

Anonymous Referee #1

The authors try to understand the uncertainties in China's energy statistics and estimate their impacts on China's emissions during the period of 1990-2013 using MEIC. The uncertainty of energy consumption statistics in China were appointed out in the previous many studies. This work is highly motivated and the authors try to understand the uncertainties of national statistics from China inside. Particularly, the discussion in the section '4.1 Understanding the reliability of energy statistics' is important. And also the authors analysis the uncertainties of emission inventory for air pollutants in China caused by those of energy statistics. In my knowledge, this is a first work. Additionally, the manuscript indicates the variations at energy consumption could be an important source of energy-induced emission uncertainties in China. The topic certainly is suitable for ACP.

Response: We thank Referee #1 for the encouraging comments. We address the comments as below.

The authors define the apparent uncertainty as the maximum discrepancy among different datasets of energy consumption. My question is that this definition is appropriate. For example, the converging in 2013 may be caused by any artificial modification because the trajectories in two datasets during 2010-2013 are quite different. This converging indicates small uncertainty? I think the "uncertainty" is unsuitable term and should be replaced to another term, such as "discrepancy in statistics" or other. In conclusion, the reviewer is recommending the minor revision of the manuscript.

Response: We agree with the referee that the terminology of "apparent uncertainty" may make some confusion. In the introduction section of the revised manuscript, in order to avoid confusion, we have clarified the meaning of "apparent uncertainty" defined in this study as compared to the meaning of "actual uncertainty". Apparent uncertainty is a straightforward metric used to quantitatively gauge the apparent discrepancies between different existing datasets. Apparent uncertainty ratio is a metric to quantify the relative deviation. Thus apparent uncertainty could partly reflect actual uncertainty. In general, large apparent uncertainty reflects large discrepancies, which might indicate large actual uncertainty. However, it should be noted that apparent uncertainty could not fully represent actual uncertainty, and apparent uncertainty would likely to be conservative estimates as it might be subjected to the datasets used. Thus small apparent uncertainty does not necessarily mean to small actual uncertainty. For example, the small apparent uncertainties before 1996 might become larger if a new energy dataset that revises the data of this period is included. The converging apparent uncertainties in 2013 may be caused by the third economic census. We have clarified this in the Section 3.2 of the revised manuscript.

Anonymous Referee #2

I have read the paper "Variations of China's emission estimates response to uncertainties in energy statistics" by Hong et al. This is a well structured study that addresses an important issue. The paper will be a solid addition to the literature. The paper should have a bit more background material along with some additional methodological details, as discussed below.

Response: We thank Referee #2 for the constructive comments. We address the comments as below.

The sectoral resolution of the different datasets should be briefly discussed. First, is the sectoral resolution similar across all the datasets? I assume these data all distinguish between key sectors that have quite different emission factors - if so this should be stated? (e.g. iron and steel, vs boilers in industry; agricultural machinery vs road vehicles, etc.). If the sectoral resolution of the different datasets is not the same, then how this was treated in the data processing needs to be discussed (at least for sectors that are a significant portion of total emissions of one of the targeted species).

Response: The sectoral categories are consistent across all the energy datasets from NBS. In the supplement of the revised manuscript, we provide the sector information of the NBS energy statistics. The same scale factor in fuel consumption was applied for all the sub-categories in same major sector (e.g. industrial coal-fired boilers and kilns in industry sector; on-road diesel vehicles and off-road mobile sources in transportation sector). We have clarified this in the Section 2.2 of the revised manuscript.

More details on the processing of the energy data are needed. All the text says now is "five emission inventories based on different sets of energy statistics (i.e., CT-CESYOri, CT-CESY-1C, CT-CESY-2C, CT-CESY-3C and PBP-CESY) were established.". In general, energy data sets do not contain all the information needed for an inventory, so additional assumptions (such as technology splits over time and technology retirements) would likely need to be made. Some assumptions likely had to be applied at some point, and these need to be described. Basically, the process of going from the energy datasets to the data needed in MEIC needs to be described. Then how this methodology might impact the results should be discussed. (If there are differences in the sectoral resolution of the different datasets, this could be an additional source of uncertainty, for example.)

Response: The emissions in MEIC were estimated as a product of the activity rate (such as energy consumption or material production), the technology distributions of fuel/production and emission control, the unabated emission factor, and the removal efficiency. Thus, the emission estimates can be simplified as the activity rates multiplied by their respective net emission factors of different fuel/product types in different sectors. Note that the net emission factors in MEIC change dynamically driven by the technology renewal process year by year. Technology distributions within each sector are obtained from Chinese statistics, a wide range of unpublished statistics by various industrial association and technology reports. For example, technology distributions in the power sector were obtained based on unit-base database (Liu et al., 2015). Technology distributions in the transportation sector were estimated based on fleet model (Zheng et al., 2014). The methods on emission estimates has been documented in our previous work (Zhang et al., 2007; Zhang et al., 2009; Zheng et al., 2014; Liu et al., 2015). We have described this in Section 2.2 of the revised manuscript.

Also, where fuel consumption differs between the datasets, how was this mapped to the technology

detail in the inventory? For example, were the same emission factors applied for fuel consumption in a given sector in each year (even though different fuel consumption data would imply different rates of new purchases and/or retirements). Greater growth in coal consumption in one dataset as compared to another would tend to imply a greater amount of new equipment, which could have different emission factors as compared to older equipment. Note also that these assumptions would likely add additional uncertainty.

Response: For different energy datasets, the same net emission factors were applied for fuel consumption in a given sector in each year during the emission calculations. MEIC already simulates the dynamic changes in net emission factors driven by the technology renewal process year by year. In fact, energy differences might change the technology renewal process, and further change the net emission factors. However, considering that those assumptions would likely add additional uncertainty and we do not discuss the uncertainties in emission factors, such indirect impacts on emission factors are not included in this study. We have clarified this in the Section 2.2 of the revised manuscript.

My understanding is the MEIC has province level detail. Were these calculations performed with province-specific emission factors, or national average emission factors. If the former, how were differences in national data allocated to provinces?

Response: As the emission calculations were performed with province-level data, energy consumption in the national energy statistics were directly allocated to provinces by using the ratios derived from the provincial energy statistics. We have clarified this in the Section 2.2 of the revised manuscript.

It would be useful to see a bit of a discussion of how these apparent uncertainties might extend back further in time. One point in particular, it should be noted that the narrowing of the uncertainty toward 1995 is due, in part, due to fewer different datasets. Can it be presumed that the methodologies for data collection did not evolve as much during this earlier period as compared to the latter statistical surveys (in which methodologies apparently became more consistent between provincial and national statistics)?

Response: In the Section 3.2 of the revised manuscript, we have added a paragraph to discuss how these apparent uncertainties extend in time. It should be noted that the apparent uncertainties calculated in this study are subjected to the energy datasets used. For example, the small apparent uncertainties before 1996 might become larger if a new energy dataset that revises the data of this period is included. Apparent uncertainties during the recent period of rapid growth (2004-2012) are higher than the early period (1996-2003), implying that the discrepancies might be accumulated and expanded for a period of rapid growth. For example, underestimates of the growth trends of small enterprises might result into accumulated underestimations. Note that the energy consumption apparently became more consistent between provincial and national statistics after the three economic censuses, indicating that the new energy statistics after the economic census may include evolved methodologies for data collection and more cross-checks to reduce the discrepancies. In this case, conducting censuses in some interval years could help to reduce the accumulated discrepancies. The apparent uncertainty ratio in years economic censuses newly conducted (i.e., 2004, 2008 and 2013) is generally less than that of previous years (i.e., 2003, 2007 and 2012), as shown in Figure 4. The converging uncertainties in 2013 may also be caused by the third economic census.

For this reason, I like the author's choice of terminology of "apparent uncertainty", but this possible

bias in the results – e.g., actual uncertainty earlier in the series shown is likely be underestimated due to lack of multiple datasets – should be more explicitly discussed in the paper.

Response: In the introduction section of the revised manuscript, in order to avoid confusion, we have clarified the meaning of "apparent uncertainty" defined in this study as compared to the meaning of "actual uncertainty". Apparent uncertainty is a straightforward metric used to quantitatively gauge the apparent discrepancies between different existing datasets. Apparent uncertainty ratio is a metric to quantify the relative deviation. Thus apparent uncertainty could partly reflect actual uncertainty. In general, large apparent uncertainty reflects large discrepancies, which might indicate large actual uncertainty. However, it should be noted that apparent uncertainty could not fully represent actual uncertainty, and apparent uncertainty would likely to be conservative estimates as it might be subjected to the datasets used. Thus small apparent uncertainty does not necessarily mean to small actual uncertainty. For example, the small apparent uncertainties before 1996 might become larger if a new energy dataset that revises the data of this period is included. We have clarified this in the Section 3.2 of the revised manuscript.

It would be useful if the authors could discuss a bit more possible reasons why the provincial and national statistics agree during earlier time periods. Was this because both of these statistics contained similar biases? Or were there some potential sources of bias that increased over this time period. The authors have substantial experience with these datasets and their insights (although likely no firm answers!) into these issues, and a more complete discussion would greatly strength and add to the value of this paper.

Response: Apparent uncertainties during the recent period of rapid growth (2004-2012) are higher than the early period (1996-2003), implying that the discrepancies might be accumulated and expanded for a period of rapid growth. For example, underestimates of the growth trends of small enterprises might result into accumulated underestimations. In this case, conducting censuses in some interval years could help to reduce the accumulated discrepancies. We have discussed this in the Section 3.2 of the revised manuscript.

SPECIFIC COMMENTS

In Table 1" is described as "The energy statistics for China used in this work." and IEA data are included in this table. However, the text states that "The IEA energy statistics were excluded from the emission calculations because they are based on NBS's national Energy Balance Sheets". Please clarify (I believe it is useful to have IEA data in Table 1, since it gives context for this widely used dataset, but perhaps add a footnote that these data are not used in the current work, or re-title the table.)

Response: We have changed the title of Table 1 as "The energy statistics for China involved in this work.", and add a footnote that the IEA energy statistics were used for comparison, but they were excluded from the uncertainty calculations in the current work. The IEA energy statistics are generally based on NBS's national Energy Balance Sheets, and currently quite consistent with CT-CESY-2C. They may soon be updated based on CT-CESY-3C. We have also changed the description in Section 2 accordingly.

Page 6, line 31 "contributions (approximately 70%) from industrial process emissions". It would be useful to clarify by adding (I assume this is the case) "contributions (approximately 70%) from industrial process emissions. Note that non-combustion emission uncertainty was not addressed in this

study."

Response: We have clarified this by adding "Note that non-combustion emission uncertainty was not addressed in this study." in the Section 3.2 of the revised manuscript.

This brings up an additional point. Were all fuel consumption differences assumed to be applied to combustion sectors? Or was some portion of these differences assumed to be feedstocks? This should be clarified in the paper.

Response: We only applied all the fuel consumption differences to the combustion sectors. In fact, differences in energy consumption would imply differences in feedstocks and products. However, the possible uncertainties in feedstocks and products resulted from energy uncertainties are not included in this study for some reasons. First, energy statistics and industrial products statistics in China are independent statistics. Inconsistencies may be existed between the energy data and the production data, and some studies used them for cross-checks (Guan et al., 2012; Korsbakken et al., 2016). Also, feedstocks and products usually have more detailed categories than energy sectors (e.g., iron and steel vs. industry sector). Thus, estimates of feedstocks and products based on energy data would introduce additional uncertainties. Without considering the possible uncertainties in feedstocks and products, our estimates of emission uncertainties are likely on the conservative side. We have clarified this in Section 2.2 of the revised manuscript.

Page 7, line 7 "The contributions of gas and other fuels are negligible because their emissions are relatively small." This is not necessarily true for biomass (which often contributes substantially to CO emissions in particular). I assume that uncertainty in biomass consumption was not included in this study? If uncertainty in biomass consumption was not considered this would be useful to state here (and also needs to be mentioned earlier in the methodology section).

Response: In the original manuscript, biomass emissions were put into "process emissions". In the revised manuscript, to make it be more straightforward, biomass emissions were moved to "other fuels", which also changed Figure 3 and Table 2. The contributions of gas and other fuels are negligible because uncertainties in biomass consumption are not included in this study and other emissions are relatively small. Note that biomass consumption, which is usually thought to be quite uncertain, would contribute more uncertainties in emissions. We have clarified this in the Section 2.2 and the Section 3.2 of the revised manuscript.

Page 8, line 23 "Third, although there is no ample evidence of such activity" ample is not quite the correct word to use here (is ambiguous). Depending on what the authors mean, a clearer words should be used.

Response: In order to avoid confusion, we have removed the sentence "although there is no ample evidence of such activity," in the revised manuscript.

Page 11, line 11 "Top-down estimates of the CO₂-to-NO_x emission ratios". Give the reader a short definition of how top-down differs from bottom up. Presumably this is observationally based?

Response: We have clarified this by adding "using satellite observations" in the revised manuscript.

Page 11, line 14. "The MEIC inventory reports a larger CO₂ trend in China (10.4% yr⁻¹) " it looks like this is not larger, it is well within the uncertainty of the top-down estimate.

Response: We have changed the word "larger" to "similar" in the revised manuscript.

page 11, conclusion section Re-define "apparent uncertainty" here so that the conclusion is more easily understood on its own.

Response: To re-define "apparent uncertainty" in the conclusion section of the revised manuscript, we have added the term "maximum discrepancy" after "apparent uncertainty", and the term "the ratio of the maximum discrepancy to the mean value" after "apparent uncertainty ratios".

Figure 5 is a bit difficult to interpret due to the many different parings of inventories. The authors might want to experiment to see if a consistent set of differences (e.g. showing the difference between each dataset vs one dataset that spans all years (if available) would communicate the points they wish to make, so that there is a consistent reference over the entire period). This might be more straightforward for the readers to interpret.

Response: We have combined different parings of the national statistics into one figure, and removed some figures. In the revised manuscript, Figure 5(a) compares different national statistics, showing that the coal consumption data from the national energy statistics were revised upward after the three censuses because of increasing coal production; Figure 5(b) shows that inconsistencies in interprovincial transport manifest as interprovincial net imports, resulting in a higher coal supply in the provincial energy statistics, implying that either coal production is underestimated or coal consumption is overestimated.

Anonymous Referee #3

Overall Quality

Although this paper seeks to address an important topic and is well written, it lacks sufficient scientific merit for publication. It repeats the general strategy of an earlier paper by one of the co-authors (Guan et al. 2012) that sought to repackage the existence of large inconsistencies between different official Chinese datasets concerning energy as an analytical research finding. Those inconsistencies are important to understanding China's air pollution and greenhouse gas emissions, but their existence is not newly recognized (Sinton 2001; Akimoto et al. 2006) and, more importantly, processing them with pre-packaged emission estimation protocols does not yield findings that should be considered publishable original research.

Response: We thank Referee #3 for the constructive comments. Emission inventories over China are thought to be quite uncertain due to incomplete knowledge of activity rates and emission factors. For a long period, the emission inventory community assumed that the uncertainties in energy statistics are small and attributed the main sources of uncertainties to emission factors (Streets et al., 2003; Lu et al., 2011; Zhao et al., 2011; Kurokawa et al., 2013). For example, Zhao et al. (2011) assumed normal distributions with CV of 10% for energy consumption in the industry sector. Large differences among different statistics (Sinton 2001) and their impacts on emission estimates for CO₂ (Guan et al., 2012) and NO_x (Akimoto et al., 2006) have been identified by previous studies, however, the impacts on the emission estimates of different air pollutants covering a long-term period were not well recognized from previous studies.

In this work, we evaluate the impacts on major air pollutants (i.e., SO₂, NO_x, VOC and PM_{2.5}) and include the recent energy statistics covering a full period (1990-2013). We found that the uncertainties induced by energy statistics are much higher than the assumptions in previous studies. For example, we identified that using different statistics could introduce as high as 30% differences in SO₂ emission estimates over China, which is larger than the previously estimated uncertainty range of SO₂ emissions in China (i.e., -14%~13% from Zhao et al., 2011). We also found increasing uncertainties in China's energy consumption during 2004-2012, and converging uncertainties in 2013. Our findings indicate that variations in energy statistics could be an important source of China's emission uncertainties. Given that, we believe that our study provides important and new findings on the knowledge of uncertainties in bottom-up emission inventories and merits publication in ACP.

Both referee #1 and #2 endorsed the novelty of our work. As indicated by Referee #1, "In my knowledge, this is a first work." As indicated by Referee #2, "The paper will be a solid addition to the literature." The results and methods presented in this study could be used to distinguish how many differences in emissions between two existing inventories might come from those inconsistencies in energy data, as presented in Section 4.2. We believe the paper will be helpful to improve understanding of East Asia emissions, and it is quite suitable for the special issue of "East Asia emissions assessment (EA2)".

The paper essentially does the following. First, it assembles a set of publicly available energy datasets. Second, it processes these datasets using the pre-existing MEIC model for calculating atmospheric emissions. And third, it uses statistically questionable comparisons of the resulting disparities in both energy and emission datasets to draw inferences about the scale and sources of emission uncertainty. The mechanical processing of existing datasets using preexisting (and opaque) research tools is neither innovative nor novel. Importantly, it is also not reproducible, at least as currently presented. Last, the

inferences about uncertainty are speculative, as no rationales for use of the metrics defined and employed in the paper are presented.

Response: We clarified the question about reproducibility here. For the question about the uncertainty metrics defined in this study, please refer to the following responses to “Individual Questions/Issues”.

The MEIC emission inventory model (available at <http://www.meicmodel.org>) was used in this study to investigate the emission responses to different energy statistics. MEIC is a dynamic technology-based inventory developed by Tsinghua University. The methodology and data used in developing the MEIC model has been extensively documented in our previous publications, ensuring the transparency and reproducibility of the MEIC model (e.g., Zhang et al., 2007; Zhang et al., 2009; Lu et al., 2010; Lei et al., 2011; Zheng et al., 2014; Huo et al., 2015; Liu et al., 2015). The MEIC inventory has been widely used in supporting air quality models (e.g., Geng et al., 2015; Li et al., 2015; Zhang et al., 2015; Liu et al., 2016), and evaluated against surface and satellite-based observations (e.g., Chen et al., 2015; Zheng et al., 2015; Hu et al., 2016). To make the paper be more reproducible, we have provided more detailed methods in the Section 2.2 of the revised manuscript. The MEIC is developed following the work of INTEX-B (Zhang et al., 2009), with several updates, such as a unit-based emission inventory of power plants (Liu et al., 2015), a high-resolution vehicle emission inventory at the county level (Zheng et al., 2014), and an improved NMVOC speciation approach for various chemical mechanisms (Li et al., 2014). MEIC inventory includes recent control policies based on the available official reports (Ministry of Environmental Protection of China (MEP), 1991-2014, 2000-2014). The emissions in MEIC were estimated as a product of the activity rate (such as energy consumption or material production), the technology distributions of fuel/production and emission control, the unabated emission factor, and the removal efficiency. Thus, the emission estimates can be simplified as the activity rates multiplied by their respective net emission factors of different fuel/product types in different sectors. Note that the net emission factors in MEIC change dynamically driven by the technology renewal process year by year. Technology distributions within each sector are obtained from Chinese statistics, a wide range of unpublished statistics by various industrial association and technology reports. For example, technology distributions in the power sector were obtained based on unit-base database (Liu et al., 2015). Technology distributions in the transportation sector were estimated based on fleet model (Zheng et al., 2014). The methods on emission estimates has been documented in our previous work (Zhang et al., 2007; Zhang et al., 2009; Zheng et al., 2014; Liu et al., 2015).

The methods of estimating emissions applied to different energy consumption datasets have been clarified more carefully in the Section 2.2 of revised manuscript. To further explore the impact of energy data inconsistencies on estimates of China's emissions, five emission inventories based on five sets of energy statistics (i.e., CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C, CT-CESY-3C and PBP-CESY) were established in the framework of the MEIC inventory. Note that only energy data were changed in the calculations of these emission inventories, while other data such as net emission factors remained the same as MEIC inventory. Thus the emission uncertainties derived from these inventories are only those associated with energy uncertainties. They do not include uncertainties in the emission factors and other parameters in MEIC inventory, which is not addressed in this study. For different energy datasets, the same net emission factors were applied for fuel consumption in a given sector in each year during the emission calculations. In fact, energy differences might change the technology renewal process, and further change the net emission factors. However, considering that those assumptions would likely add additional uncertainty and we do not discuss the uncertainties in emission factors, such indirect impacts on emission factors are not included in this study. We only

applied all the fuel consumption differences to the combustion sectors. The sectoral categories are consistent across all the energy datasets from NBS (Table S1). The same scale factor in fuel consumption was applied for all the sub-categories in same major sector (e.g. industrial coal-fired boilers and kilns in industry sector; on-road diesel vehicles and off-road mobile sources in transportation sector). The possible uncertainties in feedstocks and products resulted from energy uncertainties are not included in this study, and also the uncertainties in biomass consumption are not included due to lack of multiple datasets, thus our estimates of emission uncertainties are likely on the conservative side. As the emission calculations were performed with province-level data, energy consumption in the national energy statistics were directly allocated to provinces by using the ratios derived from the provincial energy statistics.

The extent to which the results are interesting is derived from the scale of the inconsistencies of the underlying data, not from the analysis itself. While the authors appear positioned to undertake a more rigorous assessment of their important topic, the current paper is too formulaic, unsupported, and speculative to justify publication.

Response: We agree that besides the “apparent uncertainty”, the inconsistencies of the underlying data are also interesting, so we also presented and discussed the inconsistencies in the manuscript. For example, we presented the results from different datasets in Figure 1-3, Figure 5 and Table 3, and also discussed those inconsistencies in the results section and discussion section. In particular, we also discussed the inconsistencies of the energy data and possible sources for the inconsistencies in the section of “4.1 Understanding the reliability of energy statistics”.

Individual Questions/Issues

1. The paper is irreproducible, as it does not describe the methods of estimating emissions applied to different energy consumption datasets. It instead refers the reader to the website of the MEIC model, which does not present all of the underlying data and assumptions of the emission estimation model. To be reproducible, methods and assumptions must be described for each category of energy use (industrial subsector, for example, or vehicle type) treated uniquely in the assessment. Other researchers therefore cannot replicate the emission estimation as currently presented, except by blind trust in the same MEIC model.

Response: We have clarified the question about reproducibility in the above response.

2. The paper draws inferences about uncertainty based on two values defined in lines 9-10 of page 3: “We defined the apparent uncertainty as the maximum discrepancy among different datasets and the apparent uncertainty ratio as the ratio of the maximum discrepancy to the mean value from the different datasets.” These two concepts sound attractive but the rationales for their use to draw inferences about statistical uncertainty are currently lacking in the paper.

Response: We have clarified rationales for use of the metrics defined and employed in the paper in the introduction section of the revised manuscript. We defined the apparent uncertainty as the maximum discrepancy among different datasets and the apparent uncertainty ratio as the ratio of the maximum discrepancy to the mean value from the different datasets. Apparent uncertainty is a straightforward metric used to quantitatively gauge the apparent discrepancies between different existing datasets. Thus apparent uncertainty could partly reflect actual uncertainty. In general, large apparent uncertainty reflects large discrepancies, which might indicate large actual uncertainty. However, it should be noted

that apparent uncertainty could not fully represent actual uncertainty, and apparent uncertainty would likely to be conservative estimates as it might be subjected to the datasets used. Thus small apparent uncertainty does not necessarily mean to small actual uncertainty. Actual uncertainty, however, is difficult to be quantified and might need judgments.

Both concepts appear problematic. Regarding “apparent uncertainty,” a case has been made that a rough estimate of the uncertainty of energy data might be based on differences in values of subsequently revised data in the same official series (Marland et al. 2009). The rationale rests on a reasonable expectation that revisions represent increasing accuracy in the data and/or calculations, or “learning and convergence.” In the current paper, however, any connection to this rationale is lost because the authors simply compile datasets from different series (national, provincial, and IEA) and seek a maximum differential. Some sort of conceptual rationale for readers to find meaning in the value defined as apparent uncertainty is required for this calculation to be interpretable.

Response: It should be noted that this study focused on quantifying the discrepancy rather than giving best estimates. Although revisions might represent increasing accuracy, or “learning and convergence”, actual uncertainty, however, is difficult to be quantified and might need judgments. An alternative approach is to use “apparent uncertainty” which is used in this study to present the apparent discrepancies observed from the existing datasets rather than estimating uncertainties based on judgments. Apparent uncertainty is a straightforward metric used to quantitatively gauge the apparent discrepancies between different existing datasets. This kind of apparent uncertainty exists not only in the energy datasets, but could also transfer to emission inventories. We believe “apparent uncertainty” is useful for understanding the “actual uncertainty”. Apparent uncertainty could partly reflect actual uncertainty. In general, large apparent uncertainty reflects large discrepancies, which might indicate large actual uncertainty. However, it should be noted that apparent uncertainty could not fully represent actual uncertainty, and apparent uncertainty would likely to be conservative estimates as it might be subjected to the datasets used. Thus small apparent uncertainty does not necessarily mean to small actual uncertainty. We have clarified this in the introduction section of the revised manuscript.

The “apparent uncertainty ratio” is problematic first because the numerator is apparent uncertainty, with the conceptual concern just noted, but then compounded by a denominator that is also hard to rationalize because of autocorrelation. Taking the mean of all datasets, including sequential revisions of the same dataset (CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C, and CT-CESY-3C), implicitly assumes that they are independent. Without a defensible justification of this assumption, the calculations should recognize that revisions represent improving accuracy and should not be treated equally (as in a mean) in assessment of uncertainty.

Response: The question about apparent uncertainty is clarified in above response. Apparent uncertainty ratio is a metric to quantify the relative deviation. As we did not perform best estimates, the mean of all datasets gives an alternative median estimate. We notice that changing the denominator from the mean to the newest revised dataset (i.e., CT-CESY-3C) do not significantly impact the calculations of the apparent uncertainty ratio.

The paper requires a more rigorously conceived statistical basis to draw the sort of inferences about uncertainty that it seeks as its primary conclusions.

Response: We have clarified that our statistical approach could provide indirect but still useful

information about uncertainty in the above responses.

Technical Corrections:

The authors need to revisit the above fundamental issues first before they (and reviewers) put time into other issues and technical corrections that this paper needs.

Response: We have clarified all the issues in the above responses.

Reference

- Akimoto, H., Ohara, T., Kurokawa, J., and Horii, N.: Verification of energy consumption in China during 1996-2003 by using satellite observational data, *Atmos. Environ.*, 40, 7663–7667, doi:10.1016/j.atmosenv.2006.07.052, 2006.
- Chen, Y., Zhang, Y., Fan, J., Leung, L. R., Zhang, Q., and He, K.: Application of an Online-Coupled Regional Climate Model, WRF-CAM5, over East Asia for Examination of Ice Nucleation Schemes: Part I. Comprehensive Model Evaluation and Trend Analysis for 2006 and 2011, *Climate*, 3, 627–667, doi:10.3390/cli3030627, 2015.
- Geng, G., Zhang, Q., Martin, R. V., van Donkelaar, A., Huo, H., Che, H., Lin, J., and He, K.: Estimating long-term PM_{2.5} concentrations in China using satellite-based aerosol optical depth and a chemical transport model, *Remote Sens. Environ.*, 166, 262–270, doi:10.1016/j.rse.2015.05.016, 2015.
- Guan, D. B., Liu, Z., Geng, Y., Lindner, S., and Hubacek, K.: The gigatonne gap in China's carbon dioxide inventories, *Nat. Clim. Change*, 2, 672–675, doi:10.1038/Nclimate1560, 2012.
- Hu, J., Chen, J., Ying, Q., and Zhang, H.: One-year simulation of ozone and particulate matter in China using WRF/CMAQ modeling system, *Atmos. Chem. Phys.*, 16, 10333–10350, doi:10.5194/acp-16-10333-2016, 2016.
- Huo, H., Zheng, B., Wang, M., Zhang, Q., and He, K.: Vehicular air pollutant emissions in China: evaluation of past control policies and future perspectives, *Mitig. Adapt. Strat. Gl.*, 20, 719–733, doi:10.1007/s11027-014-9613-0, 2015.
- Korsbakken, J. I., Peters, G. P., and Andrew, R. M.: Uncertainties around reductions in China's coal use and CO₂ emissions, *Nat. Clim. Change*, 1–5, doi:10.1038/Nclimate 2963, 2016.
- Kurokawa, J., Ohara, T., Morikawa, T., Hanayama, S., Greet, J.-M., Fukui, T., Kawashima, K., and Akimoto, H.: Emissions of air pollutants and greenhouse gases over Asian regions during 2000–2008: Regional Emission inventory in ASia (REAS) version 2, *Atmos. Chem. Phys. Discuss.*, 13, 10049–10123, doi:10.5194/acpd-13-10049-2013, 2013.
- Lei, Y., Zhang, Q., Nielsen, C., and He, K.: An inventory of primary air pollutants and CO₂ emissions from cement production in China, 1990–2020, *Atmos. Environ.*, 45, 147–154, doi:10.1016/j.atmosenv.2010.09.034, 2011.
- Li, M., Zhang, Q., Streets, D. G., He, K. B., Cheng, Y. F., Emmons, L. K., Huo, H., Kang, S. C., Lu, Z., Shao, M., Su, H., Yu, X., and Zhang, Y.: Mapping Asian anthropogenic emissions of non-methane volatile organic compounds to multiple chemical mechanisms, *Atmos. Chem. Phys.*, 14, 5617–5638, doi:10.5194/acp-14-5617-2014, 2014.
- Li, X., Zhang, Q., Zhang, Y., Zheng, B., Wang, K., Chen, Y., Wallington, T. J., Han, W., Shen, W., Zhang, X., and He, K.: Source contributions of urban PM_{2.5} in the Beijing-Tianjin-Hebei region: Changes between 2006 and 2013 and relative impacts of emissions and meteorology, *Atmos. Environ.*, 123, 229–239, doi:10.1016/j.atmosenv.2015.10.048, 2015.
- Liu, F., Zhang, Q., Tong, D., Zheng, B., Li, M., Huo, H., and He, K. B.: High-resolution inventory of technologies, activities, and emissions of coal-fired power plants in China from 1990 to 2010, *Atmos. Chem. Phys.*, 15, 13299–13317, doi:10.5194/acp-15-13299-2015, 2015.
- Liu, J., Mauzerall, D. L., Chen, Q., Zhang, Q., Song, Y., Peng, W., Klimont, Z., Qiu, X., Zhang, S., Hu, M., Lin, W., Smith, K. R., and Zhu, T.: Air pollutant emissions from Chinese households: A major and underappreciated ambient pollution source, *P. Natl. Acad. Sci. Usa.*, 113, 7756–7761, doi:10.1073/pnas.1604537113, 2016.
- Lu, Z., Streets, D. G., Zhang, Q., Wang, S., Carmichael, G. R., Cheng, Y. F., Wei, C., Chin, M., Diehl,

T., and Tan, Q.: Sulfur dioxide emissions in China and sulfur trends in East Asia since 2000, *Atmos. Chem. Phys.*, 10, 6311–6331, doi:10.5194/acp-10-6311-2010, 2010.

Lu, Z., Zhang, Q., and Streets, D. G.: Sulfur dioxide and primary carbonaceous aerosol emissions in China and India, 1996–2010, *Atmos. Chem. Phys.*, 11, 9839–9864, doi:10.5194/acp-11-9839-2011, 2011.

Marland, G., Hamal, K., and Jonas, M.: How uncertain are estimates of CO₂ emissions?, *J. Ind. Ecol.*, 13, 4–7, 2009.

Sinton, J. E.: Accuracy and reliability of China's energy statistics, *China Economic Review*, 12, 373–383, 2001.

Streets, D. G., Bond, T. C., Carmichael, G. R., Fernandes, S. D., Fu, Q., He, D., Klimont, Z., Nelson, S. M., Tsai, N. Y., Wang, M. Q., Woo, J. H., and Yarber, K. F.: An inventory of gaseous and primary aerosol emissions in Asia in the year 2000, *J. Geophys. Res.*, 108, doi:10.1029/2002jd003093, 2003.

Zhang, Q., Streets, D. G., He, K., Wang, Y., Richter, A., Burrows, J. P., Uno, I., Jang, C. J., Chen, D., Yao, Z., and Lei, Y.: NO_x emission trends for China, 1995–2004: The view from the ground and the view from space, *J. Geophys. Res.*, 112, D22306, doi:10.1029/2007jd008684, 2007.

Zhang, Q., Streets, D. G., Carmichael, G. R., He, K. B., Huo, H., Kannari, A., Klimont, Z., Park, I. S., Reddy, S., Fu, J. S., Chen, D., Duan, L., Lei, Y., Wang, L. T., and Yao, Z. L.: Asian emissions in 2006 for the NASA INTEX-B mission, *Atmos. Chem. Phys.*, 9, 5131–5153, 2009.

Zhao, Y., Nielsen, C. P., Lei, Y., McElroy, M. B., and Hao, J.: Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China, *Atmos Chem Phys*, 11, 2295–2308, doi:10.5194/acp-11-2295-2011, 2011.

Zheng, B., Huo, H., Zhang, Q., Yao, Z. L., Wang, X. T., Yang, X. F., Liu, H., and He, K. B.: High-resolution mapping of vehicle emissions in China in 2008, *Atmos. Chem. Phys.*, 14, 9787–9805, doi:10.5194/acp-14-9787-2014, 2014.

Zhang, B., Wang, Y., and Hao, J.: Simulating aerosol-radiation-cloud feedbacks on meteorology and air quality over eastern China under severe haze conditions in winter, *Atmos. Chem. Phys.*, 15, 2387–2404, doi:10.5194/acp-15-2387-2015, 2015.

Zheng, B., Zhang, Q., Zhang, Y., He, K. B., Wang, K., Zheng, G. J., Duan, F. K., Ma, Y. L., and Kimoto, T.: Heterogeneous chemistry: a mechanism missing in current models to explain secondary inorganic aerosol formation during the January 2013 haze episode in North China, *Atmos. Chem. Phys.*, 15, 2031–2049, doi:10.5194/acp-15-2031-2015, 2015.

Variations of China's emission estimates response to uncertainties in energy statistics

Chaopeng Hong^{1,2}, Qiang Zhang^{1,5}, Kebin He^{2,4,5}, Dabo Guan^{1,3}, Meng Li^{1,2}, Fei Liu^{1,2}, and Bo Zheng²

¹Ministry of Education Key Laboratory for Earth System Modeling, Center for Earth System Science, Tsinghua University, Beijing, China

²State Key Joint Laboratory of Environment Simulation and Pollution Control, School of Environment, Tsinghua University, Beijing, China

³School of International Development, University of East Anglia, Norwich NR4 7TJ, United Kingdom

⁴State Environmental Protection Key Laboratory of Sources and Control of Air Pollution Complex, Beijing, China

⁵Collaborative Innovation Center for Regional Environmental Quality, Beijing, China

Correspondence to: Qiang Zhang (qiangzhang@tsinghua.edu.cn)

Abstract. The accuracy of China's energy statistics is of great concern because it contributes greatly to the uncertainties in estimates of global emissions. This study attempts to improve the understanding of uncertainties in China's energy statistics and evaluate their impacts on China's emissions during the period of 1990-2013. We employed the Multi-resolution Emission Inventory for China (MEIC) model to calculate China's emissions based on different official datasets of energy statistics using the same emission factors. We found that the apparent uncertainties (maximum discrepancy) in China's energy consumption increased from 2004 to 2012, reaching a maximum of 646 Mtce (million tons of coal equivalent) in 2011, and that coal dominated these uncertainties. The discrepancies between the national and provincial energy statistics were reduced after the three economic censuses conducted during this period, and converging uncertainties were found in 2013. The emissions calculated from the provincial energy statistics are generally higher than those calculated from the national energy statistics, and the apparent uncertainty ratio (the ratio of the maximum discrepancy to the mean value) owing to energy uncertainties in 2012 took values of 30.0%, 16.4%, 7.7%, 9.2% and 15.6%, for SO₂, NO_x, VOC, PM_{2.5} and CO₂ emissions, respectively. SO₂ emissions are most sensitive to energy uncertainties because of the high contributions from industrial coal combustion. The calculated emission trends are also greatly affected by energy uncertainties - from 1996 to 2012, CO₂ and NO_x emissions, respectively, increased by 191% and 197% according to the provincial energy statistics but by only 145% and 139% as determined from the original national energy statistics. The energy-induced emission uncertainties for some species such as SO₂ and NO_x are comparable to total uncertainties of emissions as estimated by previous studies, indicating variations at energy consumption could be an important source of China's emission uncertainties.

1 Introduction

China is facing a considerable challenge related to cleaning its air (Zhang et al., 2012). Emission inventories of air pollutants and greenhouse gases are of fundamental importance for the scientific analysis of complex air pollution problems and climate change as well as for assisting policy-makers in designing mitigation policies. Reliable emission inventories are becoming increasingly important, especially for large and rapidly growing countries such as China. To date, emissions have generally been estimated based on bottom-up approaches that combine available statistical information on relevant activities with known emission factors for different sectors and fuel types. Although a number of emission inventories covering China have been conducted, such as TRACE-P (Streets et al., 2003), INTEX-B (Zhang et al., 2009), MEIC (<http://www.meicmodel.org/>), REAS (Ohara et al., 2007; Kurokawa et al., 2013), EDGAR (<http://edgar.jrc.ec.europa.eu/index.php>) and GAINS (<http://gains.iiasa.ac.at/models/>), China's emission inventories are thought to be quite uncertain because of uncertainties in activity-related data, such as energy consumption data, and a lack of local emission factors (Zhao et al., 2011).

China has now become the world's top consumer of primary energy; however, the reliability of China's energy statistics has frequently been questioned (Sinton, 2001; Akimoto et al., 2006; Guan et al., 2012). The accuracy of China's energy statistics is of great concern because it contributes greatly to uncertainties in estimates of global emissions (Marland et al., 2012). Several inconsistencies exist among different sets of official energy statistics, namely, the national (CT-CESY, country-total) and provincial (PBP-CESY, province-by-province) Energy Balance Sheets from the China Energy Statistical Yearbook (CESY) and the Energy Balance Sheets from the International Energy Agency (IEA). These inconsistencies in energy consumption may lead to significant discrepancies in China's emission estimates. As previously reported (Akimoto et al., 2006), the increases in NO_x emissions estimated based on the PBP-CESY and IEA2004 data from the 1996-2002 period are 25% and 15%, respectively, and that estimated from the CT-CESY data is even lower. Zhao et al. (2011) used Monte Carlo methods to quantify the uncertainties of a bottom-up inventory of Chinese anthropogenic atmospheric pollutants and found that emission factors, rather than activity levels (e.g., energy consumption), are the main source of uncertainties in Chinese emission estimates. However, relatively small uncertainties in the activity levels for the year 2005 (i.e., CVs of 5%, 10% and 20% for the activity levels of the power sector, industrial combustion and residential fossil fuel use) were considered in their study. Some studies have noted the large uncertainties in energy statistics in recent years and their impacts on CO₂ emission estimates (Guan et al., 2012; Liu et al., 2015; Korsbakken et al., 2016). Guan et al. (2012) found that CO₂ emissions calculated on the basis of two publicly available energy datasets (i.e., CT-CESY and PBP-CESY) for 2010 differ by 1.4 gigatons, which is equivalent to approximately 5% of the global total. Liu et al. (2015) estimated that total energy consumption in China was 10 per cent higher in 2000–2012 than the value reported by China's national statistics. Korsbakken et al. (2016) used correlated economic quantities to constrain growth rates in total coal-derived energy use. They pointed out uncertainties around reductions in China's coal use and CO₂ emissions in recent years, and questioned the 2.9% drop in Chinese coal consumption in 2014 in preliminary official statistics, and showed that it was inappropriate for

estimating CO₂ emissions. Previous studies on the uncertainties in China's energy statistics and emissions are typically applicable either to an early period or for only a few species (usually CO₂ and NO_x).

This paper strives to present a full evaluation of the uncertainties in China's energy statistics and their effects on emission estimates for China during the period from 1990 to 2013. The evaluated species include SO₂, NO_x, VOC, PM_{2.5} and CO₂. In

5 this study, apparent uncertainties in China's energy statistics were evaluated through detailed comparisons of publicly available energy statistics to provide indirect but still useful information regarding the range of uncertainty of existing energy activity data. We defined the apparent uncertainty as the maximum discrepancy among different datasets and the apparent uncertainty ratio as the ratio of the maximum discrepancy to the mean value from the different datasets. **Apparent**

uncertainty is a straightforward metric used to quantitatively gauge the apparent discrepancies between different existing
10 **datasets. Apparent uncertainty ratio is a metric to quantify the relative deviation. Thus apparent uncertainty could partly reflect actual uncertainty. In general, large apparent uncertainty reflects large discrepancies, which might indicate large actual uncertainty. However, it should be noted that apparent uncertainty could not fully represent actual uncertainty, and apparent uncertainty would likely to be conservative estimates as it might be subjected to the datasets used. Thus small apparent uncertainty does not necessarily mean to small actual uncertainty.** To evaluate the impact of these energy

15 uncertainties on China's emissions and the emission trends, we established several emission inventories based on these energy statistics in the framework of the MEIC inventory using the same emission factors.

This paper is organized as follows. Section 2 summarizes the methods and data that were used in this work, including the energy statistics for China, and the MEIC emission inventory. In Sect. 3, we evaluate the apparent uncertainties in China's energy statistics and their impacts on China's emissions and the emission trends. In Sect. 4, we discuss the reliability of

20 China's energy statistics and the implications for other inventories.

2 Data and methods

2.1 China's energy statistics

China publishes its official energy statistics annually in the China Energy Statistical Yearbook (CESY) released by the National Bureau of Statistics (NBS), including both national and provincial Energy Balance Sheets for each province. The
25 national Energy Balance Sheets are revised each time an economic census is completed, and the revisions are published in the next Energy Statistical Yearbook. The China Energy Statistical Yearbooks from 2005 (CESY2005), 2009 (CESY2009) and 2014 (CESY2014) contain the revised national energy data for the periods of 1999-2003, 1996-2007 and 2000-2012, respectively, based on the results of the first, second and third national economic censuses conducted during this time. The International Energy Agency (IEA) also publishes energy statistics for China, which have been widely used in international
30 emission inventories (such as EDGAR). The IEA also regularly revises its energy statistics and is now operating in

cooperation with the NBS, who annually provides the IEA with China's energy statistics, and in recent years, the IEA statistics are found to be quite consistent with the NBS's national Energy Balance Sheet.

Six datasets of energy statistics **were involved in this study**: the original edition of the national Energy Balance Sheets from the CESY (CT-CESY-Ori) and its revisions following the first economic census (CT-CESY-1C), the second economic census (CT-CESY-2C) and the third economic census (CT-CESY-3C); the provincial Energy Balance Sheets from the CESY (PBP-CESY); and the 2012 edition of China's energy statistics from the IEA (CT-IEA-2012). These datasets are summarized in Table 1. Note that here CT-CESY-Ori represents the first edition of national energy statistics covering the whole period 1990-2013. For revised national energy statistics (i.e., CT-CESY-1C, CT-CESY-2C, CT-CESY-3C), the data were taken from previous edition for years that revised data were unavailable. Although energy statistics for 2014 is already published, we did not include year 2014, for the reason that the emission inventory is being updated. **The IEA energy statistics were used for comparison, but they were excluded from the uncertainty calculations in the current work. The IEA energy statistics are generally based on NBS's national Energy Balance Sheets, and currently quite consistent with CT-CESY-2C, as shown in Fig. 1. They may soon be updated based on CT-CESY-3C.**

2.2 Emission inventory

The MEIC emission inventory model (available at <http://www.meicmodel.org>) was used in this study to investigate the emission responses to different energy statistics. MEIC is a dynamic technology-based inventory developed for China covering the years from 1990 to 2013 by Tsinghua University following the work of INTEX-B (Zhang et al., 2009), with several updates, such as a unit-based emission inventory of power plants (Liu et al., 2015), a high-resolution vehicle emission inventory at the county level (Zheng et al., 2014), and an improved NMVOC speciation approach for various chemical mechanisms (Li et al., 2014). MEIC inventory includes recent control policies based on the available official reports (Ministry of Environmental Protection of China (MEP), 1991-2014, 2000-2014). The MEIC version 1.1 (MEIC v1.1) uses energy consumption data from PBP-CESY, excluding diesel and gasoline consumption data, which are taken from the national energy statistics (currently CT-CESY-1C) because the diesel consumption data provided in the national energy statistics were thought to might be more reliable (Zhang et al., 2007). **The emissions in MEIC were estimated as a product of the activity rate (such as energy consumption or material production), the technology distributions of fuel/production and emission control, the unabated emission factor, and the removal efficiency. Thus, the emission estimates can be simplified as the activity rates multiplied by their respective net emission factors of different fuel/product types in different sectors. Note that the net emission factors in MEIC change dynamically driven by the technology renewal process year by year. Technology distributions within each sector are obtained from Chinese statistics, a wide range of unpublished statistics by various industrial association and technology reports. For example, technology distributions in the power sector were obtained based on unit-base database (Liu et al., 2015). Technology distributions in the transportation sector were estimated**

based on fleet model (Zheng et al., 2014). The methods on emission estimates has been documented in our previous work (Zhang et al., 2007; Zhang et al., 2009; Zheng et al., 2014; Liu et al., 2015).

To further explore the impact of energy data inconsistencies on estimates of China's emissions, five emission inventories based on five sets of energy statistics (i.e., CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C, CT-CESY-3C and PBP-CESY) were established in the framework of the MEIC inventory. Note that only energy data were changed in the calculations of these emission inventories, while other data such as **net** emission factors remained the same as MEIC inventory. Thus the emission uncertainties derived from these inventories are only those associated with energy uncertainties. They do not include uncertainties in the emission factors and other parameters in MEIC inventory, **which is not addressed in this study.** For different energy datasets, the same net emission factors were applied for fuel consumption in a given sector in each year during the emission calculations. In fact, energy differences might change the technology renewal process, and further change the net emission factors. However, considering that those assumptions would likely add additional uncertainty and we do not discuss the uncertainties in emission factors, such indirect impacts on emission factors are not included in this study. We only applied all the fuel consumption differences to the combustion sectors. The sectoral categories are consistent across all the energy datasets from NBS (Table S1). The same scale factor in fuel consumption was applied for all the sub-categories in same major sector (e.g. industrial coal-fired boilers and kilns in industry sector; on-road diesel vehicles and off-road mobile sources in transportation sector). The possible uncertainties in feedstocks and products resulted from energy uncertainties are not included in this study, and also the uncertainties in biomass consumption are not included due to lack of multiple datasets, thus our estimates of emission uncertainties are likely on the conservative side. As the emission calculations were performed with province-level data, energy consumption in the national energy statistics were directly allocated to provinces by using the ratios derived from the provincial energy statistics.

3 Results

3.1 Apparent uncertainties in China's energy statistics

Apparent uncertainties in China's energy consumption for the period of 1990-2013 were quantified based on **five** publicly available energy statistics (i.e., CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C, CT-CESY-3C, and PBP-CESY), as shown in Fig. 1. Before 1996 there are no annual provincial data, and essentially just one national data set, which has not been revised. But since 1996, multiple data sets and/or revisions are available for each year. Notable apparent uncertainties have been observed since then, which can be divided into three periods: an early period (1996-2003); a more recent period of rapid growth (2004-2012); and the most recent period of convergence (2013). During the early period (1996-2003), China's energy consumption grew slowly, from 1352-1389 Mtce in 1996 to 1709-1971 Mtce in 2003. The average apparent uncertainty in total energy consumption during this period is 133 Mtce, with a peak of 261 Mtce in 2003, and the corresponding apparent uncertainty ratios are 9.0% for the period as a whole and 14.3% for 2003. During the recent period

of rapid growth (2004-2012), along with the rapid growth in China's economy and energy consumption, the apparent uncertainty in the total energy consumption also increased, with a mean uncertainty of 449 Mtce for this period and a maximum of 646 Mtce in 2011; the corresponding apparent uncertainty ratios are 14.5% for this period overall and 16.9% for 2011. The inconsistencies during the early period have been reported in many previous studies (Sinton, 2001; Akimoto et al., 2006; Zhang et al., 2007), but few studies (Guan et al., 2012; Liu et al., 2015; Korsbakken et al., 2016) have noted the more recent rapid growth period. Converging uncertainties are observed in 2013, with the release of the newest energy statistics based on the third economic census—the apparent uncertainty in total energy consumption for 2013 is reduced to 62 Mtce, and the corresponding apparent uncertainty ratio is only 1.5%. We notice that the apparent uncertainty for 2014 (not shown here) is similar to that for 2013, also much smaller than that during the recent period of rapid growth (2004-2012).

With regard to different types of energy, coal dominates the apparent uncertainties in total energy consumption. The average apparent uncertainties in coal consumption for 1996-2003, 2004-2012 and 2013 are 147 Mtce, 428 Mtce and 194 Mtce, respectively, and the corresponding apparent uncertainty ratios are 14.2%, 19.4% and 6.7%. The sum of the provincial data (PBP-CESY) is generally higher than the national total (i.e., CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C and CT-CESY-3C) with regard to total energy consumption and coal consumption. After each of the three economic censuses, the national total energy consumption data (CT-CESY-1C, CT-CESY-2C and CT-CESY-3C) were revised upward to approach the provincial totals, primarily by adjusting the coal-related data. The apparent uncertainties in oil consumption during 1996-2003 are relatively large, with a mean of 48 Mtce and an average apparent uncertainty ratio of 15.8%. The provincial total oil consumption is lower than the national total for 1996-2003, but this situation is reversed between 2005 and 2011. The apparent uncertainties in the consumption of natural gas and other types of energy are smaller than the uncertainties in coal and oil, suggesting that the statistical data for natural gas and other energy sources may be more accurate because their use is generally metered.

The apparent uncertainties in coal consumption were further analyzed by sector, as shown in Fig. 2. As the largest consumer of coal in China, the power sector is found to exhibit less uncertainty in its coal consumption than other sectors. Coal consumption in the industrial sector is highly uncertain, with an apparent uncertainty ratio for 2012 of 45.4%, which represents the greatest contribution to the total uncertainty in coal consumption. A significant decrease in coal consumption in the industrial sector during 1996-2002 is observed in the CT-CESY-Ori data, and this decrease resulted in a slight decrease in the total coal consumption. For the heating sector and the residential sector, although the levels of coal consumption in these two sectors are smaller than those in the power and industrial sectors, comparable apparent uncertainties are also found; the apparent uncertainty ratios for the heating and residential sectors in 2012 are 37.8% and 46.9%, respectively.

3.2 Effects on China's emission estimates

To evaluate the effects of uncertainties in the energy statistics on China's emission estimates, five emission inventories based on different sets of energy statistics (i.e., CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C, CT-CESY-3C and PBP-CESY) were established. Figure 3 shows the apparent uncertainties in China's emissions during 1990-2013. Figure 4 shows the apparent uncertainty ratio in China's emissions during 1990-2013. It should be noted that the emission uncertainties discussed below, which were derived from these five emission inventories, are based only on uncertainties in the energy data; thus, they could reflect the impacts of energy uncertainties on emission estimates. For the early period (1996-2003), the average apparent uncertainties for SO₂, NO_x, VOC, PM_{2.5} and CO₂ are 2.10 Tg, 0.83 Tg, 0.41 Tg, 0.34 Tg and 278 Tg, respectively, and the corresponding apparent uncertainty ratios are 10.2%, 6.7%, 3.2%, 2.8% and 6.7%. For the recent period of rapid growth (2004-2012), the apparent uncertainties are increasing over time and are more significant than those in the early period, although this fact has rarely been discussed in the literature; the average apparent uncertainties during this period for SO₂, NO_x, VOC, PM_{2.5} and CO₂ are 5.77 Tg, 2.98 Tg, 1.60 Tg, 0.80 Tg and 1026 Tg, respectively, and the corresponding apparent uncertainty ratios are 20.4%, 12.6%, 7.7%, 6.4% and 12.4%. For 2012, the apparent uncertainties for these species are 7.76 Tg, 4.68 Tg, 1.90 Tg, 1.10 Tg and 1633 Tg, respectively, and the corresponding apparent uncertainty ratios are 30.0%, 16.4%, 7.7%, 9.2% and 15.6%. The apparent uncertainty for CO₂ in 2010 is 1283 Tg in this study, which is similar with the discrepancy (~1400 Tg) reported by Guan et al. (2012), but lower than the uncertainty in 2012. In the most recent period of convergence (2013), the apparent uncertainty ratio in emissions is less than 5% for most species because of the lower apparent uncertainties in the energy statistics after the third economic census. Note that the emission discrepancies calculated from the provincial and national energy statistics are getting smaller after the third economic census (i.e., PBP-CESY and CT-CESY-3C), compared with that before the third economic census (e.g., PBP-CESY and CT-CESY-2C). For example, CO₂ emission discrepancy in 2010 between PBP-CESY and CT-CESY-3C is only 548 Tg, much less than that reported by Guan et al. (2012), in which the NBS's data before the third economic census were used.

It should be noted that the apparent uncertainties calculated in this study are subjected to the energy datasets used. For example, the small apparent uncertainties before 1996 might become larger if a new energy dataset that revises the data of this period is included. Apparent uncertainties during the recent period of rapid growth (2004-2012) are higher than the early period (1996-2003), implying that the discrepancies might be accumulated and expanded for a period of rapid growth. For example, underestimates of the growth trends of small enterprises might result into accumulated underestimations. Note that the energy consumption apparently became more consistent between provincial and national statistics after the three economic censuses, indicating that the new energy statistics after the economic census may include evolved methodologies for data collection and more cross-checks to reduce the discrepancies. In this case, conducting censuses in some interval years could help to reduce the accumulated discrepancies. The apparent uncertainty ratio in years economic censuses newly conducted (i.e., 2004, 2008 and 2013) is generally less than that of previous years (i.e., 2003, 2007 and 2012), as shown in Figure 4. The converging uncertainties in 2013 may also be caused by the third economic census.

As seen, the energy-induced uncertainties in emissions differ by species; the largest uncertainties are observed for SO₂, followed by NO_x and CO₂, and the smallest are found for PM_{2.5} and VOC. Taking the year 2012 as a case in which the uncertainties are prominent, the emission uncertainties were separated by sector and by energy type, as shown in Table 2. SO₂ emissions are more sensitive to energy uncertainties than are CO₂ emissions because of the high contribution (approximately 50%) from industrial coal combustion, which is the largest source of uncertainty in SO₂ emissions (6.04 Tg). A large fraction (approximately 24%) of NO_x emissions is contributed by the use of diesel in the transportation sector; the corresponding activity data have a lower uncertainty ratio than that for coal use, leading to a lower sensitivity than that of SO₂. PM_{2.5} and VOC emissions also show less sensitivity to energy uncertainties because they represent relatively small contributions from energy consumption and high contributions (approximately 40%-60%) from industrial process emissions.

Note that non-combustion emission uncertainty is not addressed in this study. With regard to contributions by sector, industry is the dominant sector, accounting for 77.8%, 72.3%, 46.8%, 52.4% and 73.2% of the total apparent uncertainties in SO₂, NO_x, PM_{2.5}, VOC and CO₂ emissions, respectively. Although the power sector is a major source of emissions of many species (contributing approximately 25-35% of the total emissions of CO₂, NO_x and SO₂), it is estimated to contribute less than 7% to the total apparent uncertainties for all species because of the relatively low uncertainty for coal consumption in the power sector. Transportation is another key contributor to emission uncertainties for NO_x (contributing 17.3% of the uncertainty for this species), whereas the residential sector is significant for SO₂ (contributing 18.3% of the uncertainty). With regard to energy type, 97.6% and 93.8% of the emission uncertainties of SO₂ and PM_{2.5}, respectively, originate from coal, whereas 31.2% of the VOC emission uncertainties come from oil. The contributions of gas and other fuels are negligible because **uncertainties in biomass consumption are not included and other** emissions are relatively small. **Note that biomass consumption, which is usually thought to be quite uncertain, would contribute more uncertainties in emissions.**

Discrepancies in energy data affect not only the absolute emission estimates for individual years but also multi-year emission trends because of the inter-annual variability of these discrepancies. Table 3 compares the emission trends for China derived from different energy statistics. For the early period (1996-2003), slower growth rates of CO₂, NO_x and SO₂ emissions are found from the CT-CESY-Ori inventory (22.9%, 38.0% and 14.3%, respectively) than from the PBP-CESY inventory (35.5%, 47.5% and 28.0%, respectively), which is consistent with previous studies (Akimoto et al., 2006; Zhang et al., 2007). The trends derived from the national energy statistics were revised upward after each of the three economy censuses, bringing them closer to those indicated by the provincial energy statistics. SO₂ and CO₂ show a dip according to the CT-CESY-Ori inventory, but this effect is not significant in the PBP-CESY inventory. SO₂ emissions declined by 13.7% during the period of 1996-2000 according to the CT-CESY-Ori inventory but increased by 1.4% according to the PBP-CESY inventory. These differences reflect the large uncertainties in industrial coal consumption during 1996-2000—a decline of 28.4% is indicated by CT-CESY-Ori, whereas only a slight decrease of 3.8% is found from PBP-CESY. It should be noted that the dip for NO_x emissions is not as distinct as that for CO₂. This is because the fuel consumption in the power and transportation sectors, for which the NO_x emission factors are the largest, was steadily increasing during this period.

In the recent period of rapid growth (2004-2012), CO₂ and NO_x emissions, respectively, increased by 91.8% and 77.6% according to the PBP-CESY inventory but by only 70.8% and 48.4% as determined from the CT-CESY-Ori inventory; SO₂ emissions increased by 1.6% according to the PBP-CESY inventory but decreased by -18.8% as indicated by the CT-CESY-Ori inventory. For the period from 1996 to 2012, the CO₂ growth rates inferred from the CT-CESY-Ori, CT-CESY-3C and PBP-CESY inventories are 145%, 172% and 191%, respectively, similar with the growth rates in the total energy consumption (160%, 197% and 207%); the differences between different energy statistics demonstrates that trends in CO₂ emissions are good indicators of trends in energy consumption. NO_x and SO₂ also show marked differences in emission growth - increased by 197% and 45.1% during 1996-2012 according to the provincial energy statistics but by only 139% and 7.2% as determined from the original national energy statistics. From 2012 to 2013, the total energy consumption and CO₂ emissions, respectively, increased by 3.7% and 3.7% as seen from CT-CESY-3C but decreased by 0.4% and 2.1% according to PBP-CESY. The GDP increased by 7.7% between 2012 and 2013; thus, the decreasing trend in CO₂ emissions indicated by PBP-CESY is unexpected. Korsbakken et al. (2016) also pointed out that initial claims that Chinese CO₂ emissions fell in 2014 according to preliminary official statistics were probably premature. The unexpected energy and CO₂ emission decline in 2013 in PBP-CESY could be explained by the fact that the PBP-CESY data for 2013, which probably include updates based on the third economic census, are closer to the data from CT-CESY-3C. As a result, the total growth rates since 1996 indicated by PBP-CESY and CT-CESY-3C are more similar to each other for the period 1996-2013 than periods before 2013 (e.g., 1996-2012). As part of the Chinese Five Year Plan, the Chinese government established a set of targets for emission reduction, including a 10% SO₂ reduction from the 2005 levels by 2010 and reductions of 10% in NO_x and 8% in SO₂ from the 2010 levels by 2015. Our results show that because uncertainties in energy statistics can lead to the inference of different emission trends, reliable energy data are crucially important for obtaining accurate estimates of both the absolute levels of emissions and their trends.

4 Discussion

4.1 Understanding the reliability of energy statistics

The large uncertainties between the national and provincial energy statistics can be explained in terms of both inadequacies in China's statistical system and artificial factors. First, China's statistical data are generally collected and reported from bottom to top, and there is a lack of effective means of cross-checking at the local level; thus, these data are faced with problems such as data inconsistency and double counting (Wang et al., 2014). Inconsistencies between interprovincial imports and exports have been found in the provincial energy statistics—the sum of coal “interprovincial imports” is higher than the sum of coal “interprovincial exports” (Zhang et al., 2007). Also, provincial statistics more likely include double counting because certain interprovincial activities are claimed by all provinces involved. A similar situation affects economic statistics: the aggregate provincial GDP in 2012 is approximately 11% larger than the national total. Second, unlike for large- and medium-size enterprises, which have defined data collection and reporting procedures, the energy data for small

enterprises are merely estimated, which could strongly degrade the data quality of the energy statistics (Jiang et al., 2009; Wang et al., 2011; Wang et al., 2014). A typical example is that the original official statistics (CT-CESY-Ori) did not fully count the coal production of illegal small coal mines, leading to underestimations in coal production around 2000 (Wang et al., 2011; Guan et al., 2012). Third, certain signs indicate that energy data may be modified for artificial purposes (Guan et al., 2012). The energy revisions after the second economic census (CT-CESY-2C) were found to bring the country closer to achieving its energy conservation targets (Aden et al., 2010). We also notice that some provinces had zero statistical difference, i.e., the supply data matches the consumption data exactly, which might mean that some provincial data were adjusted to achieve the exact match.

We compared China's coal consumption in 1996-2013 as indicated by different energy statistics from the supply perspective, as shown in Fig. 5. In the supply approach, energy consumption is estimated based on production, trade and changes in stock (consumption = production - exports + imports + change in stock + statistical difference). From the supply perspective, the national energy statistics tend to estimate conservative production and thus underestimate coal consumption. The coal consumption data for 1996-2012 from the national energy statistics were revised upward after the first (CT-CESY-1C), second (CT-CESY-2C) and third (CT-CESY-3C) censuses because of increasing coal production, which may be largely explained by the small coal mines that were initially unaccounted for in the official statistics (Guan et al., 2012). Meanwhile, inconsistencies in interprovincial transport manifest as interprovincial net imports (see Fig. 5), resulting in a higher coal supply in the provincial energy statistics, implying that either coal production is underestimated or coal consumption is overestimated. For the years before 2008, the coal production indicated by the provincial energy statistics is reasonably consistent with that derived from the original national energy statistics (CT-CESY-Ori) and lower than that from the revised national energy statistics (CT-CESY-3C), which could help partially explain the interprovincial net imports during this period as underestimates in production. Moreover, the provincial energy statistics likely include double counting and thus might result in overestimates. This effect may be more significant in recent years with the more frequent collaboration among companies at the provincial level.

Satellite observations, which have been widely used in the assessment of emission trends in previous studies (e.g., Richter et al., 2005; van de A et al., 2008; Stavrakou et al., 2008; Lamsal et al., 2011), could be used as one independent approach to verifying energy statistics. Akimoto et al. (2006) compared trends in bottom-up NO_x emissions with satellite-derived NO_2 columns for the period of 1996–2002 and found that the emission trends derived from various energy statistics were all lower than that inferred from the satellite observations (which increased by 50%). The PBP-CESY trends were within the uncertainty of the satellite observations, whereas the IEA2004 and CT-CESY trends were apparently underestimated beyond the uncertainty of the satellite observations. Zhang et al. (2007) compared trends over China in bottom-up NO_x emissions with satellite NO_2 columns observed from 1996 to 2004 and found a larger trend in the satellite NO_2 columns than in the NO_x emissions. Berezin et al. (2013) derived top-down estimates of CO_2 emission trends by means of the satellite-derived NO_x emission trends obtained using an inverse model and CO_2 -to- NO_x emission ratios (i.e., CO_2/NO_x) from bottom-up

inventories. They also found a significant quantitative difference between bottom-up and indirect top-down estimates of the CO₂ emission trend for the period of 1996-2001, and the difference for the period of 2001-2008 was found to be in the range of possible systematic uncertainties associated with their estimation method.

Previous studies have investigated the decline in energy consumption between 1997 and 2001 indicated by CT-CESY-Ori (Akimoto et al., 2006; Sinton et al., 2000, 2001; Zhang et al., 2007; Berezin et al., 2013). This supposed decline was completely eliminated after the revisions following the three censuses. This fact may support the conclusion of these early studies that the trend in energy consumption indicated by the provincial energy statistics was more accurate than that derived from the unrevised national energy statistics during the early period. Liu et al. (2015) estimated total Chinese energy consumption by adopting the apparent consumption approach and estimated a value for 2000-2012 that was 10 percent higher than that reported in China's national statistics before the third economic census and lower than that from the provincial energy statistics. The discrepancies between the national and provincial energy statistics were reduced after the three economic censuses. These facts indicate that the newest energy statistics after the third economic census may include evolved methodologies for data collection and more cross-checks to reduce inconsistencies between the national and provincial energy statistics and thus can be recommended for use. In contrast, the energy consumption indicated by the national energy statistics from before the third economic census may be underestimated because of underestimations in energy production, whereas the energy consumption indicated by the provincial energy statistics from before the third economic census may be overestimated because of double counting.

4.2 Implications for other studies

In this study, we find that uncertainties in energy statistics have great impacts on China's emission estimates, which could also be used to partially explain different emission estimates from other inventories. The Ministry of Environmental Protection of China (MEP) tends to estimate lower SO₂ and NO_x emissions than MEIC (e.g., 30% lower for SO₂, and 20% lower for NO_x in 2012). Lower energy consumption from the national energy statistics, compared with provincial energy statistics, could help to explain the differences in emissions. Trends in CO₂ emissions are good indicators of trends in energy consumption, which can reflect the differences in energy statistics between different inventories. We compared the emission trends for CO₂ and NO_x in MEIC, the Asian inventory REAS, and the global inventory EDGAR (Fig. 6). From 1996 to 2001, CO₂ emissions increased by 9.6% and 9.2% according to MEIC and REAS, respectively, but increased by only 0.4% according to EDGAR; total energy consumption increased by 11.5% and 3.1% according to PBP-CESY and CT-CESY-1C, respectively, during the same period. From 1996 to 2008, CO₂ emissions increased by 135% according to MEIC but increased by only 114% according to EDGAR; total energy consumption increased by 138% and 110% according to PBP-CESY and CT-CESY-1C, respectively. These differences indicate that the energy consumption indicated by EDGAR, which was created using the IEA energy statistics, is likely closer to the national energy statistics.

The differences in NO_x emission trends could be partially explained by differences in the energy statistics. During the period of 1996-2008, NO_x emissions increased by 127% according to MEIC but by only 76% according to EDGAR. If the CO₂ growth trend were to be replaced with that from MEIC while keeping the same NO_x-to-CO₂ ratios, a greater (93%) increase in NO_x emissions would be found from EDGAR. However, significant differences also arise from the emission factors (i.e., the NO_x-to-CO₂ ratios): the overall NO_x-to-CO₂ ratio decreased by only 3.5% in MEIC for the 1996-2008 period but decreased by 17.9% in EDGAR. Similar trends in the overall NO_x-to-CO₂ ratio are found between MEIC and REAS: it increased from 1996 to 2001, primarily driven by a faster growth rate of diesel consumption (46-51%), which has a higher NO_x-to-CO₂ ratio, compared with the growth rate of coal consumption (-15-7%), but it then decreased after 2004, primarily because of the implementation of NO_x emission standards in the power and transportation sectors. It should be noted that EDGAR tends to estimate a much earlier and more rapid decline in NO_x emission factors compared with those seen from MEIC and REAS (see Fig. 6(c)), for which the underlying driving forces are difficult to understand. For example, the NO_x-to-CO₂ ratios in EDGAR began to decrease significantly for the power and transportation sectors in 1993 and 1990, respectively (see Fig. 6(d)), earlier than the years of implementation of major control measures regarding NO_x emissions in these sectors (1996 and 2001, respectively) (State Environmental Protection Administration of China (SEPA), 1996, 2001).

The CO₂-to-NO_x emission ratios taken from bottom-up inventories could be an important potential source of error in top-down estimates of CO₂ emission trends based on satellite NO₂ columns. Berezin et al. (2013) used the emission ratios from EDGAR and found an increase in CO₂ emissions of as high as 240% for the 1996-2008 period using the top-down approach, much larger than the trends observed in bottom-up inventories (e.g., 114% in EDGAR). These substantial differences should be attributable mainly to the rapidly increasing CO₂-to-NO_x ratios in EDGAR. If we adopt the emission ratios from MEIC (including uncertainties), we find an increase of 147-197%, much closer to the values from bottom-up inventories. Although uncertainties still exist, these results indicate that the energy consumption from EDGAR, which is similar to CT-CESY-1C, as well as energy consumption in 2008 from CT-CESY-2C, is likely to be underestimated.

Top-down estimates of the CO₂-to-NO_x emission ratios using satellite observations could offer an alternative approach. Reuter et al. (2014) used top-down estimation methods and found that the CO₂-to-NO_x emission ratio for the years 2003-2011 in East Asia had increased by $4.2 \pm 1.7\% \text{ yr}^{-1}$. They found a large positive trend in CO₂ emissions in East Asia ($9.8 \pm 1.7\% \text{ yr}^{-1}$) that exceeded the positive trend in NO_x emissions ($5.8 \pm 0.9\% \text{ yr}^{-1}$). The MEIC inventory reports a similar CO₂ trend in China ($10.4\% \text{ yr}^{-1}$) during the same period. Reuter et al. (2014) noted a considerably smaller CO₂ trend in EDGAR ($6.9\% \text{ yr}^{-1}$) compared with these top-down estimates; it appears that considering the possible underestimations in Chinese CO₂ trends in EDGAR due to uncertainties in energy statistics could help to explain this difference. The MEIC inventory reports a larger NO_x trend in China ($8.1\% \text{ yr}^{-1}$) than that reported by Reuter et al. (2014) for East Asia, which is consistent with Wang et al. (2014), who also found a faster NO_x growth rate in China (34%) compared with that in East Asia as a whole (25%) for 2005-2010.

Zhao et al. (2011) estimated the uncertainties (i.e., 95% confidence intervals around the central estimates) of Chinese total SO₂, NO_x, and PM_{2.5} emissions in 2005 to be -14~13%, -13~37%, and -17%~54%, respectively. We found that the apparent uncertainty ratios arising from the 2012 energy statistics for SO₂ and NO_x emissions could be as large as 30.0% and 16.4%, respectively, indicating the importance of energy statistics to Chinese emission estimates for recent years, especially for SO₂ and NO_x. Variations at energy consumption could be an important source of emission uncertainties for SO₂ and NO_x. For VOC and PM_{2.5}, uncertainties in energy consumption act as a minor source due to emission contributions from non-energy activities and large uncertainties from emission factors.

5 Conclusions

This study analyzed the apparent uncertainties (**maximum discrepancy**) in China's energy statistics and the impacts on China's estimated emissions for the period 1990-2013. We found increasing apparent uncertainties in China's energy consumption during 2004-2012 and converging uncertainties in 2013. Coal is the dominant type of energy contributing to these uncertainties, and coal use in the industrial sector in particular is highly uncertain. Owing to high uncertainties in the energy statistics, the apparent uncertainty ratios (**the ratio of the maximum discrepancy to the mean value**) for emissions in 2012 are as large as 30.0%, 16.4%, 7.7%, 9.2% and 15.6%, for SO₂, NO_x, VOC, PM_{2.5} and CO₂, respectively. SO₂ was found to be the most sensitive to energy uncertainties because of its high contribution from industrial coal combustion. The calculated emission trends are also greatly affected by energy uncertainties - from 1996 to 2012, CO₂ and NO_x emissions, respectively, increased by 191% and 197% according to the provincial energy statistics but by only 145% and 139% as determined from the original national energy statistics. For SO₂ and NO_x, the energy-induced emission uncertainties are comparable to total uncertainties of emissions as estimated by previous studies, indicating variations at energy consumption could be an important source of emission uncertainties. The reliability of the energy statistics cannot yet be regarded as conclusive, but possible explanations for the discrepancies include inconsistencies in interprovincial energy transport, double counting in provincial energy consumption, and underestimates in energy production from small mines. While large uncertainties are present in this study, it is of critical importance to reform the statistical system, and to introduce more cross-checks and independent methods to help to verify the quality of energy data and to reduce uncertainties in energy consumption as well as emissions.

Acknowledgements. This work was supported by China's National Basic Research Program (2014CB441301), the National Science Foundation of China (41222036), the National Key Technology R&D Program (2014BAC16B03 and 2014BAC21B02), the public welfare program of China's Ministry of Environmental Protection (201509014). This work is a contribution to the TransChina project funded by the Research Council of Norway (235523). We thank Glen Peters and Jan Ivar Korsbakken for their helpful suggestions. Qiang Zhang and Kebin He are supported by the Collaborative Innovation Center for Regional Environmental Quality.

References

- Aden, N.: Initial Assessment of NBS Energy Data Revisions, Ernest Orlando Lawrence Berkeley National Laboratory, China Energy Group, 2010.
- Akimoto, H., Ohara, T., Kurokawa, J., and Horii, N.: Verification of energy consumption in China during 1996-2003 by
5 using satellite observational data, *Atmos. Environ.*, 40, 7663–7667, doi:10.1016/j.atmosenv.2006.07.052, 2006.
- Berezin, E. V., Kononov, I. B., Ciais, P., Richter, A., Tao, S., Janssens-Maenhout, G., Beekmann, M., and Schulze, E. D.:
Multiannual changes of CO₂ emissions in China: indirect estimates derived from satellite measurements of tropospheric
NO₂ columns, *Atmos. Chem. Phys.*, 13, 9415–9438, doi:10.5194/acp-13-9415-2013, 2013.
- Guan, D. B., Liu, Z., Geng, Y., Lindner, S., and Hubacek, K.: The gigatonne gap in China's carbon dioxide inventories, *Nat.*
10 *Clim. Change*, 2, 672–675, doi:10.1038/Nclimate1560, 2012.
- International Energy Agency (IEA): World Energy Statistics and Balances (2012 edition), IEA, Paris, 2012.
- Jiang, S.: Coal production statistics data analysis, *Data*, 4, 32–33, doi:10.3969/j.issn.1006-5954.2009.04.016, 2009. (In
Chinese)
- Korsbakken, J. I., Peters, G. P., and Andrew, R. M.: Uncertainties around reductions in China's coal use and CO₂ emissions,
15 *Nat. Clim. Change*, 1–5, doi:10.1038/Nclimate 2963, 2016.
- Kurokawa, J., Ohara, T., Morikawa, T., Hanayama, S., Greet, J.-M., Fukui, T., Kawashima, K., and Akimoto, H.: Emissions
of air pollutants and greenhouse gases over Asian regions during 2000–2008: Regional Emission inventory in ASia
(REAS) version 2, *Atmos. Chem. Phys. Discuss.*, 13, 10049–10123, doi:10.5194/acpd-13-10049-2013, 2013.
- Lamsal, L. N., Martin, R. V., Padmanabhan, A., van Donkelaar, A., Zhang, Q., Sioris, C. E., Chance, K., Kurosu, T. P., and
20 Newchurch, M. J.: Application of satellite observations for timely updates to global anthropogenic NO_x emission
inventories, *Geophys. Res. Lett.*, 38, ArtId L05810, doi:10.1029/2010gl046476, 2011.
- Li, M., Zhang, Q., Streets, D. G., He, K. B., Cheng, Y. F., Emmons, L. K., Huo, H., Kang, S. C., Lu, Z., Shao, M., Su, H.,
Yu, X., and Zhang, Y.: Mapping Asian anthropogenic emissions of non-methane volatile organic compounds to
multiple chemical mechanisms, *Atmos. Chem. Phys.*, 14, 5617–5638, doi:10.5194/acp-14-5617-2014, 2014.
- 25 Liu, F., Zhang, Q., Tong, D., Zheng, B., Li, M., Huo, H., and He, K. B.: High-resolution inventory of technologies, activities,
and emissions of coal-fired power plants in China from 1990 to 2010, *Atmos. Chem. Phys.*, 15, 13299–13317,
doi:10.5194/acp-15-13299-2015, 2015.
- Liu, Z., Guan, D., Wei, W., Davis, S. J., Ciais, P., Bai, J., Peng, S., Zhang, Q., Hubacek, K., Marland, G., Andres, R. J.,
Crawford-Brown, D., Lin, J., Zhao, H., Hong, C., Boden, T. A., Feng, K., Peters, G. P., Xi, F., Liu, J., Li, Y., Zhao, Y.,
30 Zeng, N., and He, K.: Reduced carbon emission estimates from fossil fuel combustion and cement production in China,
Nature, 524, 335–338, doi:10.1038/nature14677, 2015.
- Marland, G.: Emissions accounting: China's uncertain CO₂ emissions, *Nature Clim. Change*, 2, 645–646, 2012.

- Ministry of Environmental Protection of China: State of Environment Report 1991–2014 (In Chinese), available at: <http://jcs.mep.gov.cn/hjzl/zkgb/>.
- Ministry of Environmental Protection of China: China Environment Statistical Yearbook 2000–2014 (In Chinese), available at: <http://zls.mep.gov.cn/hjtj/nb/>.
- 5 National Bureau of Statistics: China Energy Statistical Yearbook (1991–1996, 1997–1999, 2000–2002, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013 and 2014 editions), China Statistics Press, Beijing, 1997–2015.
- Ohara, T., Akimoto, H., Kurokawa, J., Horii, N., Yamaji, K., Yan, X., and Hayasaka, T.: An Asian emission inventory of anthropogenic emission sources for the period 1980–2020, *Atmos. Chem. Phys.*, 7, 4419–4444, 2007.
- Reuter, M., Buchwitz, M., Hilboll, A., Richter, A., Schneising, O., Hilker, M., Heymann, J., Bovensmann, H., and Burrows,
- 10 J. P.: Decreasing emissions of NO_x relative to CO₂ in East Asia inferred from satellite observations, *Nature Geosci.*, 7, 792–795, 2014.
- Richter, A., Burrows, J. P., Nuss, H., Granier, C., and Niemeier, U.: Increase in tropospheric nitrogen dioxide over China observed from space, *Nature*, 437, 129–132, doi:10.1038/Nature04092, 2005.
- Sinton, J. E.: Accuracy and reliability of China's energy statistics, *China Economic Review*, 12, 373–383, 2001.
- 15 Sinton, J. E., and Fridley, D. G.: What goes up: recent trends in China's energy consumption, *Energ. Policy*, 28, 671–687, doi:10.1016/S0301-4215(00)00053-7, 2000.
- State Environmental Protection Administration of China: Emission standard of air pollutants for thermal power plants GB 13223–1996, State Environ, Prot. Admin., Beijing, 1996.
- State Environmental Protection Administration of China: Limits and measurement methods for exhaust pollutants from
- 20 compression ignition (C.I.) engines of vehicles GB 17691-2001, State Environ, Prot. Admin., Beijing, 2001.
- Stavrou, T., Müller, J.-F., Boersma, K. F., De Smedt, I., and van der A, R. J.: Assessing the distribution and growth rates of NO_x emission sources by inverting a 10-year record of NO₂ satellite columns, *Geophys. Res. Lett.*, 35, L10801, doi:10.1029/2008GL033521, 2008.
- Streets, D. G., Bond, T. C., Carmichael, G. R., Fernandes, S. D., Fu, Q., He, D., Klimont, Z., Nelson, S. M., Tsai, N. Y.,
- 25 Wang, M. Q., Woo, J. H., and Yarber, K. F.: An inventory of gaseous and primary aerosol emissions in Asia in the year 2000, *J. Geophys. Res.*, 108, doi:10.1029/2002jd003093, 2003.
- van der A, R. J., Eskes, H. J., Boersma, K. F., van Noije, T. P. C., Van Roozendaal, M., De Smedt, I., Peters, D. H. M. U., and Meijer, E. W.: Trends, seasonal variability and dominant NO_x source derived from a ten year record of NO₂ measured from space, *J. Geophys. Res.*, 25 113, D04302, doi:10.1029/2007JD009021, 2008.
- 30 Wang, Q.: Suggestions on China's Energy Statistical System Reform, China Coal Consumption Cap Plan and Policy Research Project, 2014. (In Chinese)
- Wang, Y., and William, C.: Understanding Energy Intensity Data in China, Carnegie Endowment for International Peace, 2011.

- Zhang, Q., Streets, D. G., He, K., Wang, Y., Richter, A., Burrows, J. P., Uno, I., Jang, C. J., Chen, D., Yao, Z., and Lei, Y.: NO_x emission trends for China, 1995-2004: The view from the ground and the view from space, *J. Geophys. Res.*, 112, D22306, doi:10.1029/2007jd008684, 2007.
- 5 Zhang, Q., Streets, D. G., Carmichael, G. R., He, K. B., Huo, H., Kannari, A., Klimont, Z., Park, I. S., Reddy, S., Fu, J. S., Chen, D., Duan, L., Lei, Y., Wang, L. T., and Yao, Z. L.: Asian emissions in 2006 for the NASA INTEX-B mission, *Atmos. Chem. Phys.*, 9, 5131–5153, 2009.
- Zhang, Q., He, K. B., and Huo, H.: Cleaning China's air, *Nature*, 484, 161–162, 2012.
- 10 Zhao, Y., Nielsen, C. P., Lei, Y., McElroy, M. B., and Hao, J.: Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China, *Atmos Chem Phys*, 11, 2295–2308, doi:10.5194/acp-11-2295-2011, 2011.
- Zheng, B., Huo, H., Zhang, Q., Yao, Z. L., Wang, X. T., Yang, X. F., Liu, H., and He, K. B.: High-resolution mapping of vehicle emissions in China in 2008, *Atmos. Chem. Phys.*, 14, 9787–9805, doi:10.5194/acp-14-9787-2014, 2014.

Table 1. The energy statistics for China involved in this work.

Energy Statistics	Data Source	National/ Provincial Level	Description
CT-CESY-Ori	NBS	National	For each year from 1990 to 2013, the original edition of the national Energy Balance Sheets published in the CESY was used.
CT-CESY-1C	NBS	National	For 1999-2003, the revised edition of the national Energy Balance Sheets released after the first economic census (published in CESY2005) was used; for other years, the data were the same as in CT-CESY-Ori.
CT-CESY-2C	NBS	National	For 1996-2007, the revised edition of the national Energy Balance Sheets released after the second economic census (published in CESY2009) was used; for other years, the data were the same as in CT-CESY-1C.
CT-CESY-3C	NBS	National	For 2000-2012, the revised edition of the national Energy Balance Sheets released after the third economic census (published in CESY2014) was used; for other years, the data were the same as in CT-CESY-2C.
PBP-CESY	NBS	Provincial	The provincial Energy Balance Sheets for each year published in the CESY were used.
CT-IEA-2012	IEA	National	China’s energy statistics from the IEA World Energy Balances (2012 edition) were used.

Note: CESY, China Energy Statistics Yearbook; NBS, National Bureau of Statistics; IEA, International Energy Agency. CESY2005, CESY2009 and CESY2014 denote the revised national energy data for the periods of 1999-2003, 1996-2007 and 2000-2012, which were released after the first, second and third economic censuses, respectively. **Note that the IEA energy statistics were used for comparison, but they were excluded from the uncertainty calculations in the current work.**

Table 2. Apparent uncertainties in China’s emissions in 2012 by sector and energy type. The apparent uncertainties are expressed in units of Tg. The percentages shown in parentheses indicate the apparent uncertainty ratios. Note that the emission uncertainties shown here are only those associated with energy uncertainties.

	CO ₂	NO _x	SO ₂	PM _{2.5}	VOC
Total	1633 (15.6%)	4.68 (16.4%)	7.76 (30.0%)	1.10 (9.2%)	1.90 (7.7%)
Power	90 (2.7%)	0.31 (3.3%)	0.25 (3.7%)	0.02 (2.7%)	0.00 (2.6%)
Industry	1196 (23.5%)	3.39 (34.7%)	6.04 (38.3%)	0.51 (8.6%)	1.00 (6.2%)
Residential	201 (16.0%)	0.17 (15.6%)	1.42 (46.0%)	0.50 (11.0%)	0.33 (5.3%)
Transportation	149 (18.3%)	0.81 (9.9%)	0.05 (17.6%)	0.06 (11.6%)	0.58 (25.0%)
Coal	1350 (18.8%)	3.57 (19.7%)	7.58 (32.8%)	1.03 (32.9%)	1.28 (44.3%)
Petroleum	193 (19.0%)	0.90 (10.5%)	0.20 (23.8%)	0.07 (12.0%)	0.59 (25.1%)
NG	52 (20.0%)	0.05 (17.7%)	0	0	0.003 (23.7%)
Other fuels	47 (4.7%)	0.16 (11.3%)	0	0.001 (0.02%)	0.02 (0.5%)

Table 3. Emission trends for China derived from different energy statistics (growth rate, %).

Energy Statistics	CO ₂	NO _x	SO ₂	PM _{2.5}	VOC	CO ₂	NO _x	SO ₂	PM _{2.5}	VOC
	1996-2003					2004-2012				
CT-CESY-Ori	22.9	38.0	14.3	-1.6	29.5	70.8	48.4	-18.8	-11.2	45.4
CT-CESY-1C	25.6	40.8	17.9	-0.9	29.9	70.8	48.4	-18.8	-11.2	45.4
CT-CESY-2C	34.1	43.1	28.9	2.5	35.2	62.9	44.1	-23.7	-12.7	42.5
CT-CESY-3C	35.8	44.5	30.2	3.5	36.2	75.9	54.6	-10.6	-9.9	45.7
PBP-CESY	35.5	47.5	28.0	1.9	47.8	91.8	77.6	1.6	-4.9	53.7
	1996-2000					1996-2012				
CT-CESY-Ori	-5.4	8.5	-13.7	-11.9	9.2	145	139	7.2	-8.5	108
CT-CESY-1C	-0.2	13.6	-6.6	-10.2	10.2	145	139	7.2	-8.5	108
CT-CESY-2C	6.3	15.5	2.5	-7.4	14.6	149	136	10.1	-6.7	112
CT-CESY-3C	3.2	13.0	-2.3	-7.7	13.2	172	157	30.9	-2.6	119
PBP-CESY	5.4	12.4	1.4	-8.7	14.7	191	197	45.1	0.7	130

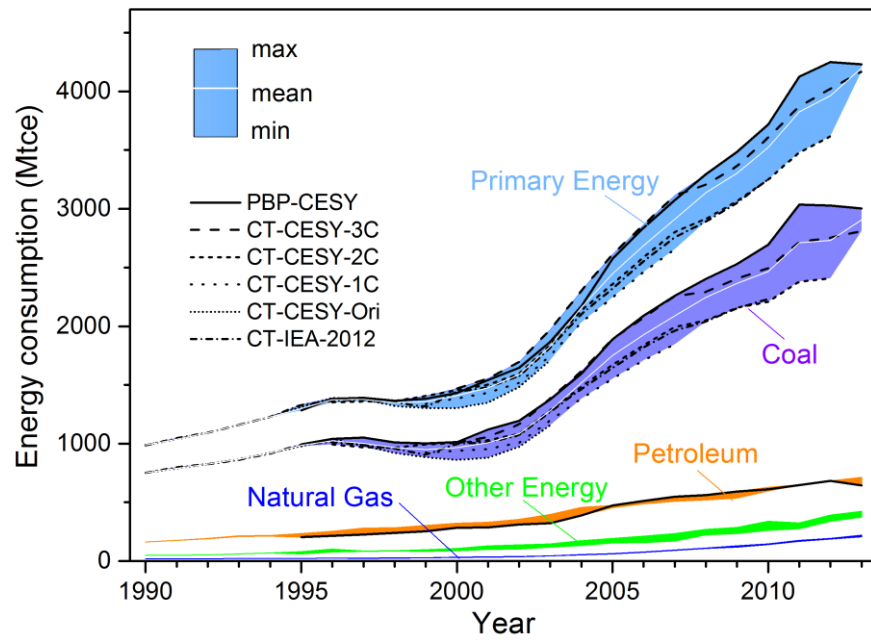


Figure 1. Apparent uncertainties (shown as filled areas) in China's energy consumption from 1990 to 2013, by energy type. Note that CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C and CT-CESY-3C are shown for 1990-2003, 1999-2007, 1996-2012 and 2000-2013, respectively.

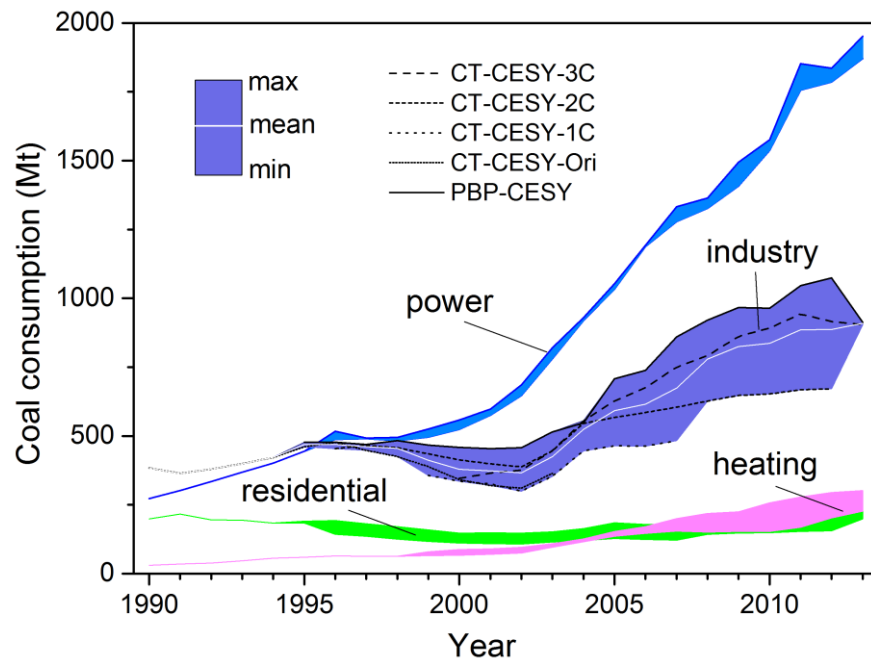


Figure 2. Apparent uncertainties (shown as filled areas) in China's coal consumption from 1990 to 2013, by sector. Note that CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C and CT-CESY-3C are shown for 1990-2003, 1999-2007, 1996-2012 and 2000-2013, respectively.

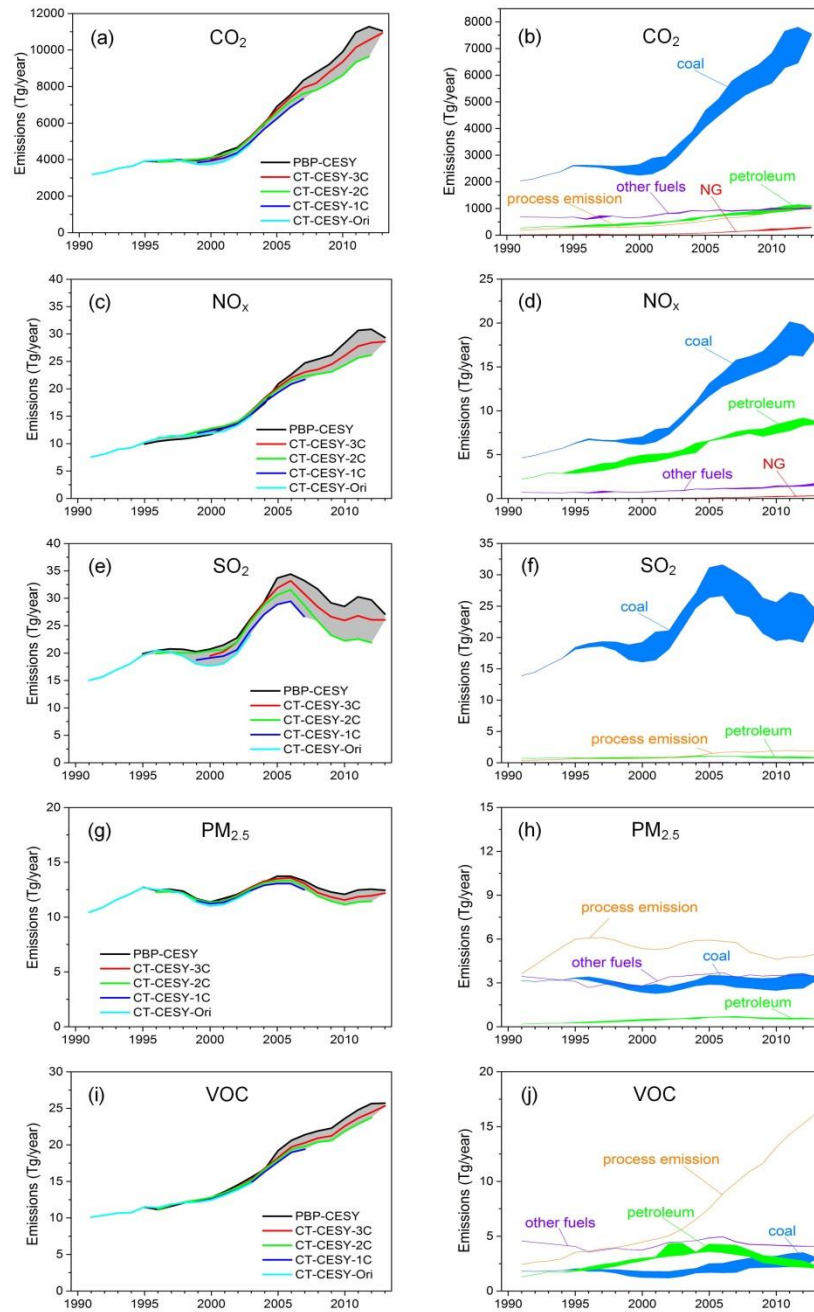


Figure 3. Apparent uncertainties (shown as filled areas) in China's emissions during 1990-2013: (left) uncertainties in total emissions; (right) uncertainties by energy type. Note that the emission uncertainties shown here are only those associated with energy uncertainties. Note also that CT-CESY-Ori, CT-CESY-1C, CT-CESY-2C and CT-CESY-3C are shown for 1990-2003, 1999-2007, 1996-2012 and 2000-2013, respectively.

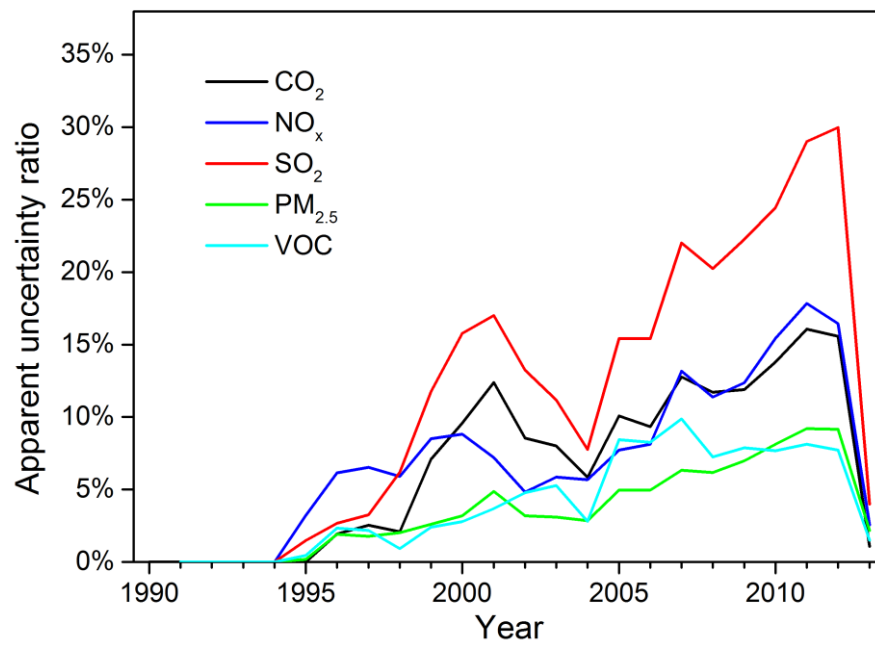


Figure 4. Apparent uncertainty ratio in China's emissions during 1990-2013. Note that the emission uncertainties shown here are only those associated with energy uncertainties.

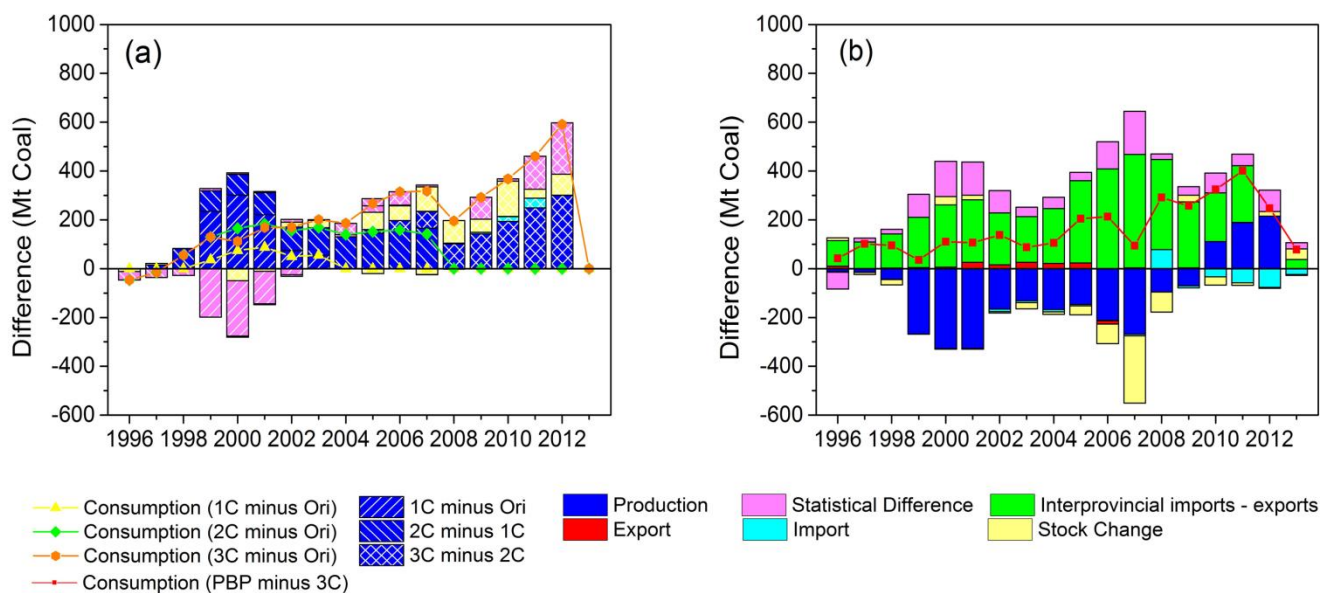


Figure 5. Differences in coal consumption between different energy statistics, from the supply perspective: (a) CT-CESY-1C (1C)/CT-CESY-2C (2C)/CT-CESY-3C (3C) minus CT-CESY-Ori (Ori); and (b) PBP-CESY (PBP) minus CT-CESY-3C (3C).

5 From the supply perspective, consumption = production - exports + imports + change in stock + statistical difference.

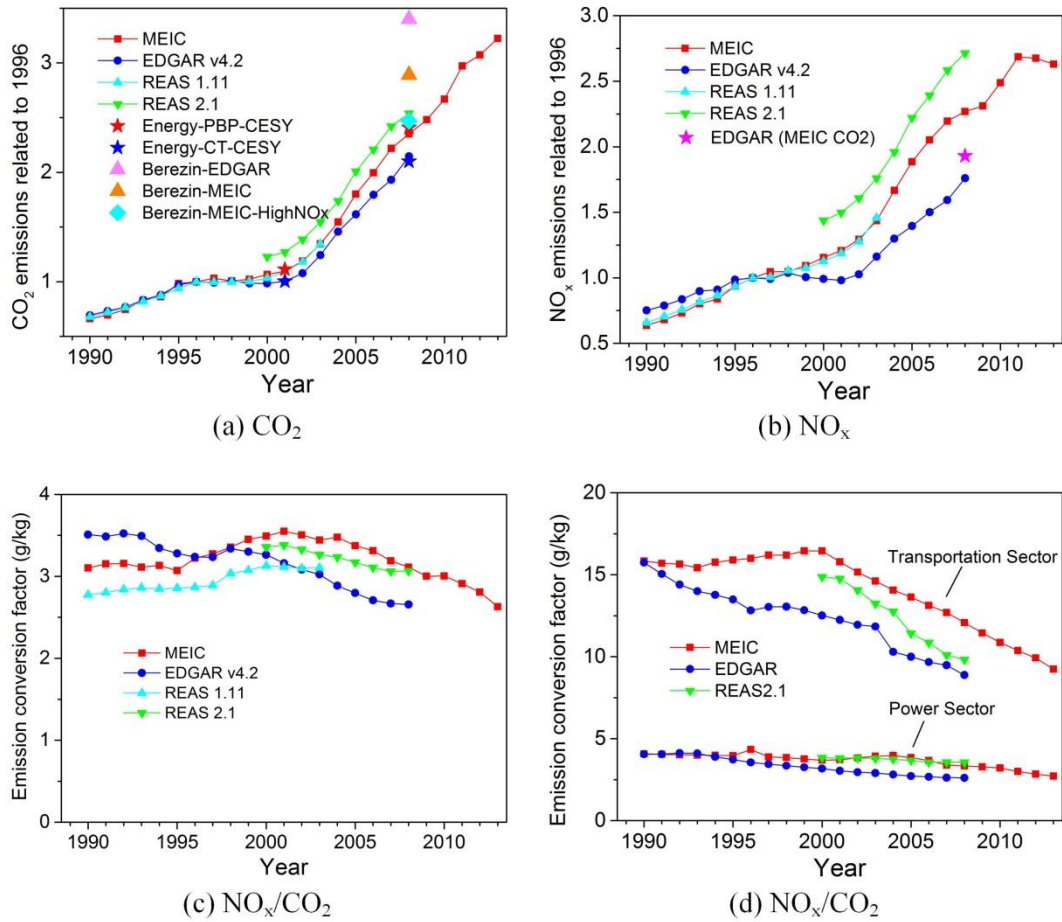


Figure 6. (a) CO_2 and (b) NO_x emission trends in China and the temporal evolution of the overall NO_x -to- CO_2 ratio (c) from different inventories and (d) in different major sectors according to the MEIC, EDGAR v4.2 and REAS (v1.11 and v2.1) emission inventories. The following trends (2008 values relative to 1996 values) are also shown: trends in total energy consumption from PBP-CESY (Energy-PBP-CESY) and CT-CESY-Ori (Energy-CT-CESY); NO_x emission trends calculated using the CO_2 trend from MEIC and the NO_x -to- CO_2 ratios from EDGAR (EDGAR - MEIC CO_2); and satellite-derived CO_2 emission trends from Berezin et al. (2013) derived using the CO_2 -to- NO_x ratios from EDGAR (Berezin-EDGAR), MEIC (Berezin-MEIC) and the lower boundary of MEIC (Berezin-MEIC-HighNO_x).