Responses to reviewers

Dear Editor and Reviewers,

We thank you for your letter and for the reviewers' constructive comments concerning our manuscript. Those comments are all very valuable and helpful for revising and improving our paper. We have studied your comments carefully and have made corrections accordingly, which we hope to have addressed your concerns. Revised parts are marked in track change mode in the paper. The main corrections in the paper and the responses to the reviewer's comments are as follows.

Anonymous Referee #1

Received and published: 28 April 2020

Reducing uncertainty in China's CO2 emissions and understanding its trends is very relevant of course. The presented attempt of a thorough comparison of nine inventories can be useful but in the current form I find it unconvincing. Some sections are not written clearly and do not present clear findings or conclusions. I find the balance between disusing the CO2 emission sources and strengths and the spatial distribution of CO2 is not right, the latter receives most of the attention while I think it should be the other way around, or in fact the discussion of emission and trends (section 4.1 is only 1 page) should be expanded. I believe, the paper needs a major revision but most of that should be deeper analysis and better characterization/discussion of reasons for differences and what does it mean for the future, ie., how can we do better. Still, I believe this work shall be published and with all the material collected and already evaluated to some extent, the manuscript can be revised successfully. Here are more specific comments that shall help to understand why I made the above statement.

Response: We thank you for understanding the value of this paper. And we revised the MS as you have suggested.

Abstract: Line 31: Bearing in mind uncertainties, using 'about/around' rather than a precise 28% might be more appropriate.

Response: Thank you. Revised accordingly.

Line 37: Suggest adding a unit for the emission factors. Additionally (and this is something more important for the section discussing emission factors), there are some good reasons for variability in CO2 EF for coal as well as change over time (this is something that is not discussed enough in the paper) and so the authors could potentially revisit this statement later after revision.

Response: Thank you. Added unit for coal EF (t C per t of coal). Indeed the EF for coal varied with time due to the changing coal quality, we added this in the discussion (lines 413-417). Averaged coal qualities are varying with time, yet we lacked such time-series quality data on raw coal. Bottom-up inventories typically use time-invariant EFs for CO_2 due to the lack of information on coal heating values over time and the MEIC model also uses constant EFs of CO_2 (Zheng et al., 2018). Teng and Zhu (2015) recommended time varied conversion factors from raw coal to standard coal, and change the raw coal to commodity coal in energy balance statistics since the latter has relatively efficient statistics on EF. Moreover, Liu et al. (2015b) considered the EFs and fractions of imported coal and local productions and thus the weighted value reflected coal quality varying to a certain degree.

Introduction: I recommend a closer look at the whole introduction and consider rewriting it. I find it lack structure and order; it contains lots of information and references but all of it appears to be arranged in a bit chaotic way. A clear separation of discussion of total emissions and trends from spatial distribution would help for example, now these are mixed in different paragraphs (see for example 2nd para).

Also, please check Reference style as in the text references use of 'single names' as authors while many of those are papers with many authors as given in the Reference section. The CO2 emission inventories are uncertain everywhere, highlighting why Chinese are possible more uncertain and why it matters would be important.

Response: Thank you so much for your constructive suggestions. We rearranged it as you suggested. We separated total emissions and spatial disaggregation through rewriting the 2nd and 3rd paragraphs. We arranged the introduction from a general background of China's fossil fuel CO_2 emissions, and then to the total estimates and spatial proxies, followed by the local inventories developed within China using more detailed provincial activity data and local optimized emission factors. Finally as you have suggested, we pointed out the importance of this study: Why Chinese are possible more uncertain and why it is important.

Thank you for the careful review. We checked and corrected the Ref styles, and the original wrong format was caused by incorrect comma used in EndNote.

Line 49-50: suggest adding a reference to IPCC AR5 too

Response: Thank you. We added this reference.

2. Emission data As shown in Table 1, the evaluated inventories are covering various periods but overlap. I'd expect that after reading this section (line 107-113) one would know for which years the evaluation will be performed. In fact, even in the method section (3), this is not evident.

Response: Thank you for this advice. We added it (year 2012) in lines 160-162.

I see that in the SI, there is an extended version of Table 1. I was wondering if adding a row with EFs for cement industry across inventories would be also useful.

Response: Thank you for this suggestion. We added EFs for cement productions.

I think it would be useful to add a short paragraph explaining why it is important to evaluate spatial distribution of CO2 emissions. It is certainly obvious for the authors and many but not for all. Not sure if this is the best place but (could be also in the introduction or method).

Response: Thank you. We added such explanations in the introduction part (lines 73-77). The gridded products provide basic understanding of where emissions come from and provide key inputs for transport and data assimilation models. Furthermore, policy makers can use this information for emissions reductions and environmental monitoring can use it for instruments deployment.

3. Methods I am struggling a little to understand the significance of the Figure 1 as the concept for the evaluation method. The figure does not show anything beyond obvious and sources of data or sectors are listed in further text anyway. In general, I

find this whole section is not written very well or informative yet; in fact, beyond the 2nd para where there is some information about spatial analysis I do not see here much of a concept or method explained. I think, this needs further work and clear statement why and how certain things are done and why priority is given to X or Y. Additionally, some of the assumptions about the considered sectors for comparison could be briefly discussed here as inventories do not have the same sources included [some of that is mentioned in the Discussion section but I believe it should be already brought in here]and for a comparison it would be sensible to assure apples are compared to apples as much as possible.

Response: Thank you for this suggestion. We added more information in lines 146-149. Actually Fig. 1 only depicts the conceptual procedure in total emissions estimates and how gridded maps are produced for all inventories for a broad range of readers, who may be not specialized or familiar with inventories, thus it is important to know the differences in activity data, EF and spatial proxy data and spatial disaggregation methods they used, to further understand the differences among inventories in total emissions estimates and spatial characteristics.

We totally agree with you on this point that assuring apples are compared to apples as much as possible. And we followed this principle to include only the fossil fuel CO_2 (FFCO2) and industry processes associated CO_2 emissions. We excluded not so comparable inventories, such as BP and IEA, which only considered FFCO2.

Line 125: Is “nearest neighbor algorithm’ a standard used name and most will be familiar with it?

Response: Thank you, and we added an explanation on this term.

4. Results I think section 4.1 needs some clearer writing and add discussion as to why the range and uncertainties grow with time. I find the discussion of total (and also sectoral) emissions and trends deserves a lot more space and I find it more important than spatial distribution.

Response: Thank you. We added discussions in lines 193-194 explaining the range and uncertainties grow with time. Although the range increased with time, the relative difference remains at around 21%, indicating the systematical differences such as EFs remains stable. And we added more discussions on EF and emissions sectors in lines 178-187, 335, and 346.

Line 146: ref to point 1); the EFs were the same for all sectors? Are these country averages? Were they changing over time in these or other inventories? I think it might be useful to add this discussion.

Response: Thank you. We added this discussion in lines 178-182. The EFs were different for different fossil fuel types and cement production (Table S2). And they are from either IPCC default values or local optimized values from different sources. They generally do not change over time in these inventories although they should due to the unavailability of EFs over time (Teng and Zhu, 2015;Zheng et al., 2018a).

Line 149: What are "differences in emission definitions"? Do you mean sources? If so, then it might be important to try to bring it to a common denominator and if not possible then say why and what implications it has rather than saying they are different.

Response: Yes, here we mean emission sources or sectors. We agree with you and added in lines 185-187. Although we tried to make these datasets as comparable as possible, there are still minor differences in emission sources (sectors). For example, EDGAR contains abundant industry processes emissions while CEADs only considered cement production.

Line 153: MEIC EF lower than EDGAR? Both average over all sectors for coal, or all fuels? In what units? How did change over time if inventories consider this (I think MEIC does).

Response: Indeed, MEIC used lower EFs from CEADs (Zheng et al., 2018) than EDGAR for coal and cement productions, while for oil and gas the EF are very close (Table S1). For coal, the EF for MEIC is 0.499 tC per t coal, while EDGAR used IPCC default values, for coal it is 0.713 tC per t coal. Bottom-up inventories typically use time-invariant EFs for CO_2 due to the lack of information on coal heating values over time and the MEIC model also uses constant EFs of CO_2 (Zheng et al., 2018).

Line 155: "minor difference" Is this good? Sensible? Or the match seems fine but maybe for wrong reason? As mentioned earlier the whole 4.1 misses actual discussion.

Response: The "minor differences in magnitude" may be misleading, so we changed this into "small differences in magnitude of total emissions estimates". As explained above, the relative difference remains around 21%, indicating the potential systematical differences in EFs, which do not change over time.

Line 184: "could be attributed"; If information is available and assume it is, then maybe one shall be more certain about it and say "is attributed" stating that this was identified as a reason.

Response: We agree with you. We changed it to "is attributed".

Line 188: editorial "ODIAC was lack"

Response: Sorry that we cannot quite understand the comment on Line 188: *editorial "ODIAC was lack"*, and we added more background information in line 228. Here we mean that ODIAC included point sources and area sources and do not have line sources in spatial disaggregation.

Fig3. The scale/ranges selected are a bit odd, changing x10/x2.5/x2/x5/x2 and so it makes interpretation of differences a bit more challenging.

Response: Thank you for the question. We revised the ranges in Fig.3 to x10. In the old versions, we tried several schemes and used those ranges to fully reflect the differences of inventories to avoid potential saturation of colors.

Line 200-2002: Why is this important for cumulative total? I assumed that the spatial distribution comes after emissions are calculated?

Response: Thank you for the question. The spatial distribution indeed comes after total emissions are calculated. Cumulative total is important in understanding the spatial distributions, potential use for assignment of responsibilities in emissions reductions, and also for modeling studies that focus on spatial distributions of carbon dioxide sources and sinks.

Line 206: I believe somewhere in Discussion section there is mention of issues/completeness of CARMA (and a reference to the paper evaluating it) but it would be useful to mention this also here I think

Response: Thank you for this good suggestion. We added completeness and issues of

CARMA in lines 305-311. CARMA is the only global database for tracking CO_2 that gathered and presented the best available estimates of CO_2 emissions for 50,000 power plants around the world, of which around 15, 000 have latitude and longitude information with emissions larger than 0. The database is responsible for 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 accurate enough, especially in China (Byers et al., 2019;Liu et al., 2013;Wang et al., 2013;Liu et al., 2015a). Therefore users have to do corrections themselves (Liu et al., 2013;Oda et al., 2018;Wang et al., 2013;Janssens-Maenhout et al., 2019b;Liu et al., 2015a).

Line 241-244: Isn't it obvious? Anything different would be strange, wouldn't it?

Response: Indeed, you are right, and this is assumed to be so and proved to be. In presenting this, we also want to indicate that when doing spatial disaggregation, national-data-based inventories can use provincial fractions as constraints. Since national inventories do not directly include provincial information, they can use the weights from provincial data based inventories to rescale and redistribute the national total estimates.

Fig 5: Editorial: The numbers are actually not always 'under' so it might be better to say that the numbers simply refer to the green bars

Response: Thank you for the careful review. Revised accordingly.

5. Discussion Suggest to revisit the whole 5.1 to improve clarity. I am struggling to understand several statements here.

Response: Thank you. We added more explanations and discussions around lines 335-347.

Line 256: "Artificial factors" – what is meant here?

Response: Added descriptions in lines 341-342. Here "Artificial factors" means data may be adjusted artificially to meet certain goals. For example, Hong et al. (2017) pointed out that some provinces had zero statistical difference; that is the supply data matches the consumption data exactly, which may indicate that some provincial data were adjusted to achieve the exact match. Moreover, the energy revisions in 2005 and

2010 have adjusted the total national energy use with special attention to the annual coal consumption (Guan et al., 2012), after the second economic census it was found to bring the country closer to achieving its energy conservation targets (Aden, 2010).

Line 257-259: I have difficulty to understand what is suggested here.

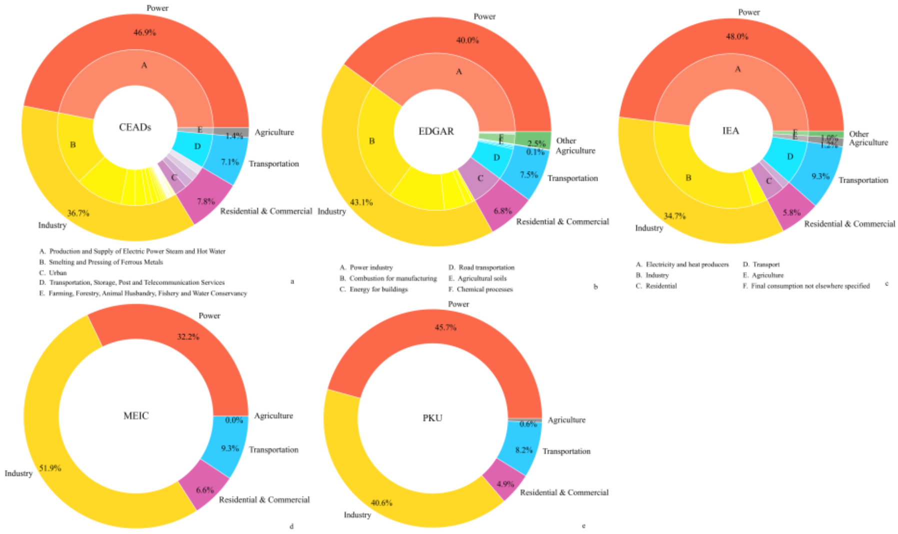
Response: Here we mean that the fractions of provincial emissions in province-data-based inventories can serve as regional constraints in spatial disaggregation of national-data-based inventories. Since national inventories do not directly include provincial activity data information, they can use the weights from provincial data based inventories to rescale and redistribute the national total estimates.

Line 265: First sentence; what does it mean? It hints that possibly the comparison is not really addressing the same sources and that in some inventories some are missing? If so, then I think this should be mentioned much earlier and then statements about which specific sectors are of concern and if the other (common) sectors compare reasonably.

Response: Yes, you are right, and we added explanations in lines 185-187. Although we tried to make the inventories as comparable as possible, some minor sources/sectors are different among inventories (see table S1 emission sectors for detail), and most datasets only provide total estimates or major sectors, and do not provide such detailed sub-sectors data.

Section 5.2 could benefit from additional discussion of: - % of CO2 from coal use vs. cement production vs. liquid fuels (transport, etc) - Differences between coals used in different sectors; where such info exists and how important it could be - Change in EFs (especially for coal) over time owing to potentially declining or improving fuel quality in specific sectors

Response: Thank you for the good suggestions. And we added such discussions in lines 346-347. Such results (see below figure) are already prepared in another sectorial comparison paper.



Fractions of sectoral emissions in inventories.

Section 5.4 – I think the title should really explicitly refer to ‘area sources and line sources’. In fact, I thought that one can have one section 5.3 for “spatial distributon’ and then sub sections on point sources and area sources.

Response: We agree with you on this good idea. We combined 5.3 and 5.4 and make point, line and area sources as sub sections.

Table S1: I find this table very difficult to read. One should consider reformatting and to show included source-sectors in each inventory I’d suggest to make a row for each sector and then ‘tick’ the ones that are covered in specific inventory. It would make reading of the table much easier.

Response: Thank you for this good suggestion, and we revised accordingly.

Anonymous Referee #2

This is a potentially very interesting paper but the current version is poorly organized and inadequately explained. It needs serious reorganization to tell a direct and clear story.

Response: Thank you for your good suggestions, and we reorganized the results from national scale (total estimates in Section 4.1 and spatial distribution in Section 4.2), to provincial scale estimates and correlations, and finally to the finer grid level.

Most of the graphics are quite adequate but need a bit more explanation. Figures4a, 4b, etc need a lot more explanation.

Response: We added more descriptions and explanations in lines 297–300 for Figures 6a, 6b, 6d, 6g.

The problems start early. This is a comparison of 9 datasets but sentence number 3 seems to accept values from one dataset (Le Quere et al.) – but this dataset does not appear to be part of the comparison.

Response: Thank you for this question. Le Quere et al. dataset is named GCP/CDIAC in this comparison because their works in Global Carbon Project (GCP) used CDIAC data set for most years and used BP data to extrapolate the most recent two years. Sentence number 3 is a general background introduction due to its relatively large impact.

Table 1 lists the properties of the datasets to be compared, but there are only 7 in the table.

Response: Thank you for this question. We agree with you to complete Table 1 and added the other two datasets (GCP/CDIAC and NCCC) in Table 1. The original intention was to only include the gridded data that have been further analyzed for spatial characteristics in the latter part.

Sentence number 2 of paragraph 2 jumps abruptly and without explanation from Chinese emissions estimates to global gridded emissions datasets.

Response: Thank you, and we reorganized the introduction as total emissions estimate and spatial disaggregation. And we used transitional words to make the conjunction smoother.

Line 58 introduces the CDIAC dataset, which also turns out to be not part of the comparison.

Response: Thank you for this question. CDIAC is used by GCP and ODIAC, thus in total estimates they were identical for most of years, except for the recent two years that were extrapolated by BP data. And we added descriptions in lines 57-58, 136-137.

In line 100 datasets from EIA, IEA, and BP are introduced, but also apparently not used in the comparison. There is no consistent story line on what is being compared and why, on the fact that comparison will be made at the national, provincial, and grid bases.

Response: These three data sets do not include cement production emissions, and to make the data sets as comparable as possible, we did not include them in the main text. Moreover, we showed them in the supplement (Figure S1) and pointed out this caveat.

Table 1, text line 110, and Figure 2 all seem to say that CHRED exists only for 2007, but it appears elsewhere, for example Figure 4, with data for 2012?

Response: Thank you for the careful review, revised. This is our overlook during data update. CHRED for year 2012 was just available in recent months through cooperation with data developer. The original comparison for CHRED was in 2007 and scaled to 2012 (Originally described in Figure 3 captions, and deleted after data update).

Interesting but ad hoc statements appear throughout the text. Line 102 says that one of the purposes of the study was to identify “spatiotemporal differences” but there is no further mention of temporal differences.

Response: Thank you for this question. We described the temporal differences in Section 4.1 (Figure 1) in lines around 168, 175, and 192.

CARMA enters the discussion in line 109, without definition or citation.

Response: Thank you. We added definition and citation in lines 304-310.

EF enters the discussion in line 88 but if it is defined it is lost in a sea of acronyms.

Response: Thank you, revised.

Biomass burning appears in line 118 but there is no mention, until the closing discussion, on how it is used.

Response: Thank you your question. Actually, only PKU included natural biomass burning from wild fire (Table S1, Emissions sectors), yet this only contributed a very small share close to 0, therefore it does not affect the estimates.

I did not find enough discussion of Figure 1 to make it useful.

Response: Thank you for this remind. We added in lines 146-149 and 334-336. Figure 1 is the summary of methodology for both total estimates and spatial disaggregation, i.e., activity data and EF determine the total emission estimates, and then affect the spatial distributions through disaggregation proxies of point, line and area sources.

IF FCPSC was defined I missed it.

Response: Sorry for the inconvenience. It first appeared in Table 1, and defined at the footnotes. We added it in the main text and also the acronym list.

Line 139 says "both are 21%". But does not say % of what. This problem appears elsewhere in the text as well.

Response: Sorry for the misleading. The range of the 9 estimates increased simultaneously from 0.7 to 2.1 Gt CO_2, both of the ranges are 21% of the corresponding years' total emissions, indicating the relative differences remained the same level.

Also checked the others and revised in lines 111, 169 and 193.

In line 299, "same" as what?

Response: Thank you. Revised in line 393. 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 locations that were identified by eyeballing in google maps (Fig. S1 in Wang t al, (2013))**.

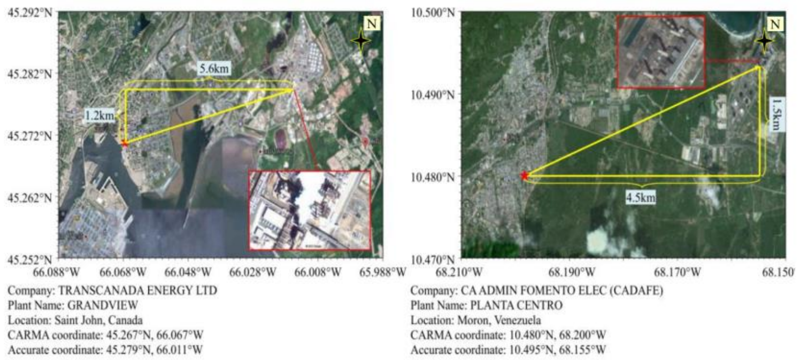


Fig. S1. Position offsets of randomly selected power stations recorded in the CARMA v2.0. The geographic positions of randomly selected 350 power stations (100 stations in China and 250 stations outside of China and U.S.A.) in the CARMA v2.0 list are checked against the presence of facility locations from visual inspection of Google imagery. The red circles are the true locations identified from Google Earth imagery, which are linked by blue lines to the CARMA v2.0 recorded locations. To do so, all stations in CARMA v2.0 were divided into 10 categories of equal sample sizes based on their annual fuel consumptions. For a stratified sampling, 50 stations (20 in China and 30 in other countries except the U.S.A.) were randomly selected from each category. The exact locations of the power stations were checked on Google Earth by searching the names of the stations and inspecting Google Earth images of power plants (chimneys and cooling towers). Roughly, 3 out of 4 stations selected were found in the Google Earth images, and 1 out of 4 stations could not be identified. As a result, 350 power stations with their locations (100 in China and 250 in other countries except the U.S.A.) were found after 476 stations were searched. The size of each circle is proportional to the emission from each power station. Two satellite images with typical views of power stations found on Google Earth are shown (the reported power stations by CARMA v2.0 are shown as red pentagrams).

Text around lines 145 to 155 is so poorly organized that it is hard to follow.

Response: Thank you. We reorganized and improved it by deleting trivial results and adding more explanations. Indeed, it is very challenging to explain all the differences among datasets, yet we provided the two main contributing factors: i.e., differences in EF for coal and systematic biases among national and provincial activity data.

Page 10 is rambling and disconnected. On line 225 do I understand that total emissions from large point sources are approximately the same even though one data set has 2320 points and the other 945? How does this fit in with the 720, 1706, and 2320 in line 303?

Response: Yes. Liu et al., (2015) reported that MEIC's power plant emissions are 2.5 Pg CO_2 from 2320 power plants, while CARMA also estimated it 2.5 Pg CO_2 from 945 plants (See below Fig. 13 from Liu et al., (2015)).

As suggested in lines 308-309, The CARMA dataset does not provide accurate geolocations (latitude and longitude) (Byers et al., 2019) for the Chinese power plants and almost all inventories have corrected the original data and thus have different power plant numbers (Janssens-Maenhout et al., 2019b;Liu et al., 2015a;Liu et al., 2013;Wang et al., 2013). Moreover, EDGAR used CARMA3.0 while ODIAC and PKU used CARMA2.0, new version included more power plants.

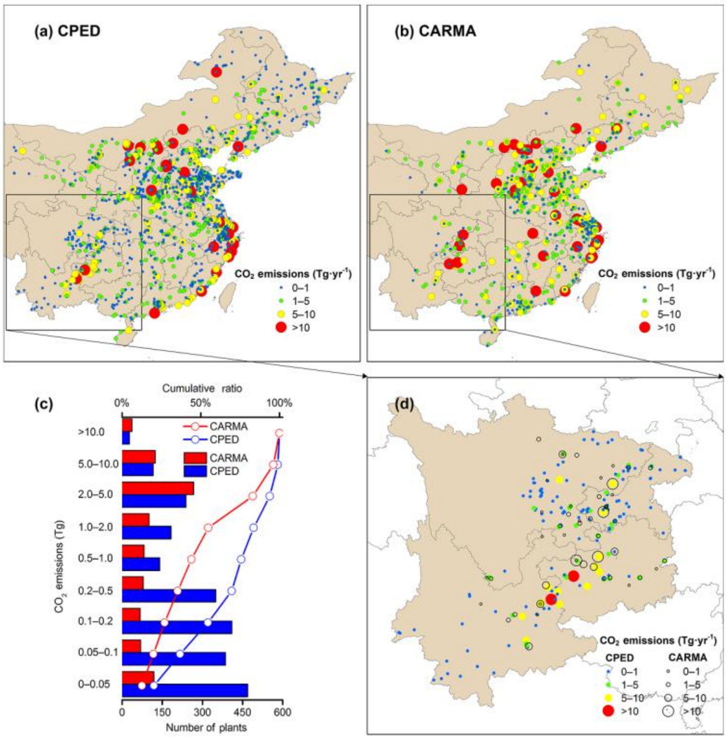


Figure 13. **(a)** Spatial distribution of CO_2 emissions in CPED in 2009. **(b)** Spatial distribution of CO_2 emissions in CARMA in 2009. **(c)** Comparisons of CO_2 emissions between CARMA and CPED by plant numbers in 2009. The plants are sorted according to ascending CO_2 emissions along the *y* axis. The red and blue lines denote the plant number cumulative ratio for CARMA and CPED, respectively. **(d)** Comparisons of the spatial distribution of CO_2 emissions in southwest China between CARMA and CPED in 2009.

I could list many additional problems of organization and flow of the text. There is much here that appears to be interesting. The paper needs a major re-organization and significant increase in explanations of what was done and why and what we learn from it.

Response: Thank you. We re-organized the Introductions, Results and added more contents in discussions. We separated total emissions and spatial disaggregation through rewriting the 2nd and 3rd paragraphs. We arranged the introduction from a general background of China's fossil fuel CO_2 emissions, and then to the total estimates and spatial proxies, followed by the local inventories developed within China using more detailed provincial activity data and local optimized emission factors. Finally we pointed out the importance of this study: Why Chinese are possible more uncertain and why it is important.

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Evaluating China's fossil-fuel CO2 emissions from a comprehensive dataset of nine inventories

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Abstract. China's fossil-fuel CO_2 emissions ($FFCO_2$) account for about 28% of the global total $FFCO_2$ in 2016. An accurate estimate of China's $FFCO_2$ is a prerequisite for global and regional carbon budget analyses and monitoring of carbon emission reduction efforts. However, large uncertainties and discrepancies exist in China's $FFCO_2$ estimations due to lack of detailed traceable emission factors and multiple statistical data sources. Here, we evaluated China's $FFCO_2$ emissions from 9 published global and regional emission datasets. These datasets show that the total emission 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 their estimates were due largely to the different emission factors (EF) (0.491-0.746 t C per t of ~~for~~ coal) and activity data. The large-scale patterns of gridded emissions showed a reasonable agreement with high emissions concentrated in major city clusters, and the standard deviation mostly ranged 10-40% at provincial level. However, patterns beyond the provincial scale vary greatly with the top 5% of grid-level account 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 physical CO_2 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 CO_2 emissions, spatial disaggregation, emission factor, activity data, comprehensive dataset

1 Introduction

Anthropogenic emission of carbon dioxide (CO_2) is one of the major contributions in accelerating global warming (IPCC, 2007). The global CO_2 emissions from fossil fuel combustion and industry processes increased to 36.23 Gt CO_2 yr^{-1} in 2016, with a mean growth rate of 0.62 Gt CO_2 yr^{-1} per year over the last decade (Le Quéré et al., 2018). In 2006, China became the world largest emitter of CO_2 (Jones, 2007). The CO_2 emission from fossil fuel combustion and cement production of China was 9.9 Gt CO_2 in 2016, accounting for about 28% of all global fossil-fuel based CO_2 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 CO_2 emissions by 2030 or earlier and to reduce the CO_2 emission per unit gross domestic product (GDP) by 60-65% below 2005 levels (SCIO, 2015). Thus, an accurate quantification of China's CO_2 emissions is the first step in understanding its carbon budget and making carbon control policy.

Chinese 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 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 CO_2 (PKU-CO_2, 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, provincial data based inventories developed within China all used provincial energy balance sheet in 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, i.e., 1) The Intergovernmental Panel on Climate Change (IPCC) default values that has 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); 4) The China Emission Accounts and Datasets (CEADs) EF that are locally optimized through large sample measurements (Liu et al., 2015b). The existing estimates of global total $FFCO_2$ emissions are comparable in magnitude-, with an uncertainty generally

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within ±10% (Le Quéré et al., 2018;Oda et al., 2018). However, there are great differences at national scale (Marland et al., 2010;Olivier et al., 2014), with the uncertainty ranging from a few percent to more than 50% in estimated emissions for individual countries (Andres et al., 2012;Boden et al., 2016;Oda et al., 2018).

Along with the total emissions estimates, spatial distributions are also important for several reasons: 1) Spatial gridded products provide basic understandings on CO_2 emissions; 2) They are key inputs (as priors) for transport and data assimilation models and influenced the carbon budget (Bao et al., 2020); 3) For high emissions areas recognized by multiple inventories, they can be used for policy making in emissions reductions and can provide useful information for deployment of instruments in emissions monitoring (Han et al., 2020). At the ~~G~~global level, gridded emission datasets are often based on disaggregation of country scale emissions (Janssens-Maenhout et al., 2017;Wang et al., 2013). Thus, the gridded emissions are subjected to errors and uncertainties from the total emission calculation and emission 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 population density as a proxy (Andres et al., 2016;Andres et al., 2011). Further, to improve spatial resolution of emission 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). ~~The Emissions Database for Global Atmospheric Research~~ (EDGAR) derived emissions from the energy balance statistics of the International Energy Agency (IEA), and 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 0.1~~°~~×0.1~~° degree~~ were 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_2 emissions was developed at Peking University ~~(PKU-CO_2, hereafter named as PKU)~~ (Wang et al., 2013). ~~The existing estimates of global total $FFCO_2$ emissions are comparable in magnitude, with an uncertainty generally within ±10%. However, there are great differences at national scale, with the uncertainty ranging from a few percent to more than 50% in estimated emissions for individual countries.~~.

In order to accurately calculate emissions, a series of efforts have been conducted to quantitatively evaluate China's CO_2 emissions using national or provincial activity data, local EF, and detailed data set 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 Mutli-resolution Emission Inventory for China (MEIC) was developed by Qiang et al. (2007), Lei et al.

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(2011) and Liu et al. (2015a) at Tsinghua University through integrating 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). MEIC used China Power Emissions Database (CPED), and 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 sources, a high-resolution mapping approach is adopted to constrain the vehicle emissions using county-level activity database. ~~The China Emission Accounts and Datasets (~~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 national and provincial scales. CEADs used coal EF~~s~~ from the large-sample measurements (602 coal samples and samples from 4,243 coal mines). And this is assumed to be more accurate than the IPCC default EFs.

Regardless of these efforts, however, the amount of China's CO_2 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 made efforts of quantifying the possible uncertainty in China's $FFCO_2$, such as differences from 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 $FFCO_2$, including spatial, temporal, proxy, and magnitude components, makes Chinese emissions possible more uncertain, and thus it is important to present, analyze and explain such differences among inventories ~~as one of the root causes of the uncertainty~~.

Here we evaluated the uncertainty in China's $FFCO_2$ estimates by synthesizing global gridded emissions datasets (ODIAC, EDGAR, and PKU) and China-specific emission maps (CHRED, MEIC, and the Nanjing University CO_2 (NJU) emission inventory). Moreover, several other inventories were used in the evaluation analysis, such as the Global Carbon Budget from the Global Carbon Project~~ (GCP)~~, the National Communication on Climate Change of China (NCCC)~~, the U.S. Energy Information Administration (EIA), IEA and BP~~.

The purposes of this study were to: 1) quantify the magnitude and the uncertainty in China's $FFCO_2$ estimates using the spread of values from the state-of-the-art inventories; 2) identify the spatiotemporal differences of China's $FFCO_2$ emissions between 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 publicly available carbon emission inventories for China.

2. Emissions data

The evaluation analysis was conducted from 6 gridded datasets (listed in Table 1) and 3 other statistical data. We selected year 2012 for spatial analysis since this is the most recent year available for all gridded data sets and also this is a peak year of emissions due to the strong reductions from impacts of the 12th-Five-Year-Plan. Specifically, the global fossil fuel CO_2 emission datasets included the year 2017 version of ODIAC (ODIAC2017), the version v4.3.2 of EDGAR (EDGARv4.3.2), PKU-CO_2, which all used the Carbon Monitoring for Action (CARMA) as point source. The China-specific emission data used were the year 2007 of CHRED, the MEIC v1.3, NJU-CO_2 v2017, which all used China Energy Statistical Yearbook (CESY) activity data. Moreover, 3 inventories were used as a reference, i.e., GCP/CDIAC, CEADs and NCCC, since GCP and ODIAC used CDIAC for most of the years, except for the recent two years that were extrapolated by BP data, these three were treated as one in time series comparison. Data were collected from official websites for ODIAC, EDGAR, PKU and 6 tabular statistic data, and were acquired from their authors for CHRED, MEIC and NJU. See supporting information for more details on data sources and methodology of each dataset.

3. Methodology for evaluation of multiple datasets

We evaluated these datasets from three aspects: data sources, boundary (emission sectors) and methodology (Figure 1, Table 1 and S1, S2). For 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 fire and waste for these datasets, and Table S1 listed sectors included in each inventory. And for methodology, ~~it~~ analysis of inventories includes total estimates (activity data and EF) aspect and spatial disaggregation of point, line and area sources. As Fig. 1 depicted the conceptual procedure in total emissions estimates and how gridded maps are produced for all inventories, it is important to know the differences in activity data, EF and spatial proxy data and spatial disaggregation methods they used, to understand the differences among inventories in total emissions estimates and spatial characteristics.

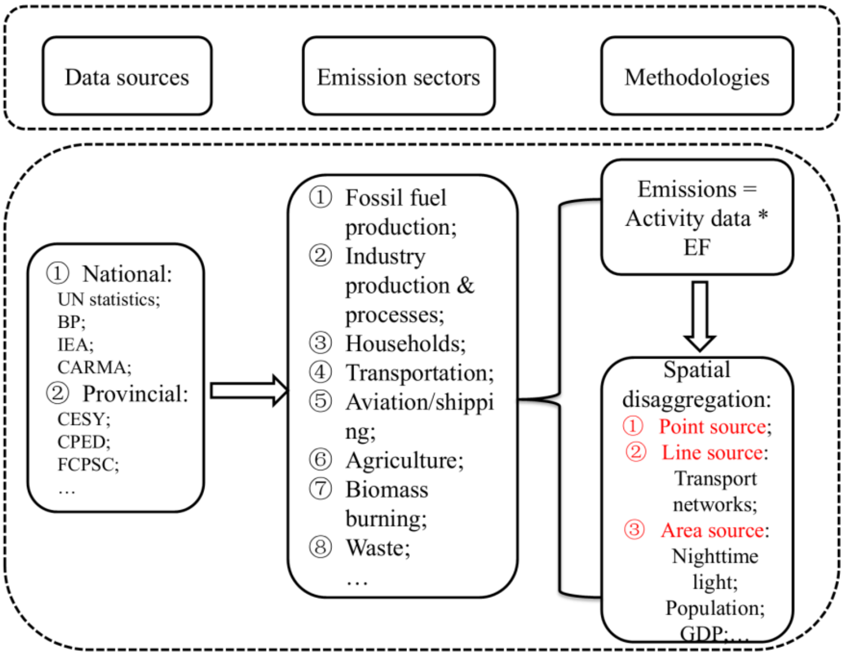

Figure 1 Conceptual diagram for data evaluation based on data sources, emission sectors and methodologies.

Preprocessing of six gridded CO_2 emission datasets included several steps that are described as follows. First, The global map of CO_2 emissions (i.e. ODIAC, EDGAR and PKU) were re-projected to Albers Conical Equal Area projection (that of CHRED). And the nearest neighbor algorithm was used to resample different spatial resolution into a pixel size of 10 km by 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 ArcGIS zonal statistics tool for CHRED while the others were from tabular data provided by 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 grid level that exceeded 50 kt CO_2 yr^{-1} km^{-2} and the top 5% emitting grids were selected for analysis.

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Table 1 General information for emission data sets*

Data	ODIAC2017	EDGARv432	PKU	CHRED	MEIC	NJU	CEADs	GCP/CDIAC	NCCC
Domain	Global	Global	Global	China	China	China	China	Global	China
Temporal coverage	2000-2016	1970-2012	1960-2014	2007, 2012	2000-2016	2000-2015	1997-2015	1959-2018	2005, 2012, 2014
Temporal resolution	Monthly	Annual	Monthly	Biennially or triennially	Monthly	Annual	Annual	Annual	Annual
Spatial resolution	1 km	0.1 degree	0.1 degree	10 km	0.25 degree	0.25 degree	N/A	N/A	N/A
Emission estimates	Global & National	Global & National	Global & National	National & Provincial	National & Provincial	National & Provincial	National & Provincial	Global & National	National
Emission factor for raw coal (tC per t of coal)	0.746	0.713	0.518	0.518	0.491	0.518	0.499	0.746	0.491
Uncertainty	17.5% (95% CI)	±15%	±19% (95% CI)	±8%	±15%	7-10% (90% CI)	-15% - 25% (95% CI)	17.5% (95% CI)	5.40%
Point	CARMA	CARMA3.0	CARMA2.0	FCPSC	CPED	CEC;A	N/A	N/A	N/A

source	2.0					CC;CC TEN			
Line source	N/A	the OpenStreetMap and OpenRailwayMap, Int. aviation and bunker	N/A	The national road, railway, navigation network, and traffic flows	Transport networks	N/A	N/A	N/A	N/A
Area source	Nighttime light	Population density, nighttime light	Vegetation and population density, nighttime light	Population density, land use, human activity	Population density, land use	Population density, GDP	N/A	N/A	N/A
Version name	ODIAC2017	EDGARv4.3.2_FT2016, EDGARv4.3.2	PKU-CO2-v2	CHRED	MEIC v.1.3	NJU-CO_2v2017	CEADs	N/A	N/A
Year published/ updated	2018	2017	2016	2017	2018	2017	2017	2019	2018

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Data sources	http://db.cger.nies.go.jp/dataset/ODIAC/	http://edgar.jrc.ec.europa.eu/overview.php?v=432_GHG&SECURE=123	http://inventory.pku.edu.cn/download/download.html	Data developer	Data developer	Data developer	http://www.ceads.net/ (registration requred)	https://www.globalcarbonproject.org/carbonbudget/19/data.htm	https://unfccc.int/sites/default/files/resource/China 2BUR_English.pdf
References	Oda (2018)	Janssens-Maenhout (2017)	Wang et al., 2013	Cai et al. (2018); Wang et al. (2014)	Zheng (2018); Liu et al. (2015)	Liu (2013)	Shan et al. (2018)	Friedlingstein et al. (2019)	NCCC (2018)

~~Data~~	~~ODIAC2017~~	~~EDGARv432~~	~~PKU~~	~~CHRED~~	~~MEIC~~	~~NJU~~	~~CEADs~~
~~Domain~~	~~Global~~	~~Global~~	~~Global~~	~~China~~	~~China~~	~~China~~	~~China~~
~~Temporal coverage~~	~~2000-2016~~	~~1970-2012~~	~~1960-2014~~	~~2007~~	~~2000-2016~~	~~2000-2015~~	~~1997-2015~~
~~Temporal resolution~~	~~Monthly~~	~~Annual~~	~~Monthly~~	~~Biennially or triennially~~	~~Monthly~~	~~Annual~~	~~Annual~~
~~Spatial resolution~~	~~1 km~~	~~0.1 degree~~	~~0.1 degree~~	~~10 km~~	~~0.25 degree~~	~~0.25 degree~~	~~N/A~~
~~Emission estimates~~	~~Global & National~~	~~Global & National~~	~~Global & National~~	~~National & Provincial~~	~~National & Provincial~~	~~National & Provincial~~	~~National & Provincial~~

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~~Emission factor for raw coal (tC per t of coal)~~	~~0.746~~	~~0.713~~	~~0.518~~	~~0.518~~	~~0.491~~	~~0.518~~	~~0.499~~
~~Uncertainty~~	~~17.5% (95% CI)~~	~~±15%~~	~~±19% (95% CI)~~	~~±8%~~	~~±15%~~	~~7-10% (90% CI)~~	~~15% - 25% (95% CI)~~
~~Point source~~	~~CARMA2.0~~	~~CARMA3.0~~	~~CARMA2.0~~	~~FCPSC~~	~~CPED~~	~~CEC;ACC;CCTEN~~	~~N/A~~
~~Line source~~	~~N/A~~	~~the OpenStreetMap and OpenRailwayMap, Int. aviation and bunker~~	~~N/A~~	~~The national road, railway, navigation network, and traffic flows~~	~~Transport networks~~	~~N/A~~	~~N/A~~

~~Area source~~	~~Nighttime light~~	~~Population density, nighttime light~~	~~Vegetation and population density, nighttime light~~	~~Population density, land use, human activity~~	~~Population density, land use~~	~~Population density, GDP~~	~~N/A~~
~~Version name~~	~~ODIAC2017~~	~~EDGARv4.3.2_FT2016, EDGARv4.3.2~~	~~PKU-CO2-v2~~	~~CHRED~~	~~MEIC v.1.3~~	~~NJU-CO$_2$v2017~~	~~CEADs~~
~~Year published/updated~~	~~2018~~	~~2017~~	~~2016~~	~~2017~~	~~2018~~	~~2017~~	~~2017~~
~~Data sources~~	~~http://db.cger.nies.go.jp/dataset/ODIAC/~~	~~http://edgar.jrc.ec.europa.eu/overview.php?v=432_GHG&SECURE=123~~	~~http://inventory.pku.edu.cn/download/download.html~~	~~Data developer~~	~~Data developer~~	~~Data developer~~	~~http://www.ceads.net/ (registration requred)~~
~~References~~	~~Oda et al. (2018)~~	~~Janssens-Maenhout et al. (2017)~~	~~Wang et al., 2013~~	~~Cai et al. (2018); Wang et al. (2014)~~	~~Zheng et al. (2018a); Liu et al. (2015b)~~	~~Liu et al. (2013)~~	~~Shan et al. (2018)~~

* CI: Confidence interval; FCPSC: the First China Pollution Source Census; CPED: China Power Emissions Database; CEC: Commission for Environmental Cooperation; 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 CO_2 emissions from 2000 to 2016 were evaluated from 6 gridded emission maps and 3 national total inventories (Figure 2). All datasets show a significant increasing trend in the period of 2000 to 2013 from 3.4 to 9.9 Gt CO_2. The range of the 9 estimates increased simultaneously from 0.7 to 2.1 Gt CO_2 (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 although they used independent activity data of IEA (2014) and Statistics (2016), and this downward trend is attributed to changes in 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 CO_2 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). This is mainly because of three reasons: 1) the EF for raw coal was higher for EDGAR and ODIAC than the others. The EFs were different for different fossil fuel types and cement production (Table S2). Since coal consumption consisted 70-80% of total emissions, coal EF is more significant than the others. The EFs were different for three major fossil fuel types (raw coal, oil and natural gas) and cement production (Table 1 and S2). And they are from either 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, NJU, MEIC and CEADs (Provincial) used provincial data from CESY (2016), while CEADs (National), PKU used national data from CESY (2016) and IEA (2014), respectively (Table 1 and S1), and sum of provincial emissions would be higher than the national total; 3) differences in emission definitions (Table 1 and S1, emissions sectors). Although we tried to make these datasets as comparable as possible, there are still minor differences in emission sources (sectors). For example, EDGAR contains abundant industry processes emissions while CEADs only considered cement production (Janssens-Maenhout et al., 2019b). EDGAR and MEIC have a similar trend, but for magnitude, MEIC is usually higher than EDGAR. This is a combined effect of the above three reasons. MEIC used provincial energy data CESY (2016) while EDGAR used national level IEA (2014). But MEIC's EF is lower than EDGAR. These opposing effects would bring them closer in magnitude. ~~CEADs (National) showed the lowest estimates from 2000—2007 and PKU afterwards.~~ The gridded products (ODIAC, EDGAR, MEIC and NJU) and national inventory (GCP/CDIAC) both show ~~minor~~ small differences in magnitude of total emissions estimates and trend from 2000—2007, and the differences in magnitude increased gradually from 2008 onward. Although the range

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increased with time, the relative difference remains at around 21% of the corresponding years' total estimates, indicating potential systematical differences such as that EFs remain stable.

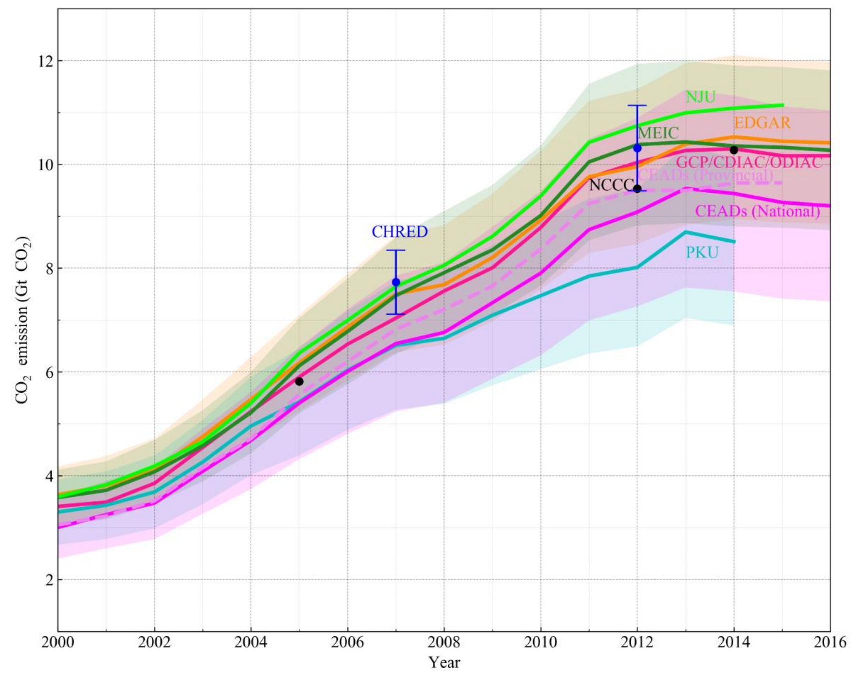
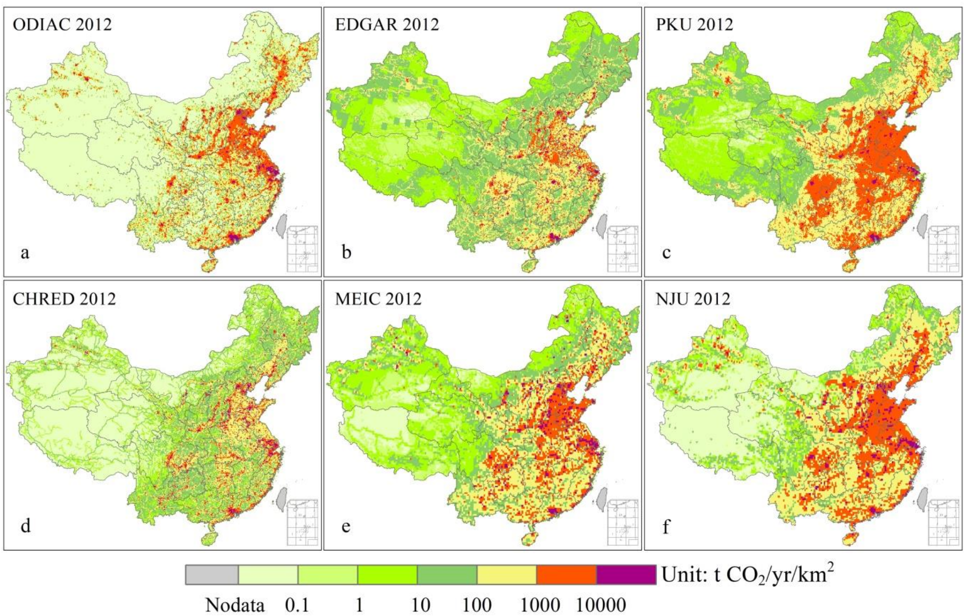


Figure 2. China's total $FFCO_2$ emissions from 2000 to 2016. The emissions are from combustion of fossil fuels and cement production from different sources (EDGARv4.3.2_FT2016 includes international aviation and marine bunkers emissions). To keep comparability and avoid differences resulted from the emissions disaggregation (e.g. Oda et al. 2018(Oda et al., 2018)). The values for 6 gridded emission inventories are tabular data provided by data developers before spatial disaggregation. Prior to 2014, GCP data was taken from CDIAC and 2015-2016 was calculated based on BP data and fraction of cement production emissions in 2014. Shading area (error bar for CHRED) indicates uncertainties from 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 grid scales (e.g. (Oda et al., 2018)). We thus attempted to characterize the spatial patterns of China's carbon emissions by presenting emission estimates available. We compared 6 gridded products including ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012. The year 2012 was the most recent year for which all the six datasets were available. Spatially, CO_2 emissions from different datasets are concentrated in eastern China (Figure 3). 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 in accordance with previous studies (Guan et al., 2018;Shan et al., 2018). However, there were notable differences among different estimates at finer spatial scales. The large carbon emission 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 ~~5000~~ 10, 000 t CO_2/km^2. However, the high emissions located in the Sichuan Basin were found from PKU, MEIC and NJU, but not from ODIAC. This discrepancy in identifying the large CO_2 emissions was probably due to the emissions from rural settlements with high population densities (e.g. Sichuan Basin), did not appear strongly in satellite nighttime lights and ODIAC map (Wang et al., 2013). The more diffusive distribution for MEIC and NJU ~~could be~~is attributed to the point sources abundance, with or without line sources and area sources proxies. Besides, EDGAR, PKU, CHRED, MEIC and NJU all showed relatively low emissions in western China, but the emission from ODIAC was zero due to no nighttime light there, which tended to distribute more emissions towards strong nightlights urban regions (Wang et al., 2013).

EDGAR, CHRED and MEIC all showed the traffic line source emissions by inducing traffic networks in spatial disaggregation. The line emissions (such as expressway, arterial highway) depicted a more detailed spatial distribution in CHRED than EDGAR and MEIC. This discrepancy could be attributed to the different road networks and corresponding weighting factors they used. 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 lack of line source emissions in spatial disaggregation, which would put more emissions towards populated areas than 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 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 due largely to mismatches between downscaling proxies and the actual vehicle activity distribution.


ODIAC 2012
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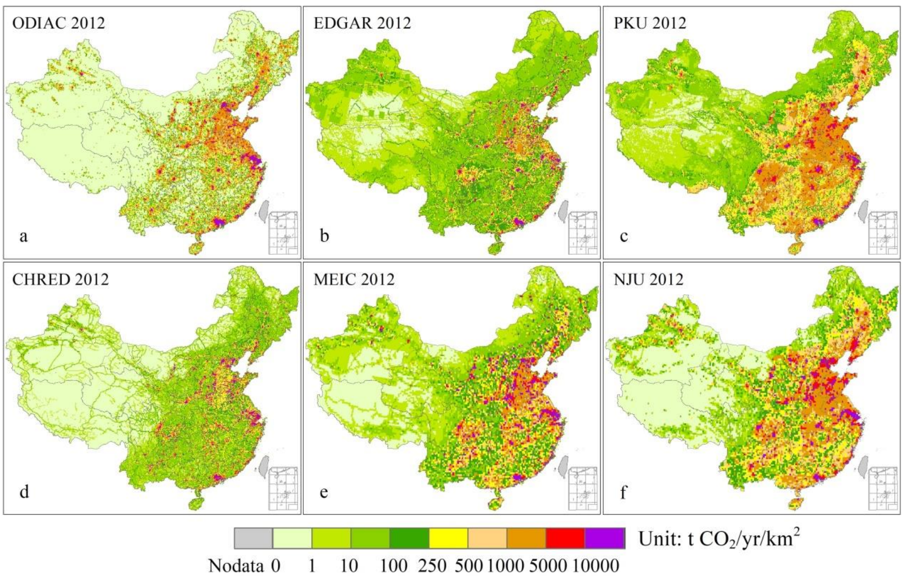


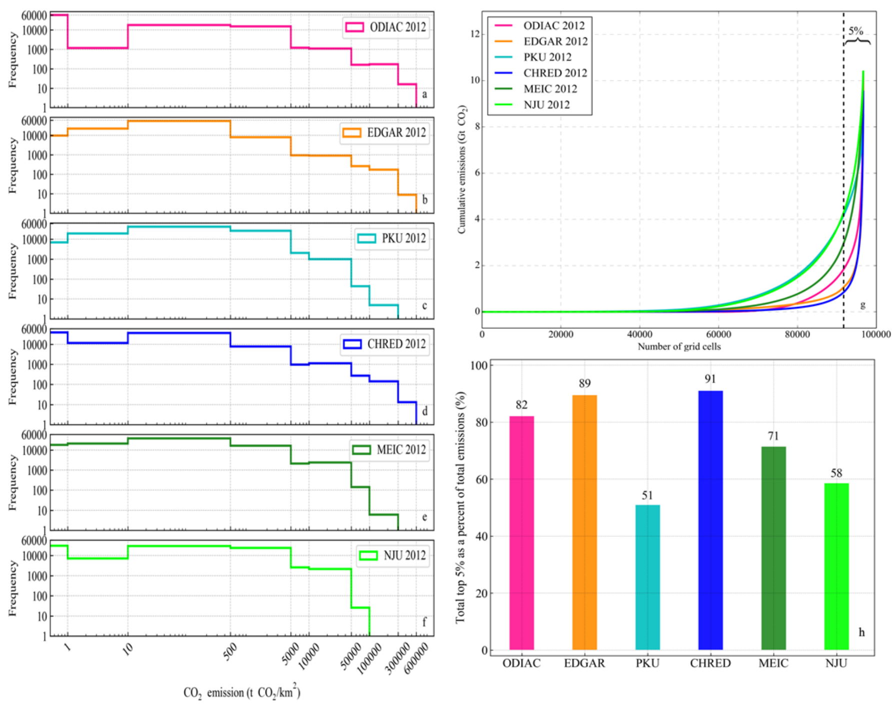
Figure 3. Spatial distributions of ODIAC (a), EDGAR (b), PKU (c), CHRED (d), MEIC (e) and NJU (f) at 10 km resolution for 2012. ODIAC was aggregated from 1 km data, MEIC, PKU, and EDGAR was resampled from 0.25, 0.1 and 0.1 degree~~, CHRED was scaled from 2007 data using 2012 total emission~~.

~~4.3 Statistics of CO_2 emissions at 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 4). As illustrated in Figure 4a, ODIAC showed a large number of cells with zero emissions (62%) (Figure 4a). While low emissions cells (1 ~ 500 t CO_2/km^2) were mainly located in EDGAR and CHRED (Figure 4b and d). This could have a notable impact on cumulative national total emissions. The frequency distribution of high emission grids revealed the different point source data. MEIC showed the largest number of high-emitting cells (500~500000 t CO_2/km^2, 5% compared with others 2-3%, Figure 4c) by using a high-resolution emission database (CPED) including more power plant information (Li, 2017;Liu, 2015). Furthermore, ODIAC and EDGAR showed a good agreement in high emissions (> 100000 t CO_2/km^2), because their point source emissions were both from CARMA database (Table 1).(Byers et al., 2019;Liu, 2013;Wang, 2013;Liu, 2015)(Liu, 2013;Oda, 2018;Wang, 2013;Janssens-Maenhout et al., 2019;Liu, 2015)~~

~~As depicted by the cumulative emissions plot (Figure 4g), PKU and NJU showed very similar cumulative curves, and so did 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 cumulative curves (Figure 4g), and the top 5%~~

~~emitting grids accounted for ~90% of the total emissions (Figure 4e), higher than those of 82%, 71%, 58% and 51% in ODIAC, MEIC, NJU and PKU, respectively. The emissions from PKU, MEIC and NJU were relatively evenly distributed. This could be due to CHRED was mainly derived from enterprise-level point sources (Cai et al., 2018). In contrast, the emissions of PKU showed the most even pattern, and the emissions from top 5% emitting grids only accounted for 51% (Figure 4g). This was because PKU had 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). Similarly, MEIC and NJU exhibited a even distribution because of the same activity data from CESY, National Bureau of Statistics (Table 1).~~



~~**Figure 4.** Frequency counts (a-f), cumulative emissions (g) (grids were sorted from low to high), and top 5% emitting grids plots (h) for ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012 at 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 CO_2/km^2. CHRED, EDGAR and ODIAC showed a similar pattern, 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 the 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 the numbers of power plants had a large difference (2320~~

~~vs. 945) (Liu, 2015). This implied that CARMA tended to allocate similar emissions to fewer plants than CPED.~~

4.~~4~~ 3 CO_2 emissions at provincial level

The provincial level results showed more consistency than the grid level in spatial distribution. All products agree that eastern and southern provinces are high emitters (>400 Mt CO_2/yr, Figure ~~5~~ 4 and S3), and western provinces were low emitters (<200 Mt CO_2/yr, Figure ~~5~~ 4 and S3). The top 5 emitting provinces were Shandong, Jiangsu, Hebei, Henan, and Inner Mongolia with the amount ranging from 577 ± 48 Mt to 820 ± 102 Mt CO_2 in 2012 (Figure ~~5~~4). While provinces located in western area with low economic activity and population density showed low carbon emissions (<200 Mt CO2, Figure ~~5~~ 4 and S3). There is a clear discrepancy in provincial-level emissions among different estimates, and the mean standard deviation (SD) for 31 provinces' emissions was 62 Mt CO_2 (or 20%) in 2012. A large SD (>100 Mt CO2) occurs in high emitting provinces, such as Shandong, Jiangsu, Inner Mongolia, Shanxi, Hebei, and Liaoning. For Shandong province, the inventories vary from 675-965 Mt CO_2/yr, with a relative SD of 12% (Figure ~~5~~ 4 and ~~6~~5), and for other high emitting provinces the relative SD ranged 12% - 48%. This implied that there is still room to reduce uncertainty.

Since estimates based on provincial energy statistics are assumed to be more accurate than those derived from disaggregation of national total using spatial proxies, we evaluated the provincial emissions of each inventory using the provincial-based inventory mean (CHRED, MEIC, and NJU) (Figure ~~6~~5). The results showed that emissions derived from the provincial energy statistics are highly correlated, with R ranging from 0.99 to 1.00 and slope 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 5 emitting provinces, suggesting the large impact of spatial disaggregated approaches in allocating total emissions. The potential implication is when doing spatial disaggregation, national-data-based inventories can use provincial fractions as constraints.

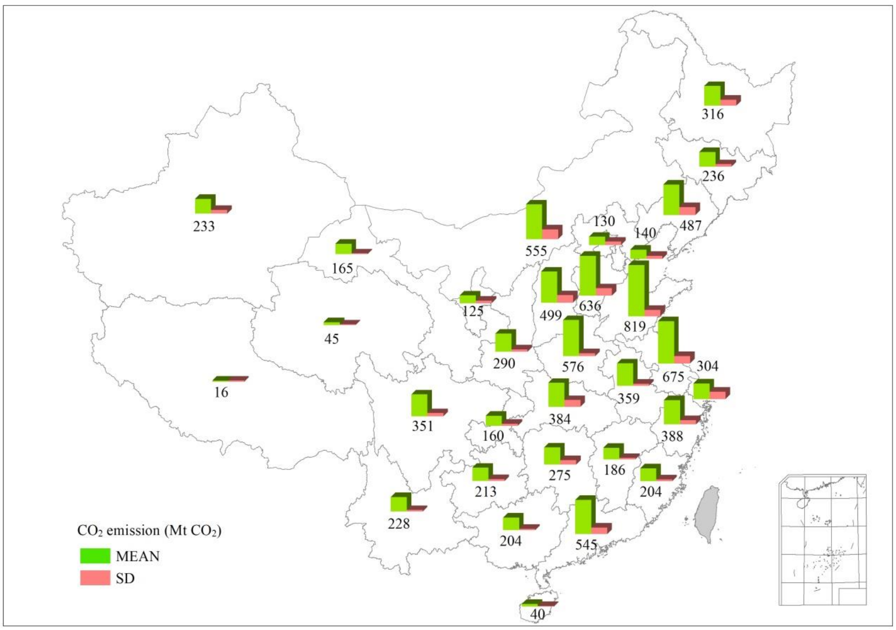


Figure ~~5~~4. Provincial mean total emissions for ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012. Numbers ~~under~~ refer to the green bar are provincial total CO_2 emissions in Mt.

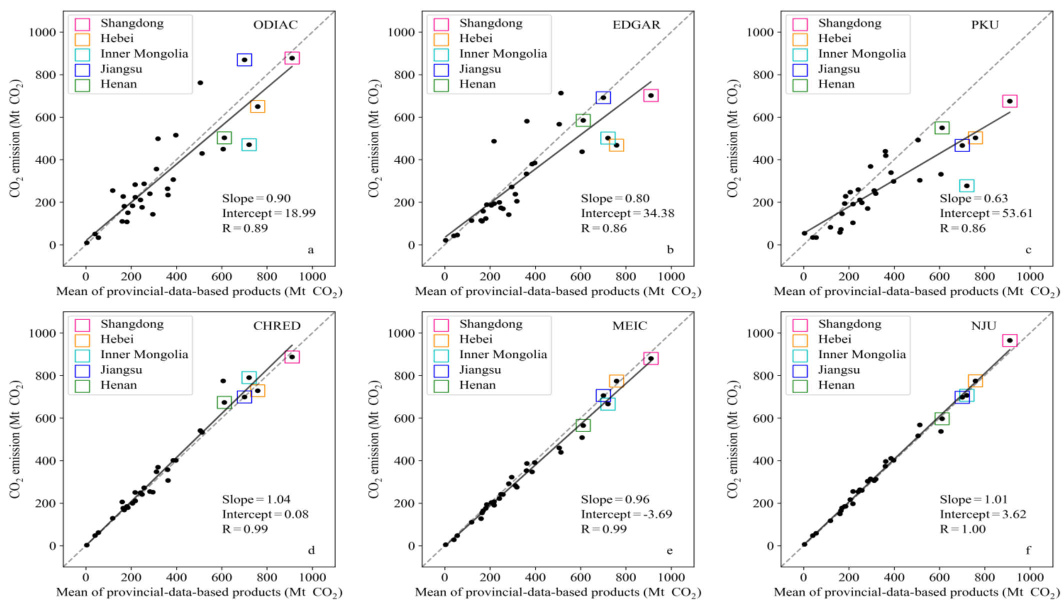


Figure ~~6~~5. Scatter plots of provincial total emissions for ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012 with top 5 provinces highlighted, and the x axis is the mean of provincial-data-based products (CHRED, MEIC and NJU).

4.4 Statistics of CO_2 emissions at 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 number of cells with zero emissions (62%) (Figure 6a), medium emitting grids (500-50000 t CO_2/km^2) consisted 30%, while high emitting grids (>50000 t CO_2/km^2) consisted 3%. While low emissions cells (1 ~ 500 t CO_2/km^2) were mainly located in EDGAR (58%) and CHRED (69%) (Figure 6b and d), and medium emitting grids consisted 30-40%, while high emitting grids consisted 2-3%. This could have a notable impact on cumulative national total emissions (Figure 6g). The frequency distribution of high emission grids revealed the different point source data. MEIC showed the largest number of high-emitting cells (500~500000 t CO_2/km^2, 5% compared with others 2-3%, Figure 6e) by using a high-resolution emission database (CPED) including more power plant information (Li et al., 2017;Liu et al., 2015a). Furthermore, ODIAC and EDGAR showed a good agreement in high emissions (> 100000 t CO_2/km^2), because their point source emissions were both from CARMA database (Table 1). Moreover, CARMA is the only global database for tracking CO_2 that gathered and presented the best available estimates of CO_2 emissions for 50,000 power plants around the world, of which around 15, 000 have latitude and longitude information with emissions larger than 0.

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The database is responsible for 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 accurate enough, especially in China (Byers et al., 2019;Liu et al., 2013;Wang et al., 2013;Liu et al., 2015a). Therefore users have to do 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 by the cumulative emissions plot (Figure 6g), PKU and NJU showed very similar cumulative curves, and so did 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 cumulative curves (Figure 6g), and the top 5% emitting grids accounted for ~90% of the total emissions (Figure 6e), higher than those of 82%, 71%, 58% and 51% in ODIAC, MEIC, NJU and PKU, respectively. The emissions from PKU, MEIC and NJU were relatively evenly distributed. This was due to CHRED was mainly derived from enterprise-level point sources (Cai et al., 2018). In contrast, the emissions of PKU showed the most even pattern, and the emissions from top 5% emitting grids only accounted for 51% (Figure 6g). This was because PKU had 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 spatial disaggregation proxy using 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).

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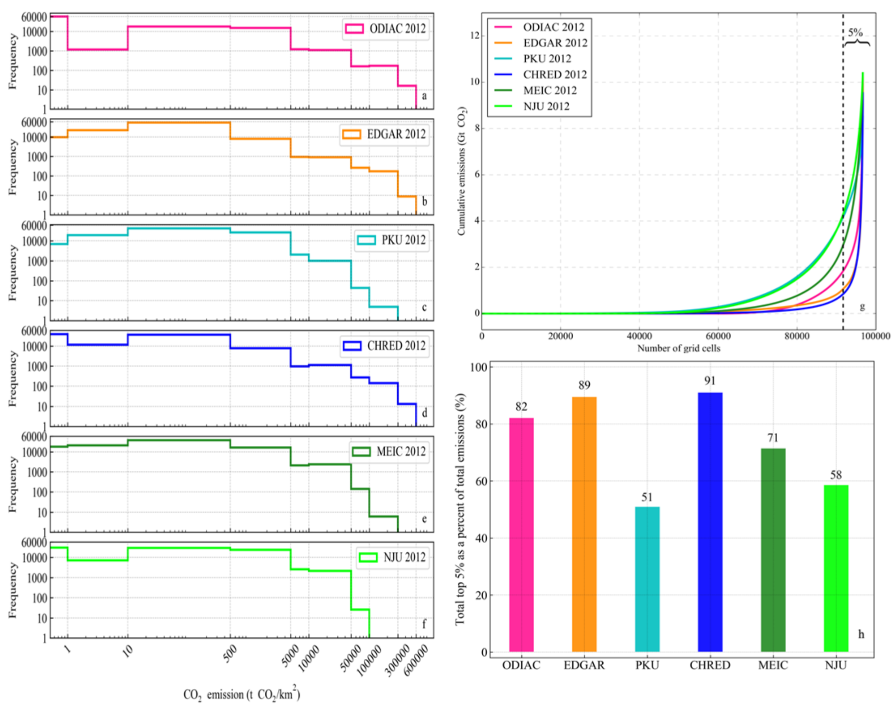

Figure 6. Frequency counts (a-f), cumulative emissions (g) (grids were sorted from low to high), and top 5% emitting grids plots (h) for ODIAC, EDGAR, PKU, CHRED, MEIC and NJU in 2012 at 10 km resolution.

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 CO_2/km^2. CHRED, EDGAR and ODIAC showed a similar pattern, 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 the 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 the numbers of power plants had a large difference (2320 vs. 945) (Liu et al., 2015a). This implied that CARMA tended to allocate similar emissions to fewer plants than CPED.

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5. Discussion

5.1 Activity data differences in datasets and their effects

Activity data source, data level and sectors determined the total emissions largely. 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 sum of provincial data is larger 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 (Provincial) is 8-18% higher than CEADs (National) after year 2008 (Figure 2). And thus province-based estimates (e.g. NJU and MEIC) are higher than CEADs (National). This could be attributed to the differences in national and provincial statistical systems and artificial factors, such as that some of provincial energy balance sheets were adjusted to make to achieve the exact match between supply and consumption (Hong et al., 2017). For example, the provincial statistics has data inconsistency and double counting problems (Qiang et al., 2007;Guan et al., 2012). One possible way to improve this is to use the provincial consumption fractions to rescale the national total consumptions 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 different versions of national and provincial data in CESY. Ranges of 32-47% of CO_2 emissions from power sector (mainly coal use) were found among inventories, while for transport sector (mainly liquid fuels) the fractions ranged from 7-9%. Apart from such differences, one peak of FFCO2 emissions was identified by most dataset in 2013, which was due largely to the slowing economic growth (NBS, 1998–2017), changes in 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), and strategies for reducing emissions could be based on such uniformed trends, while making reduction policies for provinces needs the support of provincial-energy-based datasets instead of national-energy-based ones. Estimates with more sectors would usually be higher than those with fewer. For different emission sectors, EDGAR has international aviation and bunkers (Janssens-Maenhout et al., 2017) and NJU has wastes sector(Liu et al., 2013) (Table S1), and thus were higher than others. Moreover, for MEICv.1.3 downloaded from official website, it included biofuel combustion (which accounted for ~5.7% of the total), and the version used here was specially prepared to exclude biofuel to increase comparability. For another instance, CEADs industry processes only take account of cement production and was thus lower than those (e.g., NJU and EDGAR) with more processes (iron and steel, etc.) (Janssens-Maenhout et al., 2017;Shan et al., 2018;Liu et al., 2013). For PKU dataset, it used IEA energy statistics with more detailed energy sub-types. The emission factors was based on more detailed energy sub-types with lower EFs, and other inventories used average of large groups (Table 1) and sum of more detailed sub-types might not equal to the total of large groups due to incomplete of the statistics, and these could be reasons for its lower estimate (Wang et al., 2013). A further comparison with IEA, EIA and BP estimates with only energy related emissions also confirm that estimates with more sectors would be higher than those with fewer (Figure S1).

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5.2 Emission factor effects on total emissions

Carbon emissions are calculated from activity data and EF, and the uncertainty in estimates is typically reported as 5% - 10%, 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 are due largely to the low quality and high ash content of Chinese coal. The variability of lignite and coal quality is quite large. In Liu et al., (2015) the carbon content of lignite ranged from 11% to 51% with mean±SD of 28%±13 (n=61). Furthermore, another study showed that the uncertainty from EF (-16 – 24%) was much higher than that from activity data (-1 – 9%) (Shan et al., 2018). We recommended substituting IPCC default coal EF with the CEADs EF. Regarding the plant-level emissions from coal consumptions, the collection of their EFs measured at fields representing the quality and type of various coals are highly needed to calibrate the large point source emissions, and we call for inclusion of physical measurements for 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 emission factors, i.e., for the same net heating value, natural gas emitted lowest 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 successful example for reducing air pollutants and CO_2 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 comparing with a default non-oxidation fraction of 0% recommended by IPCC (2006) in EDGAR (Janssens-Maenhout et al., 2017). Moreover, averaged coal qualities are varying with time, yet we lacked such time-series quality data on raw coal. Bottom-up inventories typically use time-invariant EFs for CO_2 due to the lack of information on coal heating values over time and the MEIC model also uses constant EFs of CO_2 (Zheng et al., 2018). Teng and Zhu (2015) recommended time varied conversion factors from raw coal to standard coal, and change the raw coal to commodity coal in energy balance statistics since the latter has relatively efficient statistics on EF.

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5.3 Spatial distribution of point, line and area sources

5.3.1 Point sources in datasets and the effects on spatial distribution

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Point sources emissions account for a large proportion of 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 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 locations that were identified by eyeballing in google maps (Wang et al., 2013), because CARMA generally treats the city-center latitudes and longitudes as the approximate coordinates of the power plants (Wheeler and Ummel, 2008).

Liu et al. (2015a) found that CARMA neglected about 1300 small power plants in China. Thus CARMA allocated similar emissions to a 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 elimination of wrong geolocations. The high-emitting grids in CHRED were attributed to the 1.58 million industrial enterprises from the First China Pollution Source Census (FCPSC) 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 Chinese scientists need to adjust the locations of point sources from CARMA.

5.3.24 Effects of spatial disaggregation methods on ~~spatial distribution~~line and area sources

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Downscaling methods are widely used for its uniformity and simplicity because of the lack of detailed spatial data. Disaggregation methods used (e.g. nighttime light, population) by inventories strongly affect the spatial pattern. For example, ODIAC mainly use nighttime light from satellite to distribute emissions. Thus the hotspots concentrated more in strong nighttime light regions. However, using 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 by transmission lines. Electricity generation and use are usually happened at different places, and stronger night-time light does not always mean 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 used three road types and 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 the traffic flows and vehicle kilometers travelled (VKT) data, and thus the weighting factors method are much 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 emission maps originally used a static population data to distribute emissions and recently have changed to a temporally varying population proxy, which largely reduced the uncertainty. However, the unified algorithm for spatial disaggregation such as population density approach has difficulties in depicting the uneven development of rural and urban areas, and it usually use interpolation for limited 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 virtually eliminated use of coal (Guan et al., 2018;Zheng et al., 2018a), while in rural areas use of coal even 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 has impacts on spatial distribution of both CO_2 and air pollutants. And the high resolution CO_2 emissions have a potential proxy for fossil fuel emissions (Wang et al., 2013), thus further improvements on spatial disaggregation should consider these transitions and the surveyed data.

Data availability. The data sets of ODIAC, EDGAR, PKU and CEADs are freely available from http://db.cger.nies.go.jp/dataset/ODIAC/, http://edgar.jrc.ec.europa.eu/overview.php?v=432_GHG&SECURE=123,

http://inventory.pku.edu.cn/download/download.html and http://www.ceads.net/ respectively. And CHRED, MEIC and NJU are available from data developers upon request.

Author contributions. PFH and NZ conceived and designed the study. PFH and XHL collected and analyzed the data sets. PFH, XHL, NZ and TO led the paper writing with contributions from all coauthors.

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

Acknowledgments. This work was supported by National Key R&D Program of China (No. 2017YFB0504000). We thank Dr. Bofeng Cai from Chinese Academy for Environmental Planning for kindly providing CHRED data and his suggestions for improving the manuscript.

Supporting Information. Data and methodology descriptions on the 9 datasets and supplementary figures on emission estimates

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