Evaluating China's fossil-fuel CO$_2$ emissions from a comprehensive dataset of nine inventories

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Abstract. China’s fossil-fuel CO$_2$ emissions (FFCO$_2$) accounted for about approximately 28% of the global total FFCO$_2$ in 2016. An accurate estimate of China’s FFCO$_2$ emissions is a prerequisite for global and regional carbon budget analyses and the monitoring of carbon emission reduction efforts. However, large-sicious uncertainties and discrepancies exist in estimations of China’s FFCO$_2$ emissions due to a lack of detailed traceable emission factors (EF) and multiple statistical data sources. Here, we evaluated China’s FFCO$_2$ emissions from nine published global and regional emission datasets. These datasets show that the total emissions increased from 3.4 (3.0-3.7) in 2000 to 9.8 (9.2-10.4) Gt CO$_2$ yr$^{-1}$ in 2016. The variations in these estimates were largely due to the different EF (0.491-0.746 t C per t of coal) and activity data. The large-scale patterns of gridded emissions showed a reasonable agreement with high emissions being
concentrated in major city clusters, and the standard deviation mostly ranged from 10-40% at the provincial level. However, patterns beyond the provincial scale varied significantly, with the top 5% of the grid-level accounting for 50-90% of total emissions for these datasets. Our findings highlight the significance of using locally measured EF for the Chinese coals. To reduce the uncertainty, we call on the enhancement of recommend using physical CO2 measurements and use them for datasets validation, key input data sharing (e.g., point sources) and finer resolution validations at various levels.

Keywords: fossil-fuel CO2 emissions, spatial disaggregation, emission factor, activity data, comprehensive dataset

1 Introduction

Anthropogenic emissions of carbon dioxide (CO2) is one of the major contributions accelerators of global warming (IPCC, 2007). The global CO2 emissions from fossil fuel combustion and industry processes increased to 36.23 Gt CO2 yr\(^{-1}\) in 2016, with a mean growth rate of 0.62 Gt CO2 yr\(^{-1}\) per year over the last decade (Le Quéré et al., 2018). In 2006, China became the world’s largest emitter of CO2 (Jones, 2007). The CO2 emissions from fossil fuel combustion and cement production in China were 9.9 Gt CO2 in 2016, accounting for about 28% of all global fossil-fuel based CO2 emissions (Le Quéré et al., 2018; IPCC AR5, 2013). To avoid the potential adverse effects from climate change (Zeng et al., 2008; Qin et al., 2016), the Chinese government has pledged to peak its CO2 emissions by 2030 or earlier and to reduce the CO2 emissions per unit gross domestic product (GDP) by 60-65% below less than the 2005 levels (SCIO, 2015). Thus, an accurate quantification of China’s CO2 emissions is the first step toward understanding its carbon budget and making carbon control policy.

For China, the total emission estimates are thought to be uncertain or biased due to the lack of reliable statistical data and/or the use of generic emission factors (EF) (e.g., (Guan et al., 2012); (Liu et al., 2015b)). National and provincial data-based inventories used activity data from different sources. The Carbon Dioxide Information Analysis Center (CDIAC) used national energy statistics from the United Nations (UN) (Andres et al., 2012), and both the Open-Data Inventory for Anthropogenic Carbon Dioxide (ODIAC) and Global Carbon Project (GCP) mainly use CDIAC total estimates and thus, they are identical in time series (Le Quéré et al., 2018; Oda et al., 2018). The Emissions Database for Global Atmospheric Research (EDGAR) and Peking University CO2 (PKU-CO2, hereafter named as PKU) derived emissions from the energy balance statistics of the International Energy Agency (IEA) (Janssens-Maenhout et al., 2019a; Wang et al., 2013). On the other hand, the provincial data-based inventories developed within China all used the provincial energy balance sheet from the China Energy Statistics Yearbook (CESY), from National Bureau of Statistics of China (NBS) (Cai et al., 2018; Liu et al., 2015a; Liu et al., 2013; Shan et al., 2018). As for EF, there are generally four sources of EF, i.e., 1) The Intergovernmental Panel on Climate Change (IPCC) default values, which have been adopted by ODIAC and EDGAR (Andres et al., 2012; Janssens-Maenhout et al., 2019b; Oda et al., 2018); 2) National Development and Reform
Commission (NDRC) (NDRC, 2012b); 3) China’s National Communication, which reported to the United Nations Framework Convention on Climate Change (UNFCCC) (NDRC, 2012a); and 4) The China Emission Accounts and Datasets (CEADs) EF, which are locally optimized through large sample measurements (Liu et al., 2015b). The existing estimates of global total FF\textsubscript{CO}\textsubscript{2} emissions are comparable in magnitude, with an uncertainty that is generally within ±10% (Le Quéré et al., 2018; Oda et al., 2018). However, there are great-significant differences in these values at the national scale (Marland et al., 2010; Olivier et al., 2014), with the uncertainty ranging from a few percent to more than 50% in the estimated emissions for individual countries (Andres et al., 2012; Boden et al., 2016; Oda et al., 2018).

Along with the total emissions estimates, the spatial distribution of emissions are also important for several reasons: 1) Spatial gridded products provide enhance our basic understandings on of CO\textsubscript{2} emissions; 2) They spatial distributions are key inputs (as priors) for transport and data assimilation models, and which influenced the carbon budget (Bao et al., 2020); and 3) For high-emissions areas recognized by multiple inventories, their spatial distributions can be used for policy making in-toward emissions reductions and can provide useful information for the deployment of instruments in emissions monitoring for high-emissions areas recognized by multiple inventories (Han et al., 2020). At the global level, gridded emissions datasets are often based on the disaggregation of country-scale emissions (Janssens-Maenhout et al., 2017; Wang et al., 2013). Thus, the gridded emissions data are subjected to errors and uncertainties from due to the total emissions calculations and emissions spatial disaggregation (Andres et al., 2016; Oda et al., 2018; Oda and Maksyutov, 2011). For example, the Carbon Dioxide Information Analysis Center (CDIAC) distributes national energy statistics at a resolution of 1° × 1° using the population density as a proxy (Andres et al., 2016; Andres et al., 2011). Further, to improve the spatial resolution of the emissions inventory, the Open-Data Inventory for Anthropogenic Carbon dioxide (ODIAC) distributes national emissions based on CDIAC and BP statistics with satellite nighttime lights and power plant emissions (Oda et al., 2018; Oda and Maksyutov, 2011). - (EDGAR, j-derived emissions from the energy balance statistics of the International Energy Agency (IEA), and obtains country-specific activity datasets from BP plc, United States Geological Survey (USGS), World Steel Association, Global Gas Flaring Reduction Partnership (GGFR)/U.S. National Oceanic and Atmospheric Administration (NOAA) and International Fertilizer Association (IFA). Gridded emission maps at a resolution of 0.1°×0.1° were are produced using spatial proxy data based on the population density, traffic networks, nighttime lights and point sources, as described in Janssens-Maenhout et al. (2017). Based on the sub-national fuel data, population and other geographically resolved data, a high-resolution inventory of global CO\textsubscript{2} emissions was developed at Peking University (Wang et al., 2013).

In order to accurately calculate emissions, a series of efforts have been conducted to quantitatively evaluate China’s CO\textsubscript{2} emissions using national or provincial activity data, local EF and detailed data-sets of point sources (Cai et al., 2018; Li et al., 2017; Wang et al., 2013). The China High Resolution Emission Database (CHRED) was developed by Cai et al. (2018) and
Wang et al. (2014) based on the provincial statistics, traffic network, point sources and industrial and fuel-specific EF. CHRED was featured by its exclusive point source data for 1.58 million industrial enterprises from the First China Pollution Source Census. The Multi-resolution Emission Inventory for China (MEIC) was developed by Zhang et al. (2007), Lei et al. (2011) and Liu et al. (2015a) at Tsinghua University through integrating the integration of provincial statistics, unit-based power plant emissions, population density, traffic networks, and emission factor (EF) (Li et al., 2017; Zheng et al., 2018b; Zheng et al., 2018a). The MEIC uses the China Power Emissions Database (CPED), and in which the unit-based approach is used to calculate emissions for each coal-fired power plant in China with detailed unit-level information (e.g., coal use, geographical coordinates). For the mobile emissions sources, a high-resolution mapping approach is adopted to constrain the vehicle emissions using a county-level activity database. CEADs was constructed by (Shan et al., 2018; Shan et al., 2016) and Guan et al. (2018) based on different levels of inventories to provide emissions at the national and provincial scales. CEADs used coal EF from the large-sample measurements (602 coal samples and samples from 4,243 coal mines). And this is, which are assumed to be more accurate than the IPCC default EFs.

However, regardless of these efforts, however, the amount of China’s CO₂ emissions remains uncertain due to the large discrepancy among current estimates, of which the difference ranges from 8-24% of the total estimates (Shan et al., 2018; Shan et al., 2016). Several studies have made efforts of quantifying the possible uncertainty in China’s FFCO₂, such as differences from due to estimation approaches (Berezin et al., 2013), energy statistics (Hong et al., 2017; Han et al., 2020), spatial scales (Wang and Cai, 2017), and point source data. Importantly, the authors would like to point out that the lack of a comprehensive understanding and comparison of the potential uncertainty in estimates of China’s FFCO₂, including spatial, temporal, proxy, and magnitude components, makes causes Chinese emissions possible data to be more uncertain, and thus, it is important to present, analyze and explain such differences among inventories.

Here, we evaluated the uncertainty in China’s FFCO₂ estimates by synthesizing global gridded emissions datasets (ODIAC, EDGAR, and PKU) and China-specific emission maps (CHRED, MEIC, and the Nanjing University CO₂ (NJU) emission inventory). Moreover, several other inventories were used in the evaluation analysis, such as the Global Carbon Project— and the National Communication on Climate Change of China (NCCC).

The purposes of this study were to: 1) Quantify the magnitude and the uncertainty in China’s FFCO₂ estimates using the spread of values from the state-of-the-art inventories; 2) identify the spatiotemporal differences of China’s FFCO₂ emissions between among the existing emission inventories and explore the underlying reasons for such differences. To our knowledge, this is the first comprehensive evaluation of the most up-to-date and mostly predominantly publicly available carbon emission inventories for China.
2. Emissions data

An evaluation analysis was conducted from 9 inventories including six gridded datasets (listed in Table 1, ODIAC, EDGAR, PKU, CHRED, MEIC, and NJU) and three other datasets (GCP/CDIAC, CEADs, and NCCC) containing statistical data. We selected the year 2012 for spatial analysis since this is the most recent year available for all the gridded data-sets and also because this is when 2012 was a peak year of emissions due to the strong reductions from following the impacts of the 12th-Five-Year-Plan. Specifically, the global fossil fuel CO₂ emissions datasets included the year 2017 version of ODIAC (ODIAC2017), the version 4.3.2 of EDGAR (EDGARv4.3.2) and, PKU-CO₂, all of which all-used the Carbon Monitoring for Action (CARMA) as the point source. The China-specific emissions data used were the dated from the year from 2007 of CHRED, the MEIC v1.3 and, NJU-CO₂ v2017, all of which all-used China Energy Statistical Yearbook (CESY) activity data. Moreover, three inventories were used as a reference, i.e., GCP/CDIAC, CEADs and NCCC, since because GCP and ODIAC used CDIAC for most the majority of the years, except for the most recent two years, that which were extrapolated by using BP data. These three inventories were treated as inventory one-in a time series comparison. Data were collected from the official websites of ODIAC, EDGAR, PKU, and six tabular statistical data sets, and were also acquired from the authors who developed CHRED, MEIC and NJU. See the supporting information for more details on the data sources and the methodology of used for each dataset.

3. Methodology for the evaluation of multiple datasets

We evaluated these the abovementioned datasets from three aspects: data sources, boundary (emission sectors) and methodology (Figure 1, Table 1 and S1, S2). For In regard to the data source, there are two levels: national data, such as UN or IEA statistics, and provincial-level data, such as CESY. The emission sectors mainly include fossil fuel production, industry production and processes, households, transportation, aviation/shipping, agriculture, natural biomass burning from wild fires and the waste for from these datasets, and where Table S1 lists the sectors included in each inventory. And In addition, for methodology, the analysis of the inventories includes the total estimates (activity data and EF) aspect and the spatial disaggregation of point, line and area sources. As Fig. 1 depicted shows depicted the conceptual procedure followed in for the total emissions estimates and how the gridded maps were produced for all the inventories, and thus, it is important to know the differences in the activity data, EF and spatial proxy data and spatial disaggregation methods they used by previous scholars to understand the differences among the inventories in regard to total emissions estimates and spatial characteristics.
Preprocessing. The preprocessing of six gridded CO$_2$ emission datasets included several steps, which are described as follows. First, the global maps of CO$_2$ emissions (i.e., ODIAC, EDGAR and PKU) were re-projected to using the Albers Conical Equal Area projection (that of CHRED). And Next, the nearest neighbor algorithm was used to resample different spatial resolutions into a pixel size of 10 km$\times$10 km, and this method takes the value from the cell closest to the transformed cell as the new value. Second, the national total emissions were derived using the ArcGIS zonal statistics tool from CHRED, while the other emissions were from tabular data provided by the data owners. Finally, the grids for each inventory were sorted in ascending order and then plotted on a logarithmic scale to represent the distribution of emissions. To identify the contribution of high emission grids, emissions at the grid level that exceeded 50 kt CO$_2$ yr$^{-1}$ km$^{-2}$ and the top 5% emitting grids were selected for analysis.
Table 1 General information for the emission data-sets*

<table>
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<tr>
<th>Data</th>
<th>ODIAC2 017</th>
<th>EDGARv432</th>
<th>PKU</th>
<th>CHRED</th>
<th>MEIC</th>
<th>NJU</th>
<th>CEADs</th>
<th>GCP/CDIAC</th>
<th>NCCC</th>
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<td>Global</td>
<td>Global</td>
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<td>China</td>
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<td>China</td>
<td>Global</td>
<td>China</td>
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<td>coverage</td>
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<tr>
<td>Temporal</td>
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<td>Annual</td>
<td>Monthly Biennially or triennially</td>
<td>Monthly</td>
<td>Annual</td>
<td>Annual</td>
<td>Annual</td>
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<tr>
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<tr>
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<td>10 km</td>
<td>0.25 degree</td>
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<td>0.518</td>
<td>0.491</td>
<td>0.518</td>
<td>0.499</td>
<td>0.746</td>
<td>0.491</td>
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<tr>
<td>raw coal</td>
<td>(tC per t of coal)</td>
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<td>±15%</td>
<td>±19% (95% CI)</td>
<td>±8%</td>
<td>±15%</td>
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<td>17.5% (95% CI)</td>
<td>5.40%</td>
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<td>CARMA2.0</td>
<td>FCPSC</td>
<td>CPED</td>
<td>CEC;A</td>
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<td>Transport networks</td>
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<tr>
<td>Area source</td>
<td>Nighttime light</td>
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<td>Population density, land use, human activity</td>
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<tr>
<td>NJU-CO2v2017</td>
<td>CEADs</td>
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* CI: Confidence interval; FCPSC: the First China Pollution Source Census; CPED: China Power Emissions Database; CEC: Commission for Environmental Cooperation; N/A: Not available.

ACC: China Cement Almanac; CCTEN: China Cement Industry Enterprise Indirectory; GDP: Gross domestic product; N/A: Not available.
4. Results

4.1 Total emissions and recent trends

The interannual variations of China’s CO₂ emissions from 2000 to 2016 were evaluated from six gridded emission maps and three national total inventories (Figure 2). All the datasets show a significant increasing trend in the period of 2000 to 2013 from 3.4 to 9.9 Gt CO₂. The range of the nine estimates increased simultaneously from 0.7 to 2.1 Gt CO₂ (both are 21% of the corresponding years’ total emissions). In the second period (from 2013 to 2016), the temporal variations mostly levelled off or even decreased. Specifically, the emissions estimated from PKU and CEADs showed a slight downward trend, even though they used independent activity data of IEA (2014) and National Bureau of Statistics (2016), and this downward trend is attributed to changes in the industrial structure, improved combustion efficiency, emissions control and slowing economic growth (Guan et al., 2018; Zheng et al., 2018a).

There is a large discrepancy among the current estimates, ranging from 8.0 to 10.7 Gt CO₂ in 2012. NJU has the highest emissions during the periods of 2005–2015, followed by EDGAR, MEIC and CDIAC/GCP/ODIAC, while CEADs (National) and PKU were much lower (Figure 2). These discrepancies are mainly because of three reasons: 1) the EF for raw coal was higher for EDGAR and ODIAC than the other databases. The EFs were different for different fossil fuel types and cement production (Table S2). Since coal consumption constituted 70–80% of total emissions, the coal EF was more significant than the others. The EFs were different for the three major fossil fuel types (raw coal, oil and natural gas) and cement production (Table 1 and S2). And, in addition, the EFs were obtained from either the IPCC default values or local optimized values from different sources. They do not change over time in these inventories, although they should, due to the unavailability of EFs over time; 2) differences in activity data, i.e., NJU, MEIC and CEADs (Provincial) used provincial data from CESY (2016), while CEADs (National) and PKU used national data from CESY (2016) and IEA (2014), respectively (Table 1 and S1), and such that the sum of provincial emissions would be higher than the national total; and 3) differences in emission definitions (Table 1 and S1, emissions sectors). Although we tried to make sure that these datasets would be as comparable as possible, there are still unforeseen minor differences in emissions sources (sectors) remained. For example, EDGAR contains abundant industry process-related emissions, while CEADs only considered cement production (Janssens-Maenhout et al., 2019b). EDGAR and MEIC have a similar trend, but except for their magnitudes, whereas MEIC is usually higher than EDGAR. This is a combined effect of the above three reasons. Moreover, MEIC uses the provincial energy data from CESY (2016), while EDGAR used the national-level data from IEA (2014). However, MEIC’s EF is lower than that of EDGAR. These opposing effects would bring them closer in magnitude. The Both the gridded
products (ODIAC, EDGAR, MEIC and NJU) and national inventory (GCP/CDIAC) both show small differences in the magnitude of total emissions estimates and trends from 2000—2007, and where the differences in magnitude increased gradually from 2008 onward. Although the range increased with time, the relative difference remains at around approximately 21% of the corresponding years’ total estimates, indicating potentially systematical differences, such as the fact that EFs remain stable.

![Graph showing CO2 emissions from 2000 to 2016](image)

**Figure 2.** China’s total FFCO$_2$ emissions from 2000 to 2016. The emissions are from the combustion of fossil fuels and cement production from different sources (EDGARv4.3.2_FT2016 includes international aviation and marine bunkers emissions). To keep maintain comparability and avoid differences resulting from the emissions disaggregation—(e.g., Oda et al. 2018(Oda et al., 2018)), the values for all six gridded emission inventories are tabular data provided by the data developers before spatial disaggregation. Prior to 2014, GCP data were taken from CDIAC, and those from 2015-2016 were calculated based on BP data and the fraction of cement production emissions in 2014. The shaded area (error bar for CHRED) indicates uncertainties from the coauthors’ previous studies (See Table 1).

### 4.2 Spatial distribution of FFCO$_2$ emissions

The evaluation of spatially explicit FFCO$_2$ emissions is fundamentally limited by the lack of direct physical measurements on the grid scales (e.g., Oda et al., 2018)). We thus attempted to characterize the spatial patterns of China’s carbon emissions by presenting the available emission estimates. We compared six gridded products, including ODIAC, EDGAR, PKU, CHRED, MEIC and NJU, in for the year 2012. The year 2012 was the most recent year for which all six datasets were available. Spatially, the CO$_2$ emissions from the different datasets are concentrated in eastern China (Figure 3). The high-emission areas were mostly distributed in city clusters (e.g., BeijingTianjin-Hebei...
(Jing-Jin-Ji), the Yangtze River Delta, and the Pearl River Delta) and densely populated areas (e.g., the North China Plain, the Northeast China Plain and Sichuan Basin). These major spatial patterns are primarily due to the use of spatial proxy data and also are in accordance with previous studies (Guan et al., 2018; Shan et al., 2018). However, there were notable differences among the different estimates at finer spatial scales. The large carbon emissions regions were found in the North China Plain and the Northeast China Plain for ODIAC (Figure 3a), PKU (Figure 3c), MEIC (Figure 3e) and NJU (Figure 3f), which ranged from 1000 to 10,000 t CO₂/km². However, the high levels of emissions located in the Sichuan Basin were found from PKU, MEIC and NJU, but not from ODIAC. This discrepancy in identifying the large significant CO₂ emissions was probably due to the emissions from rural settlements with high population densities (e.g., Sichuan Basin), which did not appear strongly in satellite nighttime lights and on the ODIAC map (Wang et al., 2013). The more diffusive distributions of MEIC and NJU were attributed to the abundance of point sources, with or without line sources and area sources proxies. Besides, Moreover, EDGAR, PKU, CHRED, MEIC and NJU all showed relatively low emissions in western China, but the emissions from ODIAC were zero due to the lack of nighttime light therein that region, which tended to distribute more emissions towards strongly nightlights lit (at night) urban regions (Wang et al., 2013).

EDGAR, CHRED and MEIC all showed the traffic line source emissions by inducing traffic networks in the spatial disaggregation. The line emissions (such as expressways, arterial highways) depicted a more detailed spatial distribution in CHRED than in either EDGAR and MEIC. This discrepancy could be attributed to the different road networks and corresponding weighting factors they that were used by each. CHRED disaggregated emissions from the transport sector based on traffic networks and traffic flows (Cai et al., 2018). MEIC applied the traffic network from the China Digital Road-network Map (CDRM) (Zheng et al., 2017), and EDGAR traffic networks were obtained from the OpenStreetMap and OpenRailwayMap (Geofabrik, 2015). ODIAC considered point and area sources and was lacking of line source emissions in the spatial disaggregation, which would places more emissions towards populated areas than in suburbs (Oda et al., 2018). Oda and Maksyutov (2011) (Oda and Maksyutov, 2011) pointed out the possible utility of the street lights to represent line source spatial distributions even without the associated specific traffic spatial data. The spatial distributions of traffic emissions are highly uncertain, with biases of 100% or more (Gately et al., 2015), which is largely due to mismatches between the downscaling proxies and the actual vehicle activity distribution.
Figure 3. Spatial distributions of ODIAC (a), EDGAR (b), PKU (c), CHRED (d), MEIC (e) and NJU (f) at a 10 km resolution for 2012. ODIAC was aggregated from 1 km data, such that MEIC, PKU, and EDGAR were resampled from 0.25, 0.1 and 0.1 degrees.

4.3 CO₂ emissions at the provincial level

The provincial level results showed more consistency than the grid level results in terms of spatial distribution. All the products agreed that the eastern and southern provinces were high emitters (>400 Mt CO₂/yr, Figure 4 and S3), and while the western provinces were low emitters (<200 Mt CO₂/yr, Figure 4 and S3). The top five greatest emitting provinces were Shandong, Jiangsu, Hebei, Henan, and Inner Mongolia, with the amounts of emissions ranging from 577 ± 48 Mt to 820 ± 102 Mt CO₂ in 2012 (Figure 4). While-Meanwhile, the provinces located in the western area with low economic activity and population density showed low carbon emissions (<200 Mt CO₂, Figure 4 and S3). There is a clear discrepancy in the provincial-level emissions among the different estimates, and the mean standard deviation (SD) for the 31 provinces’ emissions was 62 Mt CO₂ (or 20%) in 2012. A large SD (>100 Mt CO₂) occurred in the high-emitting provinces, such as Shandong, Jiangsu, Inner Mongolia, Shanxi, Hebei, and Liaoning. For the Shandong province, the inventories varied from 675-965 Mt CO₂/yr, with a relative SD of 12% (Figure 4 and 5), and for the other high-emitting provinces, the relative SD ranged from 12% to 48%, which implied that there is still room to reduce the uncertainty could be further
Since estimates based on provincial energy statistics are assumed to be more accurate than those derived from the disaggregation of national totals using spatial proxies, we evaluated the provincial emissions of each inventory using the provincial-based inventory mean (CHRED, MEIC, and NJU) (Figure 5). The results showed that emissions derived from the provincial energy statistics are highly correlated, with $R$-values ranging from 0.99 to 1.00 and slopes ranging 0.96 to 1.04. By contrast, the estimates for ODIAC, EDGAR, and PKU, which used IEA national energy statistics, showed an obvious disparity, especially in the top five emitting provinces, suggesting the large impact of spatial disaggregated approaches in allocating total emissions. The potential implication is that when doing spatial disaggregation, national-data-based inventories can use provincial fractions as constraints.

Figure 4. Provincial mean total emissions for ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012. The numbers refer to the green bars are the provincial total CO$_2$ emissions in Mt.
Figure 5. Scatter plots of the provincial total emissions for ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012 with the top-five greatest-most emitting provinces highlighted, and the x-axis is the mean of provincial-data-based products (CHRED, MEIC and NJU).

4.4 Statistics of CO$_2$ emissions at the grid level

To further characterize the spatial pattern of China’s CO$_2$ emissions, the probability density function (PDF), cumulative emissions, and top 5% emitting grids were analyzed to identify the spatial differences from the distribution of grid cell emissions (Figure 6). As illustrated in Figure 4a, ODIAC showed a large significant number of cells with zero emissions (62%) (Figure 6a), with medium-emitting grids (500-50,000 t CO$_2$/km$^2$) constituted 30%, while and high-emitting grids (>50,000 t CO$_2$/km$^2$) constituted 3%. While although the low-emissions cells (1-500 t CO$_2$/km$^2$) were mainly located in EDGAR (58%) and CHRED (69%) (Figure 6b and d), the medium-emitting grids constituted 30-40%, while nonetheless the high-emitting grids constituted only amounted to 2-3%. This situation could have a notable significant impact on the cumulative national total emissions (Figure 6g). The frequency distribution of high-emissions grids revealed the differences in the point source data. MEIC showed the largest number of high-emitting cells (500-500,000 t CO$_2$/km$^2$, 5% compared in comparison with the others, which were at 2-3%, Figure 6e) by using a high-resolution emissions database (CPED) including that included more power plant information (Li et al., 2017; Liu et al., 2015a). Furthermore, ODIAC and EDGAR showed a good agreement agreed well regarding the in high emissions (>100,000 t CO$_2$/km$^2$), because because their point source emissions were both from the CARMA database (Table 1). Moreover,
CARMA is the only global database for tracking CO₂ that gathers and presents the best available estimates of CO₂ emissions for 50,000 power plants around the world, of which approximately 15,000 have latitude and longitude information with emissions larger than 0. The database is responsible for approximately about one-quarter of all greenhouse gas emissions. However, CARMA is no longer active (the last update was November 28, 2012), and the geolocations of power plants are not sufficiently accurate enough, especially in China (Byers et al., 2019; Liu et al., 2013; Wang et al., 2013; Liu et al., 2015a). Therefore, users must perform corrections themselves (Liu et al., 2013; Oda et al., 2018; Wang et al., 2013; Janssens-Maenhout et al., 2019b; Liu et al., 2015a).

As depicted shown by the cumulative emissions plot (Figure 6g), PKU and NJU showed very similar cumulative curves, and the situation was similarly for EDGAR and CHRED. Moreover, the total emissions for EDGAR and CHRED were largely determined by a small proportion of high-emitting grids with a steep increase at the last stage of the cumulative curves (Figure 6g), and the top 5% emitting grids accounted for approximately 90% of the total emissions (Figure 6e), higher than those of other databases like ODIAC, MEIC, NJU and PKU, respectively. The emissions from PKU, MEIC and NJU were relatively evenly distributed. This was due to the fact that CHRED was mainly derived from enterprise-level point sources (Cai et al., 2018). In contrast, the emissions of PKU showed the most evenly distributed, and the emissions from the top 5% emitting grids only accounted for 51% (Figure 6g). This was because PKU had incorporated a special area source survey data for the Chinese rural areas from a 34,489-household energy-mix survey and a 1,670-household fuel-weighing campaign (Tao et al., 2018). Moreover, the use of a spatial disaggregation proxy based on population density also contributed to this spatial pattern. Similarly, MEIC and NJU exhibited a even distribution because of the same activity data from CESY, National Bureau of Statistics (Table 1).
Figure 6. Frequency counts (a-f), cumulative emissions (g) (grids were sorted from low to high), and the top 5% emitting grids plots (h) for ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012 at a 10-km resolution.

To identify the locations of hotspots, the bubble plots (Figure S2) demonstrated the spatial distribution of high-emitting grid cells that were larger than 50 kt CO₂/km². CHRED, EDGAR and ODIAC showed similar patterns, with high-emitting grids concentrated in city clusters (e.g., Jing-Jin-Ji, the Yangtze River Delta, and the Pearl River Delta) and the eastern coast (Figure S2). EDGAR and ODIAC both derived their power plant emissions from CARMA, but ODIAC was likely to put more emissions than EDGAR over urbanized regions with lights, especially in the North China Plain. The emissions of CPED and CARMA were similar in China, with a minor difference of 2%, but although the numbers of power plants had a large difference (2320 vs. 945) (Liu et al., 2015a), which implied that CARMA tended to allocate similar emissions to fewer plants than CPED.

5. Discussion

5.1 Activity data differences in the datasets and their effects

As can be seen in Fig. 1, activity data and EF determine the total emission estimates, and then affect the spatial distributions through disaggregation proxies of point, line and area sources. It has been well-discussed that the
Carbon emissions are calculated from activity data and EFs, and the uncertainty in estimates is typically reported as 5%. The sum of the provincial data is greater than the national total (Guan et al., 2012; Hong et al., 2017; Liu et al., 2015b; Shan et al., 2018; Liu et al., 2013). CEADs (pProvincial) is 8-18% greater than CEADs (nNational) after year 2008 (Figure 2).

Thus, the province-based estimates (e.g., NJU and MEIC) are higher than CEADs (nNational). This difference could be attributed to the differences in national and provincial statistical systems and artificial factors, such as the fact that some of provincial energy balance sheets were adjusted to make to achieve an exact match between supply and consumption (Hong et al., 2017). For example, the provincial statistics have suffered from data inconsistency and double counting problems (Zhang et al., 2007; Guan et al., 2012). One possible way to improve these statistics is to use the provincial consumption fractions to rescale the national total consumption when distributing emissions to grids. Hong et al. (2017) found that the ratio of the maximum discrepancy to the mean value was 16% due to the use of different versions of national and provincial data in CESY. Ranges of 32-47% of CO₂ emissions from the power sector (mainly coal use) were found among the inventories, while for the transport sector (mainly liquid fuels), the fractions ranged from 7-9%. Apart from such differences, one peak of FFCO₂ emissions was identified by most datasets in 2013, which were which was due largely found to be due to the slowing economic growth (National Bureau of Statistics, 1998–2017), changes in the industrial structure (Mi et al., 2017; Guan et al., 2018) and a decline in the share of coal used for energy (Qi et al., 2016).

Estimates with more sectors would usually higher than those with fewer sectors. For In regard to the incorporation of different emissions sectors, EDGAR has includes international aviation and bunkers (Janssens-Maenhout et al., 2017) and NJU has incorporates waste sector (Liu et al., 2013) (Table S1), and thus, both were higher than the others. Moreover, for MEIC v1.3 downloaded from the official website, it included biofuel combustion (which accounted for approximately 5.7% of the total) was included, and; however, the version used here was specially prepared to exclude biofuel to increase the datasets comparability of the database. For another instance, CEADs industry processes only take account of include cement production and was thus lower than those (e.g., NJU and EDGAR) with that include more processes (iron and steel, etc.) (Janssens-Maenhout et al., 2017; Shan et al., 2018; Liu et al., 2013). For The PKU dataset, it used IEA energy statistics with more detailed energy sub-subtypes. The emissions factors were based on more detailed energy sub-subtypes with lower EFs, and while other inventories used the averages of large groups (Table 1), and such that the sum of more detailed sub-subtypes might not equal to the total of large groups due to the incompleteness of the statistics, and these factors could be explain the reasons for its the lower emissions estimate (Wang et al., 2013). A further comparison with IEA, EIA and BP estimates with only energy-related emissions also confirmed that estimates with more sectors would be higher than those with fewer (Figure S1).

5.2 Emission factor eEffects of emission factors on the total emissions

Carbon emissions are calculated from activity data and EFs, and the uncertainty in estimates is typically reported as 5%–
19.5%, while the maximum difference in this study reached 33.8% (or 2.7 PgC) in 2012. One major reason for this difference is the EF used by these inventories (Table 1). The EF for raw coal ranged from 0.491 to 0.746. For example, CEADs used 0.499 tC per ton of coal based on large-sample measurements, while EDGAR used 0.713 from the default values recommended by IPCC (Janssens-Maenhout et al., 2017; Liu et al., 2015b; Shan et al., 2018), and the differences were largely due to the low quality and high ash content of Chinese coal. The variability of lignite and coal quality is quite significant. In Liu et al. (2015), the carbon content of lignite ranged from 11% to 51%, with a mean±SD of 28%±13 (n=61). Furthermore, another study showed that the uncertainty from EFs (-16% to -24%) was much higher than that from activity data (-1 to 9%) (Shan et al., 2018). We recommended substituting the IPCC default coal EF with the CEADs EF. Regarding the plant-level emissions from coal consumptions, the collection of the EFs measured at fields representing the quality and type of various coals is highly needed to calibrate the large point source emissions, and we call for the inclusion of physical measurements for the calibration and validation of existing datasets (Bai et al., 2007; Dai et al., 2012; Kittner et al., 2018; Yao et al., 2019). Different fuel types would contribute differently to emissions factors, i.e., for the same net heating value, natural gas emitted the least amount of carbon dioxide (61.7 kg CO2/TJ energy), followed by oil (65.3 kg CO2/TJ energy) and coal (94.6 kg CO2/TJ energy), and one. Similarly, one successful example for reducing the reduction of air pollutants and CO2 was that the Chinese government initiated the “project of replacement of coal with natural gas and electricity in North China” in 2016 (Zheng et al., 2018a). Moreover, the non-oxidation fraction of 8% used in Liu et al. (2015) (Liu et al., 2015b) for coal was attributable to the differences when comparing with a default non-oxidation fraction of 0%, as recommended by IPCC (2006) in EDGAR (Janssens-Maenhout et al., 2017). Moreover, the qualities of coal vary with time, yet we lacked such time-series quality data on raw coal. Bottom-up inventories typically use time-invariant EFs for CO2 due to the lack of information on coal heating values over time; similarly, and the MEIC model also uses constant EFs of CO2 (Zheng et al., 2018). Teng and Zhu (2015) recommended time-varyed conversion factors from raw coal to standard coal, and as well as to change the raw coal to commodity coal in energy balance statistics since the latter has relatively efficient statistics on EF.

5.3 Spatial distribution of point, line and area sources

5.3.1 Point sources in datasets and their effects on spatial distribution

Point sources emissions account for a large proportion of the total emissions (Hutchins et al., 2017). Power plants consumed about half of the total coal production in the past decade (Liu et al., 2015a). Thus, the accuracy of point sources was extremely important for improving emission estimates. ODIAC, EDGAR; and PKU all distributed power plant emissions from the CARMA dataset. However, the geolocation errors in China are relatively large, and only 45% of power plants were located in the same 0.1°×0.1° grid in CARMA v2.0 as the real power plants located that were identified by eyeballing visual inspection in Google maps (Wang et al., 2013), because. This discrepancy is due to the
CARMA generally treats the city-center latitudes and longitudes as the approximate coordinates of the power plants (Wheeler and Ummel, 2008; Ummel, 2012).

Liu et al. (2015a) found that CARMA neglected about approximately 1300 small power plants in China. Thus, CARMA allocated similar emissions to a more limited number of plants than CPED (Table S2, 720, 1706 and 2320 point sources for ODIAC, EDGAR and MEIC, respectively), and ODIAC had fewer point sources due to the elimination of wrong-incorrect geolocations. The high-emitting grids in CHRED were attributed to the 1.58 million industrial enterprises from the First China Pollution Source Census (FCPSC) that were used as point sources (Wang et al., 2014). Following the CARMA example, we call on the open source of large point sources for datasets and reinforce the importance that Chinese scientists need to adjust the locations of point sources from CARMA.

5.3.2 Effects of spatial disaggregation methods on line and area sources

Downscaling methods are widely used for because of its their uniformity and simplicity because of the due to the lack of detailed spatial data. The disaggregation methods used (e.g., nighttime light, population) by inventories strongly significantly affect the resulting spatial pattern. For example, ODIAC mainly uses nighttime light from satellite images to distribute emissions. Thus, the hotspots concentrated more in strongly in high nighttime light regions. However, using the use of remote sensing data tended to underestimate industrial and transportation emissions (Ghosh et al., 2010). For instance, coal-fired power plants do not emit strong lights and may be far away from cities because transmission lines are used. Electricity generation and use are usually happened to occur in different places locations, and stronger night-time light does not always mean indicate higher CO$_2$ emissions (Cai et al., 2018; Doll et al., 2000). Furthermore, night-time lights would ignore some other main fossil fuel emissions, such as household cooking with coal. The good correlation between night-time light and CO$_2$ emissions is usually on a larger scale basis (national or continental) (Oda et al., 2010; Raupach et al., 2010), while this relationship would fail in populated or industrialized rural areas.

Transport networks are also used in several inventories for spatial disaggregation. EDGAR and CHRED both showed clear transport emissions especially in western China. EDGAR uses three road types and their corresponding weighting factors to disaggregate line source emissions. CHRED used national traffic networks and their flows to distribute traffic emissions (Cai et al., 2018; Cai et al., 2012). It is easier to obtain the traffic networks but rather difficult to get obtain the traffic flows and vehicle kilometers travelled (VKT) data, and thus, the weighting factors method are is much significantly easier to apply. Population is widely used in spatial disaggregation (Andres et al., 2014; Andres et al., 2016; Janssens-Maenhout et al., 2017). The CDIAC emissions maps originally used a static population data to distribute emissions and but have recently have changed to a temporarily varying population proxy, which has largely reduced the uncertainty. However, the unified algorithm for spatial disaggregation such as the population density approach, has encountered difficulties in depicting the uneven development of rural and urban areas, and instead, it usually uses interpolation for a limited number of base years and does not truly vary across years at high spatial resolution (Andres et al., 2014). Furthermore, downscaling approaches may
introduce approximately 50% error per pixel, which are spatially correlated (Rayner et al., 2010), and this problem needs to be considered in future studies.

Moreover, big cities have virtually eliminated the use of coal (Guan et al., 2018; Zheng et al., 2018a), while in rural areas, the use of coal has even–often increased (Meng et al., 2019). For example, a national survey showed that China’s rural residential coal consumption fractions for heating increased from 19.2% to 27.2% (Tao et al., 2018). These transitions have impacts on the spatial distribution of both CO₂ and air pollutants. And in addition, the high-resolution CO₂ emissions have can serve as a potential proxy for fossil fuel emissions (Wang et al., 2013); thus, further improvements on to spatial disaggregation should consider these transitions and the surveyed data.


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

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Supporting Information. Data and methodology descriptions of the nine datasets and supplementary figures on emission estimates
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