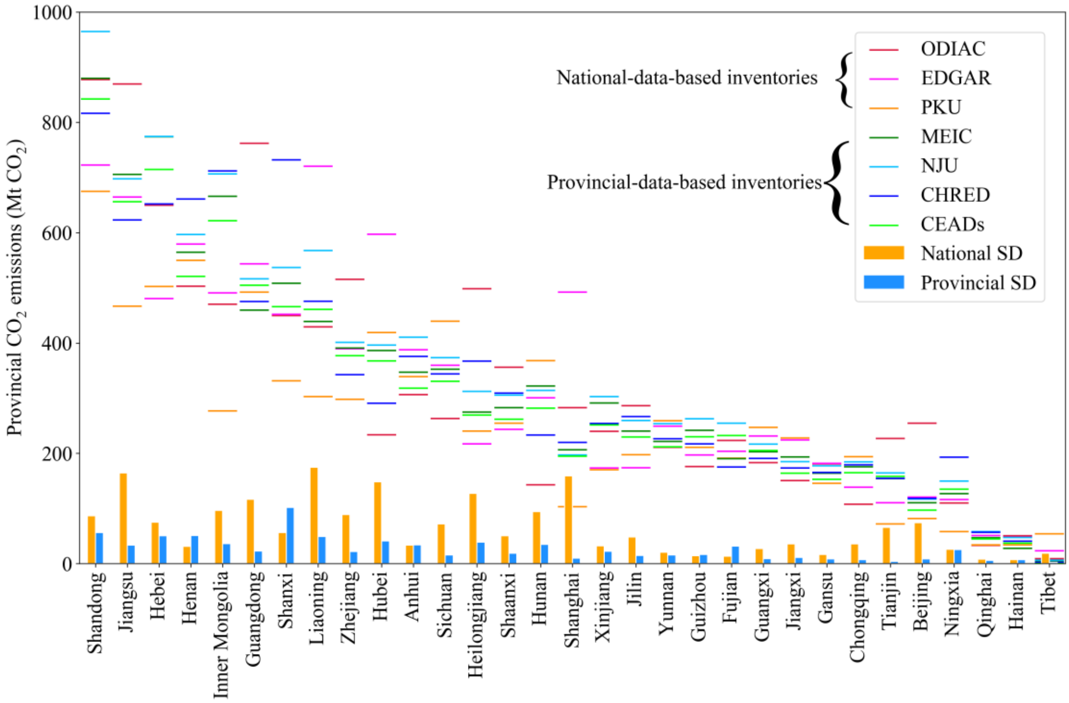


Fig. 1 Provincial $CO_2$ emissions in 2012 for 7 inventories and standard deviations (SDs) based on national- and provincial-data-based inventories.

The $CO_2$ emissions of the 31 provinces in 2012 varied greatly, ranging from dozens of Mt to approximately 900 Mt (Fig. 1). The top 5 emitting provinces were Shandong (876±56 Mt $CO_2$), Hebei (729±50 Mt $CO_2$), Inner Mongolia (677±36 Mt $CO_2$), Jiangsu (671±33 Mt $CO_2$), and Henan (586±51 Mt $CO_2$) based on provincial energy statistics. Lower levels of emissions were observed in Qinghai, Hainan and Tibet provinces (<100 Mt $CO_2$) (Fig. 1). The estimates for each province's $CO_2$ emissions in 2012 varied greatly, with differences ranging from 23% (Yunnan) to 232% (Ningxia). Moreover, the estimates for the top emitting provinces showed large uncertainties (Fig. 1). Specifically, the $CO_2$ emissions in the top 7 provinces (Shandong, Jiangsu, Hebei, Inner Mongolia, Guangdong, Liaoning, and Shanxi) account for nearly 50% of total emissions, with absolute differences ranging from 158 to 435 Mt $CO_2$ in 2012. However, western provinces with low emissions, e.g., Gansu, Qinghai, Guizhou, and Hainan, had smaller discrepancies. The SDs of the inventories based on provincial statistics were generally less (26 Mt $CO_2$) than those based on national statistics (65 Mt $CO_2$) in 2012. For example, the emission estimates in Jiangsu and Shanghai based on national statistics showed obvious differences, with SDs exceeding 150 Mt $CO_2$, whereas those based on provincial inventories exhibited SDs of 33 and 10 Mt $CO_2$, respectively.

## 3.2 The temporal evolution of provincial-level $CO_2$ emissions and emissions per GDP derived from national and provincial energy statistics

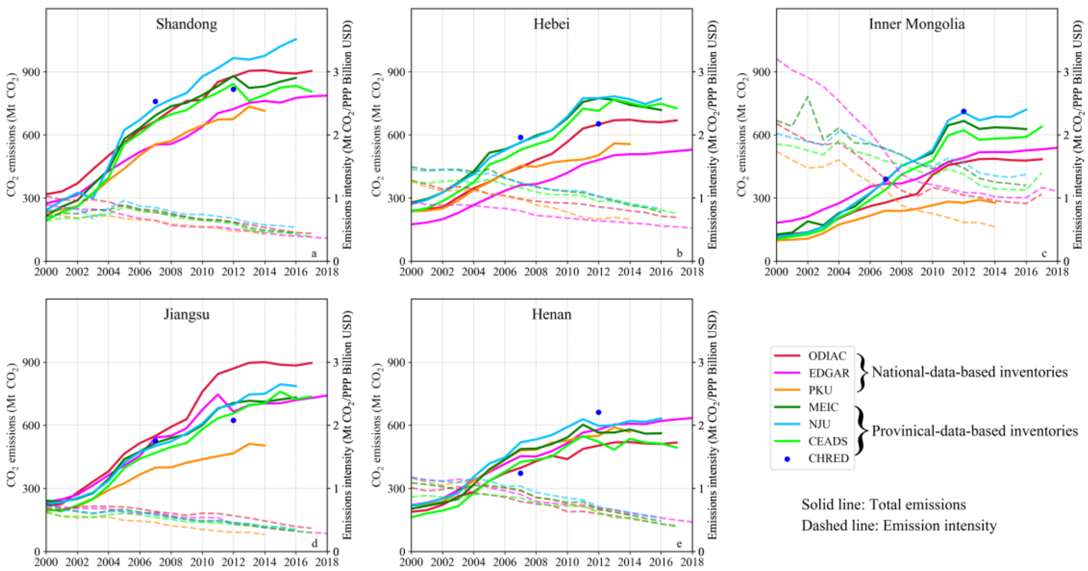


Fig. 2 $CO_2$ emissions of the top 5 provinces from 2000 to 2018

The temporal changes in the $CO_2$ emissions of the top 5 emitting provinces are shown in Fig. 2. Despite differences in magnitude, all the estimates agreed that the emissions of the top 5 emitting provinces increased from 2000 to approximately 2012 and leveled off afterwards. The interannual variation in existing emissions derived from provincial and national statistics is notably different, and these discrepancies increased over time. For the average of all the provinces during the period of 2000-2016, the $CO_2$ emissions derived from provincial statistics increased by 217%, and those derived from national statistics increased by 197% (Fig. S2). The total difference in the top 5 emissions from national and provincial statistics was 39 Mt $CO_2$ in 2000. However, it increased to 447 Mt $CO_2$ in 2016, with a peak difference of 636 Mt $CO_2$ in 2012. This trend was consistent with the findings of Guan et al. (2012). The emissions estimated from provincial statistics showed relatively consistent variations, which were able to detect apparent peak emissions in 2011 or 2012 and then leveled off or went down. Compared to emissions derived from provincial statistics, the variabilities of ODIAC, EDGAR, and PKU were relatively smooth and were unable to capture the interannual variation in $CO_2$ emissions. Moreover, PKU tended to underestimate emissions among existing estimates, except for Henan. ODIAC showed a unique trend with emissions accelerating before 2010 and subsequently leveling off in Jiangsu and Henan.

The local governments of Beijing and Shanghai have proposed clear timing targets for peaks in total and per capita $CO_2$ emissions in 2020 and 2025, respectively (Shanghai Municipal People's Government, 2018; The People's Government of Beijing Municipality, 2016). The $CO_2$ emissions per GDP decreased dramatically (from 1-3 to 0.3-1 Mt $CO_2$ per PPP billion USD) during the study period (Fig. 2 and Fig. S2). Specifically, the emissions per GDP decreased to 0.3-0.6 Mt $CO_2$ per PPP billion USD for Shandong, Hebei, Jiangsu and Henan provinces. However, they decreased from approximately 3 to 1 Mt $CO_2$ per PPP billion USD for Inner Mongolia. The spread of $CO_2$ emissions per GDP among these datasets also decreased, mainly due to the decoupling of $CO_2$ emissions and GDP increase, i.e., the leveling off of $CO_2$ emissions and the increase of GDP.

3.3 The fractions of provincial-level $CO_2$ emissions derived from national and provincial energy statistics

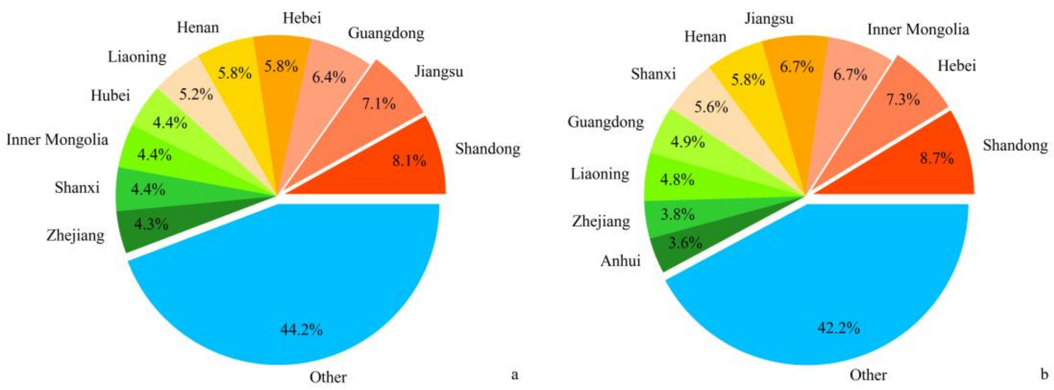


Fig. 3 The $CO_2$ emissions fractions of the top 10 provinces in 2012. Subplots (a) and (b) are the mean fractions of national- and provincial-data-based inventories.

The total fractions of the top 10 emitting provinces derived from national-data-based inventories (~56%) are rather close to those derived from provincial-data-based inventories (~58%) (Fig. 3); the remaining provinces contributed the other ~40%. However, the sequences of the top 10 provinces estimated from national statistics are quite different from those datasets calculated from provincial statistics. Shandong is the highest emission province, with mean values of up to 758 and 876 Mt $CO_2$ based on national- and provincial-data-based inventories, representing 8.1% - 8.7% of the total emissions. Moreover, there are substantial differences in other top emitting provinces. The estimated emissions in Hebei, Shanxi, and Inner Mongolia derived from provincial-data-based inventories were approximately 34%, 36%, and 64% higher than those from national-data-based inventories, respectively. Since national-data-based inventories do not include detailed provincial energy information and thus had larger SDs, we recommend that policymakers use provincial mean results to allocate responsibilities and to develop reduction policies according to local realities.

### 3.4 The relationships of provincial-level $CO_2$ emissions derived from national and provincial energy statistics

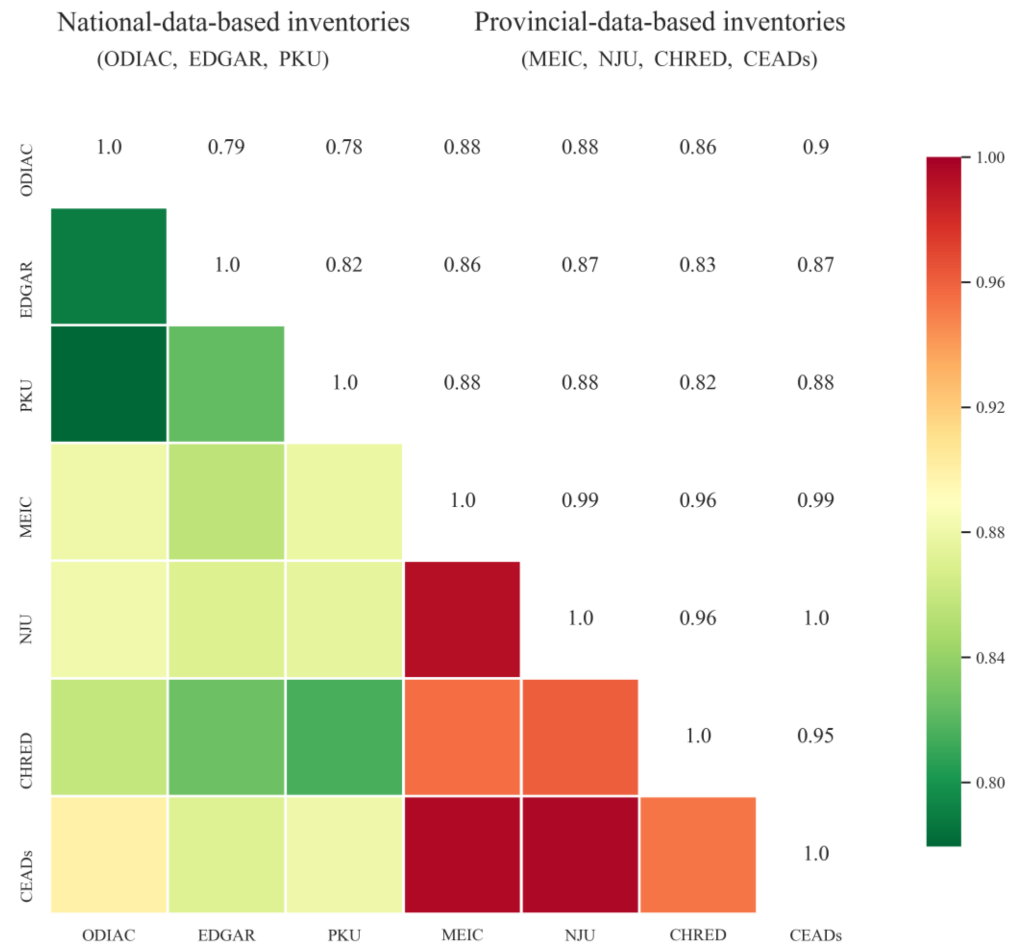


Fig. 4 Correlations of multiple $CO_2$ emission datasets at the provincial level in 2012

To interpret the commonalities and differences in provincial emissions between national- and provincial-data-based inventories, the paired correlation relationship is shown in Fig. 4. The provincial-level $CO_2$ emissions developed from provincial statistics have a good correlation relationship, with correlation coefficients (R) greater than 0.9. Emissions from MEIC, NJU, and CEADs are highly correlated, with a mean difference of less than 40 Mt $CO_2$ in 2012. This implies that the energy statistics played the main role in estimating emissions, albeit with differences in methodology. However, the emissions derived from national statistics showed a relatively weaker correlation ($R < 0.85$). The correlation between ODIAC and PKU was weakest among all the estimates. This was probably due to the different energy statistic input data (CDIAC for ODIAC and IEA for PKU) and spatial disaggregation proxies (nighttime light for ODIAC and population and vegetation for PKU), producing the striking contrast in provincial-level emissions between ODIAC and PKU, with differences ranging from -225 to 403 Mt $CO_2$ in 2012 (Fig. 1). Although the emissions of EDGAR and PKU were both mainly used in the IEA statistics, their correlation was not strong. First, PKU used the IEA national total and provincial fractions to distribute the emissions. Second, differences in spatial disaggregation proxies (nighttime light, population density for EDGAR and population and vegetation for PKU) to reallocate national total to provincial scale and sectoral differences could enhance uncertainties in the final provincial-level emissions. Third, differences in the version used by each dataset also produced some differences. PKU used version 2014, while EDGAR used version 2017 (Table S2); these versions estimated coal production as 3637 and 3650 Mt, respectively, for the same year 2014. Moreover, EDGAR also used other activity data, and for industrial processes, it included more sectors, such as the production of lime, soda ash, ammonia, ferroalloys and nonferrous metals.

## 3.5 Spatial differences of provincial-level $CO_2$ emissions to CHRED and CEADs

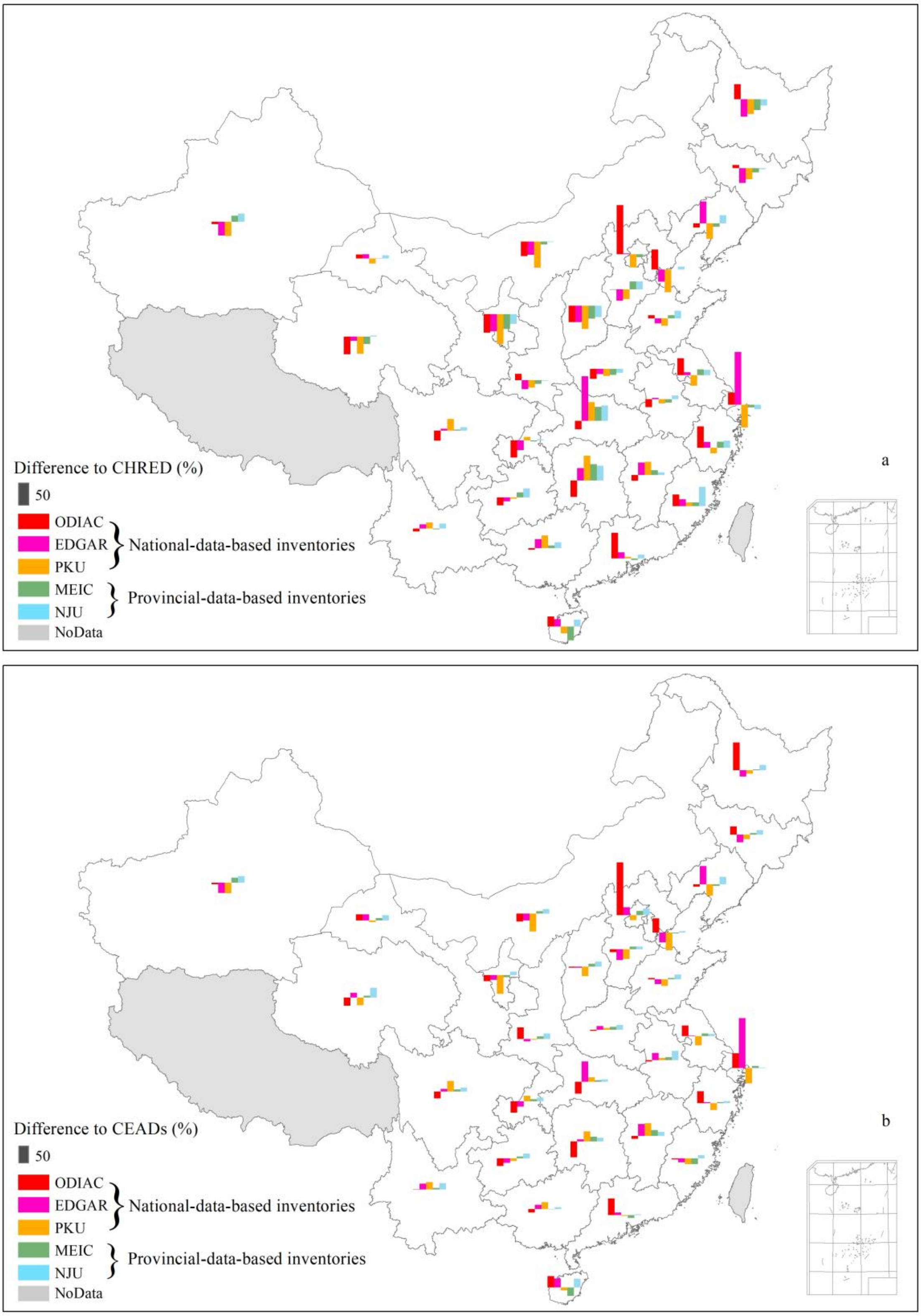


Fig. 5 Spatial differences in provincial-level $CO_2$ emissions from CHRED (a) and CEADs (b) in 2012

As CHRED used over 1.5 million enterprise-level point sources and CEADs adopted measured emission factors that are closer to China's fossil fuel quality, they were used as references to evaluate other datasets in 31 provinces. Compared to CHRED and CEADs, the national-data-based inventories produced discrepancies in provincial estimates of -57%-162%, whereas provincial-data-based inventories produced discrepancies of less than 45%. In general, the provincial carbon emissions of ODIAC and NJU were both higher than the references, while those of PKU were lower than the references (Fig. 5). EDGAR and MEIC were comparable to CHRED and CEADs, with mean differences of 3% and 8%, respectively. With respect to mean provincial $CO_2$ emissions, the estimates of PKU were 14% and 11% lower than those of CHRED and CEADs, respectively. Specifically, for Inner Mongolia, Tianjin, and Ningxia, the emissions by PKU were 50% or more lower than those of CHRED and CEADs. However, the emissions of ODIAC and NJU were 3% and 8% higher than those of CHRED and 10% and 13% higher than those of CEADs, respectively. ODIAC probably allocated more emissions to Beijing, resulting in 115% and 162% higher emissions than CHRED and CEADs, respectively. Higher estimates by ODIAC were also obvious in Heilongjiang, Tianjin, and Guangdong provinces, with differences of 35% to 85%. These differences can be attributed to the spatial mismatch between the location of emissions and spatial proxies (Gurney et al., 2009; Zheng et al., 2017). Moreover, the spatial biases tended to increase with spatial resolution (Zheng et al., 2017). The high spatial resolution of ODIAC (1 km) was found to underestimate the emissions of areas that do not have strong nighttime light (e.g., rural areas and power plants based on fossil fuels) (Wang et al., 2013). However, the saturated estimates caused by nightlight data may result in overestimated emissions in urban areas (Wang and Cai, 2017). In addition, the carbon emissions of MEIC are comparable to those of CHRED and CEADs, with mean differences of 2% to 4%. However, EDGAR tends to largely overestimate the emissions in Shanghai and Hubei, with differences of up to 123% and 105% compared to CHRED and 153% and 62% compared to CEADs, respectively.

## 4. Discussions

### 4.1 Reasons why the sum of the provincial data is greater than the national statistics

Since the national and provincial energy statistics were surveyed by two different teams, namely, the National Bureau of Statistics and the provincial bureaus of statistics, it is not surprising that the sum of the provincial energy statistics is not identical to the national total (NBS, 2013). The sum of the provincial data is systematically greater than the national statistics due to the differences in national and provincial statistical systems and artificial factors (Hong et al., 2017). To ensure the consistency between national emissions and the sum of province-level data, one possible practical way might use the national total fossil fuel consumption and provincial fractions to scale when distributing emissions to the grid and further use field measurements and remote sensing data to validate inventories.

National statistical data are usually collected by the national survey team and reported from the local level and key energy-consuming enterprises (≥ 10,000 standard coal consumption), and it is difficult to validate the locally reported data (NBS, 2013). Furthermore, data inconsistency and double counting exist in the provincial data (Hong et al., 2017; Zhang et al., 2007). Using coal data as an example, the sum of interprovincial imports was 17.6% (or 339.2 Mt) higher than that of exports in 2015, which is 27.2% that of the total coal final consumption amount (data from the energy balance sheet of provincial-level statistics). The same phenomenon is observed in the oil and natural gas data, which were 17.3% (or 81.4 Mt) and 3.3% (or $3.6*10^9$ $m^3$), or 15.6% and 2.3%, that of the total petroleum products and natural gas final consumption amount, respectively. Additionally, double counting is common in provincial statistics because some activities are counted by all provinces involved.

For small enterprises, the quality of the energy statistics reported to NBS is not as well validated and monitored as those of large enterprises (Hong et al., 2017; NBS, 2013). Moreover, energy data may be modified for artificial purposes because it correlates to GDP and thus the evaluation of the local governors (Guan et al., 2012;

Hong et al., 2017). Moreover, some of the provinces provided equal supply and consumption data, which implies that some local data were modified to achieve an exact balance. Overall, the provincial estimates are 8-18% higher than the CEADs-based national estimate after 2008. Province-based estimates (e.g., NJU and MEIC) are also higher than the CEADs (national) estimate. Hong et al. (2017) found that the ratio of the maximum discrepancy to the mean value was 16% due to different versions of national and provincial data in CESY.

### 4.2 Contributions of three emission types

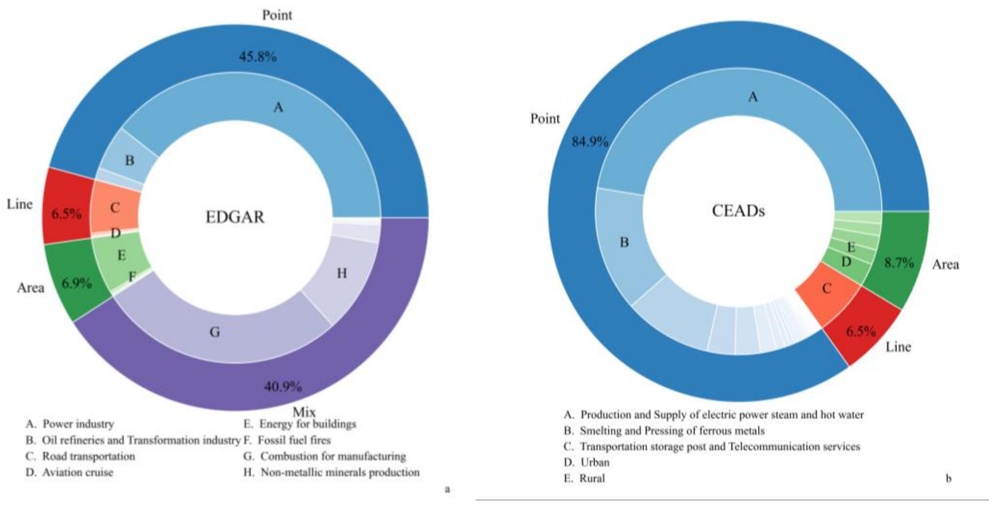


Fig. 6 Compositions for point, line and area sources for EDGAR and CEADs in 2012

The spatial allocation of national or sectoral emissions is generally performed on the basis of three groups of data sources, i.e., point sources downscaled with geocoding locations, line sources downscaled with traffic networks, and area sources relying on spatial proxies. Characterizing the discrepancy in these three categories can help us understand the bias better. Comparison of these three emission types was conducted with respect to EDGAR and CEADs, both of which include detailed sectoral emissions data. According to the characteristics of sectoral emissions and insights from the data developers, the 20 sectors in EDGAR and 47 sectors in CEADs are classified into the three groups above (Table S4). Additionally, there is an additional group of mixed sources in EDGAR. For several sectors in EDGAR, the inventory information includes multiple emission sources. CEADs presented a much larger share of point source emissions than EDGAR (Fig. 6). EDGAR estimated that approximately 46% of emissions were contributed by point sources, followed by mixed sources (41%), and the remaining emissions were line and area sources (both contributing ~7%). By contrast, CEADs assumed that point sources are the primary sources (contributing 85%), followed by area sources (9%) and line sources (7%). Both EDGAR and CEADs estimated the emissions of the sectors under the guidelines of the IPCC (Janssens-Maenhout et al., 2019; Shan et al., 2017). However, there exists a substantial difference in the point source emissions. The lower proportion of point source emissions in EDGAR is partly due to the point sources it uses (CARMA) (Janssens-Maenhout et al., 2019), which neglected small point sources. Moreover, EDGAR uses population-based proxies when no point source information is available. Another reason is that some point sources cannot be separated individually from the mixed sources.

Possible reasons for the differences between EDGAR and CEADs include activity data from national and provincial energy statistics, spatially disaggregated approaches, and point source emissions. The CEADs are based on sectoral fossil fuel consumption from the corresponding provincial statistical yearbook, while EDGAR is primarily based on IEA and other international statistics at the national scale. Guan et al. (2012) and Hong et al. (2017) pointed out that the inconsistency of energy statistics, especially coal consumption data, largely contributed to the emission discrepancy in China. The emissions based on provincial energy statistics were higher than those from national statistics, with a peak difference of 18% in 2014 (Shan et al., 2017). This can be attributed to overreporting or double counting in energy statistics at the provincial level by artificial factors (Guan et al., 2012; Hong et al., 2017). Meanwhile, the absence of emissions from small enterprises at the national scale and the lack of sectoral energy statistics in certain provinces both contributed to uncertainties in the provincial emission estimates (Guan et al., 2012; Hong et al., 2017; Shan et al., 2017).

## 4.3 Impacts of emission factors

Since carbon dioxide emissions are calculated from activity data and emission factors (EFs), differences in the EFs used by these datasets also produce large differences in emission estimates (Table S2). Coal is the major energy type and represents ~80% of the total energy consumption (Liu, Z. et al., 2015). The EF used for raw coal ranges from 0.491 to 0.746 in this study. For example, the CEADs used 0.499 tC per ton of coal based on a large number of measurements, and this coal EF is considered to be representative of Chinese coal quality, while EDGAR used 0.713 (42.9% higher than that of CEADs) based on the default value recommended by the IPCC (Janssens-Maenhout et al., 2019; Liu, Z. et al., 2015; Shan et al., 2018b). Hence, differences arise due largely to the low quality and high ash content of Chinese coal (Janssens-Maenhout et al., 2019; Liu, Z. et al., 2015). Furthermore, using the Monte Carlo method, Shan et al. (2018b) showed that EFs contributed greater uncertainty (-16 – 24%) than did activity data (-1 – 9%). We thus recommended substituting the IPCC default coal EF with the CEADs measurement-based EF. Regarding emissions from coal consumption at the plant level, the collection of their EFs measured in situ is valuable for calibrating large point source emissions, and we call for such physical measurements for the calibration and validation of existing datasets (Dai et al., 2012; Kittner et al., 2018).

## 4.4 Implications for inventory use and improvement

The bottom-up inventories are used as prior emissions in atmospheric inversion models to quantify $CO_2$ fluxes between land/oceans and the atmosphere. The errors in either the location or timing of fossil fuel carbon fluxes are directly aliased into inverse modeling (Asefi-Najafabady et al., 2014; Gurney et al., 2009). An accurate fossil fuel $CO_2$ emission inventory provides invaluable and independent information for inverse modeling and helps to reduce the uncertainty in land biosphere to atmosphere fluxes (Oda et al., 2018; Thompson et al., 2016).

Uncertainty in $CO_2$ emission estimates can have a large impact on the carbon budget simulation since atmospheric inverse models use the bottom-up emission inventory as a priori emissions. Given the targets of emissions reduction in China, it is crucial to develop specific carbon emissions mitigation policies for different provinces (Shan et al., 2019). The large discrepancy in provincial-level $CO_2$ emissions among datasets produces great challenges in the allocation of emission reduction responsibilities. Strategies for reducing emissions could be based on composited trends, and making reduction policies for provinces needs the support of provincial-energy-based datasets instead of national-energy-based ones. To reduce uncertainties in emission estimates, verification of the energy statistics by ground-based measurements and remote sensing data is urgently needed (Berezin, 2013; Yao et al., 2019).

## 5. Conclusions

We estimated China's provincial fossil fuel $CO_2$ emissions using seven of the most up-to-date inventories. We found that: 1) the provincial emissions ranged from 20-649 Mt $CO_2$, with SDs ranging from 8-159 Mt; 2) temporally, the emissions in most provinces increased from 2000 to approximately 2012 and leveled off afterwards; 3) the top 10 emitting provinces derived from national-data-based inventories contributed ~60% of the national total emissions; and 4) the provincial-level $CO_2$ emissions estimated from provincial statistics have a better correlation than the national-data-based inventories. The root causes of the differences were differences in activity data at the provincial and national levels within the statistical systems and the low locally optimized versus higher default coal EFs used. Thus, for future improvements, provincial activity data from national and global inventories should be made publicly available. Locally optimized coal EFs are better than default ones in inventories. Local governments need multiple highly detailed inventories when making policies designed to reduce emissions. Moreover, policymakers should focus on the top emitting provinces as high priorities when designing policies. In terms of emissions intensity (emissions per GDP), provinces that are higher than 0.5 still have room for improvement in industrial structure adjustment. To reduce uncertainties in emissions estimates, verification of the energy statistics by ground-based measurements and remote sensing data is urgently needed.

**Data availability**. The data sets of ODIAC, EDGAR, PKU and CEADs are freely available from http://db.cger.nies.go.jp/dataset/ODIAC/DL_odiac2018.html, https://edgar.jrc.ec.europa.eu/overview.php?v=50_GHG, http://inventory.pku.edu.cn/download/download.html and http://www.ceads.net/, respectively. CHRED, MEIC and NJU are available from the data developers upon request.

**Author contributions**. PFH, WZ and DL conceived and designed the study. PFH and XHL collected and analyzed the data sets. PFH, XHL, WZ and DL led the paper writing with contributions from all coauthors. NZ, TO and QXC helped in data plots and improved the discussion. Data developers for each inventory, i.e., MC and GJM for EDGAR, TO for ODIAC, DBG and YLS for CEADs, XLM and HKW for NJU, WJM, ST and RW for PKU, QZ and BZ for MEIC, contributed to the descriptions and discussions of the corresponding data sets.

**Competing interests.** The authors declare that they have no conflicts of interest.

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**Supporting Information.** Basic information on the 7 datasets and supplementary figures on provincial emissions.

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