RC3

General comments:

This manuscript analyzes and compares six bottom-up inventories and assesses their uncertainty. This work compares different inventories from international and domestic teams, and it will be useful to the global stocktake and accurately assess China's CO_2 emissions. The topic is interesting and meaningful, but many statements and explanations in the manuscripts are not rigorous enough. I suggest more modifications and improvements before acceptance.

Special comments:

1. Is it reasonable to use the mean and SD to assess the uncertainty of these emission inventories?

Response: We appreciate the reviewer's valuable question. Using the mean and standard deviation (SD) to assess inter-inventory variability is statistically reasonable and consistent with previous studies (Han et al., 2020; Li et al., 2017). Besides, the coefficient of variation (CV), calculated as SD/mean, is employed here to quantify uncertainties at both national and provincial scales. This metric has also been used in previous studies to assess the accuracy of emission-related activity data (Zhao et al., 2011) and determine CO_2 mole fraction variations (Christian, 2018). Compared with SD alone, CV more effectively reflects the relative magnitude of variability with respect to the mean value.

References:

Christian, E.: Evaluation of Anthropogenic Carbon Dioxide (CO2) Concentrations along River Nworie, Imo State, Nigeria, Environment Pollution and Climate Change, https://doi.org/10.4172/2573-458X.1000159, 2018.

Han, P., Zeng, N., Oda, T., Lin, X., Crippa, M., Guan, D., Janssens-Maenhout, G., Ma, X., Liu, Z., Shan, Y., Tao, S., Wang, H., Wang, R., Wu, L., Yun, X., Zhang, Q., Zhao, F., and Zheng, B.: Evaluating China's fossil-fuel CO_2 emissions from a comprehensive dataset of nine inventories, Atmospheric Chemistry and Physics, 20, 11371–11385, https://doi.org/10.5194/acp-20-11371-2020, 2020.

Li, M., Zhang, Q., Kurokawa, J., Woo, J.-H., He, K., Lu, Z., Ohara, T., Song, Y., Streets, D. G., Carmichael, G. R., Cheng, Y., Hong, C., Huo, H., Jiang, X., Kang, S., Liu, F., Su, H., and Zheng, B.: MIX: a mosaic Asian anthropogenic emission inventory under the international collaboration framework of the MICS-Asia and HTAP, Atmos. Chem. Phys., 17, 935–963, https://doi.org/10.5194/acp-17-935-2017, 2017.

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, Atmospheric

Chemistry and Physics, 11, 2295–2308, https://doi.org/10.5194/acp-11-2295-2011, 2011.

2. Activity data and emission factors are the two important factors that influence the emission inventory. I also suggest adding this important information to Table 1, although point, line, and area source proxies are listed.

Response: We thank the reviewer for this helpful suggestion. We agree that including information on activity data and emission factors is essential for understanding the basis of each inventory. Accordingly, we have added this information to Table 1, as shown below, to clearly indicate the data sources used by each inventory.

Table 1. Specification of emission inventory statistics.

	ODIAC	EDGAR	MEIC	CAMS	GEMS	CEADs
Version	ODIAC2023	EDGAR2024	v1.0	v6.2	v1.0	NA
Domain	Global	Global	Global	Global	Global	China
Temporal coverage	2000-2022	1970-2023	1970-2023	2000-2026	1700-2019	1997-2021
Time resolution	Monthly or annual	Monthly or annual	Monthly or annual	Monthly or annual	Monthly or annual	Annual
Activity data	**CDIAC, BP**	**IEA**	**CESY, IEA, BP**	**EDGAR, CAMS-GLOB-Ship**	**NBS, IEA**	**CESY, NBS**
Emission factors	**IPCC**	**IPCC**	**CEADs, national submissions in UNFCCC, IPCC**	**EDGAR**	**Literature, on-site measurements**	**on-site measurements**

3. The Chinese government also reports national greenhouse gas emissions to the UNFCCC. I think it is better to compare the national CO_2 emissions between government-reported data and the six bottom-up inventory data mentioned in this study.

Response: We thank the reviewer for this helpful suggestion. We have now included the National Greenhouse Gas Inventory (NGHGI) data submitted by the Chinese government to the UNFCCC for national-level comparison. Figure 1 has been revised to incorporate the NGHGI data. To assess the consistency of the six inventories (2000–2023), we calculated the mean absolute difference (MAD) of each inventory relative to both the NGHGI and the six-inventory mean. The results show that CAMS exhibits the greatest consistency with the NGHGI, while ODIAC agrees most closely with the six-inventory mean. These additions help provide an independent benchmark for evaluating the overall agreement of the inventories at the national scale.

Revision:

(1) ***Section 2, paragraph 2:*** *"In addition to these six datasets, the National Greenhouse Gas Inventory (NGHGI) submitted by the Chinese government to the United Nations Framework Convention on Climate Change (UNFCCC, available at: https://unfccc.int/reports) was also collected. The NGHGI provides the officially reported national total emissions and therefore serves as an independent benchmark for evaluating the reliability of the six inventories. As NGHGI covers only discrete years (2005, 2010, 2012, 2014, 2017, 2018, 2020, and 2021), it is not included in the continuous temporal analysis but is used solely for national-level comparison."*

(2) ***Section 3.1, paragraph 2:*** *"To further assess the consistency of the six inventories, we calculate the mean absolute difference (MAD), which is defined as the multi-year mean of annual absolute differences between each inventory and either the NGHGI or the six-inventory mean. Compared with NGHGI, the MADs range from 0.156 Gt year^{-1} (CAMS) to 0.835 Gt year^{-1} (MEIC). Against the six-inventory mean, the MADs range from 0.12 Gt year^{-1} (ODIAC) to 0.449 Gt year^{-1} (MEIC). EDGAR reports the highest emissions, which is about 0.370 Gt year^{-1} larger than the mean emission. MEIC shows the lowest emission levels, which is about 0.449 Gt year^{-1} less than the mean emission. Overall, CAMS exhibits the greatest consistency with the NGHGI, being at least 30% lower than that of the other inventories. In comparison, ODIAC agrees most closely with the six-inventory mean, with an MAD at least 58% lower than the others."*

(3) ***Section 4, paragraph 1:*** *"China's annual anthropogenic CO_2 total emission increases from 3.42 Gt in 2000 to 12.03 Gt in 2023. When compared with the officially reported NGHGI and the six-inventory mean, CAMS shows the smallest deviation from the NGHGI, while ODIAC agrees most closely with the multi-inventory mean. The six inventories display a broadly consistent emission trend, but their discrepancies among the inventories have widened from 0.41 Gt year^{-1} to 1.63 Gt year^{-1}, …"*

(4) ***Section 4, paragraph 4:*** *"…The pronouncedly higher emissions in the coastal megacities (e.g., Shanghai, Jiangsu, and Guangdong) by ODIAC and the abnormal increase in CAMS by 50-230% in Liaoning, Hubei, and Shanghai exacerbate this divergence. Despite these inconsistencies, CEADs and MEIC exhibit broadly consistent estimates across nine provinces, especially in Inner Mongolia, Shandong, Henan, Hubei, and Shanghai."*

Section 3.1, Figure 1:

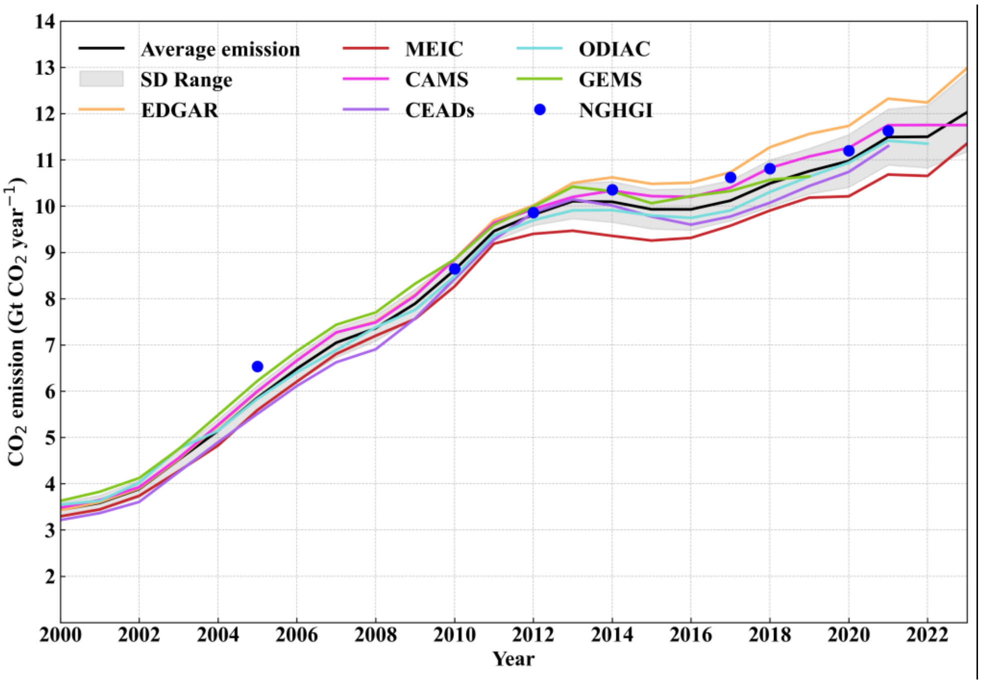


Figure 1. *Annual anthropogenic CO_2 emissions in mainland China from 2000 to 2023, as reported by six emission inventories: EDGAR, MEIC, CAMS, CEADs (up to 2021), ODIAC (up to 2022), and GEMS (up to 2019), and one government-reported data (NGHGI). Apart from ODIAC, all inventories provide national totals directly. We calculated China's emissions by summing the grid values within China for ODIAC. The shaded area indicates the standard deviation of the six inventories. It's noteworthy that the inter-inventory mean and SD were calculated from the above mentioned six inventories.*

4. Line 168-174. Many studies report that China's emissions peaked in 2013 or 2014, so the first phase is better set as 2000-2013 or 2014. Also, the second phase is mainly due to the air control policy, besides the adjustment of energy and industrial structure.

Response: We thank the reviewer for this valuable comment. It's important to identify the corresponding year of China's emissions peak. Accordingly, we have adjusted the phase division in our analysis to set the first phase as 2000–2013 and the second phase as 2013–2016. We also acknowledge that the emission stabilization during the second phase is influenced not only by energy structure adjustments and industrial upgrading under China's 12th Five-Year Plan, but also by the implementation of air clean policy since 2013 (Han et al., 2020b; Shi et al., 2022; Zheng et al., 2025). The corresponding text and linear regression statistics in the first and second emission phase has been revised for clarity.

Revision:

(1) ***Abstract:*** *"…The national total CO_2 emissions increase from 3.43 (3.21–3.63) Gt year^{-1} in 2000 to 12.03 (11.35–12.98) Gt year^{-1} in 2023, with three growth periods: rapid growth (2000–2013, 0.56±0.013 Gt year^{-1}), near-stagnation (2013–2016, -0.07±0.022 Gt year^{-1}), …"*

(2) ***Section 3.1, paragraph 3:*** *"The increase in CO_2 emissions shows three different phases (Fig. 1, Table 2). The first phase (2000–2013) shows the most rapid growth, with an average growth rate of* 0.56 ± 0.013 *Gt year^{-1}, driven by industrialization, urbanization, and rising energy demand. In*

contrast, emissions become relatively stable from 2013 to 2016, with all inventories showing a slight decline (-0.07 ± 0.022 Gt year^{-1} on average). This short-term stagnation is mainly influenced by the adjustment of energy structure and industrial upgrades under China's 12th Five-Year Plan, and the implementation of air clean policy since 2013 (Han et al., 2020b; Shi et al., 2022; Zheng et al., 2025). …"

(3) ***Section 4, paragraph 2:*** *"The six inventories in this study agree on three emission phases: a rapid increase of 0.56 ± 0.013 Gt year^{-1} (2000–2013), a near-stagnation phase of -0.07 ± 0.022 Gt year^{-1} under the 12th Five-Year Plan and air clean policy (2013–2016), …"*

5. Line 180-185. Although the global stocktake is held every five years, the stocktake assesses the achievement of NDCs of each country. Also, the baseline year of the Chinese 2020 and 2030 carbon reduction targets is 2005. I suggest the authors rewrite these sentences.

Response: We thank the reviewer for this insightful suggestion. According to the *Paris Agreement* (Article 14; UNFCCC, 2015), the first global stocktake is scheduled for 2023, followed by subsequent assessments every five years. In light of this, we revised the text to clarify that our five-year interval analysis is designed to correspond with the global stocktake cycle rather than the Nationally Determined Contributions (NDC) baseline year of 2005. Accordingly, we use 2003 as the starting point for the first five-year assessment period and have rewritten the sentences to reflect this rationale.

Revision:

Section 3.1, paragraph 4: *"In response to the Paris Agreement's requirement of a global stocktake every five years starting in 2023 (https://unfccc.int/sites/default/files/paris_agreement_english_.pdf), we analyze China's emissions variation every five years, using 2003 as the baseline year corresponding to the first global stocktake (Fig. 2). The highest growth is recorded in the period from 2003 to 2008 (> 0.52 Gt year^{-1}) and 2008-2013 (> 0.45 Gt year^{-1}), followed by a stable period in the years from 2013 to 2018, in which the CEADs even records a slight decline (-0.01 Gt year^{-1}). Growth then resumed in 2018-2023, averaging 0.21 Gt year^{-1}."*

Section 3.1, paragraph 4:

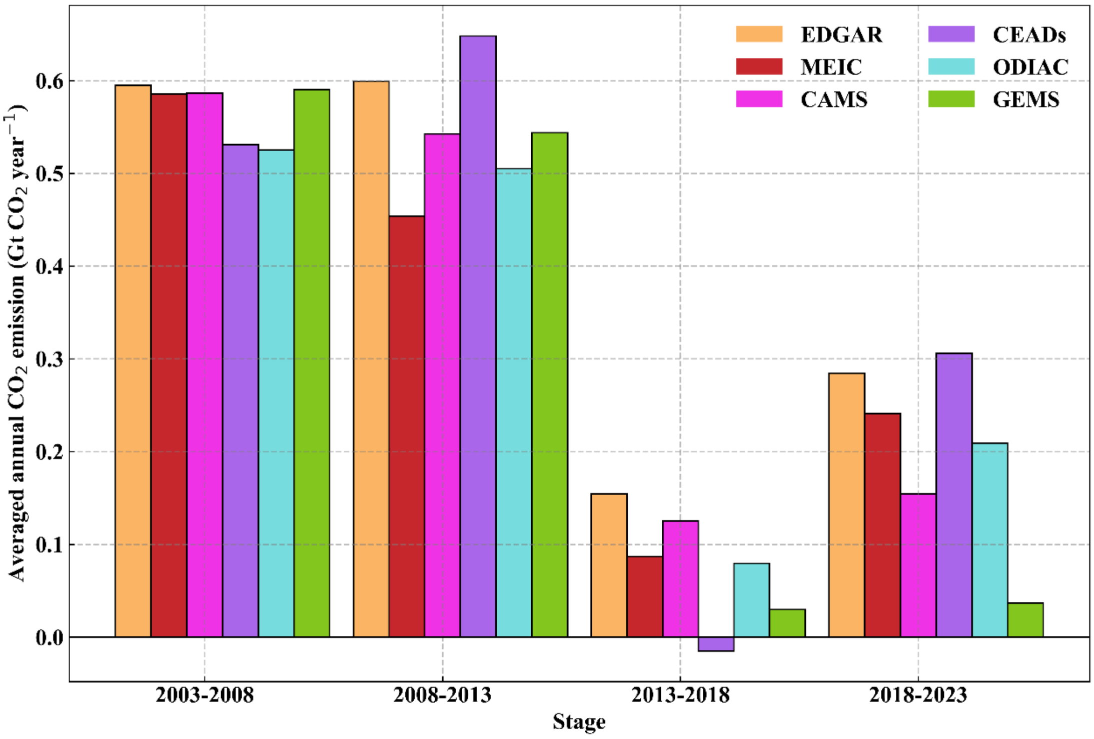


Figure 2. *Average annual CO_2 emission growth rate during the five-year periods.*

6. Figure 4. Point and line sources of CAMS originated from EDGAR (Table 1). Why is the line source information lost in Figure 4d, especially in western China? Furthermore, the map of means (Figure 4f), most of the line and area information was lost.

Response: We thank the reviewer for this valuable comment. We have carefully examined the sectoral emissions of CAMS and found that the spatial gaps over western China are not due to missing line or point source data but rather to the absence of aviation emissions. Specifically, CAMS includes only three transportation subsectors—Off-road transportation, Road transportation, and Ships—but does not account for aircraft emissions. To verify this, we compared the spatial distributions of transportation emissions among EDGAR, CAMS, MEIC, and GEMS (ODIAC does not provide sectoral data). As shown in Figure S1 below, EDGAR, MEIC, and GEMS all display distinct emission patterns along major flight corridors over western China, while CAMS only shows road transport patterns. This confirms that the absence of aviation emissions in CAMS leads to the spatial gaps observed in that region. We have added this explanation to Section 3.2.1 to enhance clarity and integrity of our research.

Regarding the mean emission map (Fig. 4f), only grid cells with valid values in all inventories were included in the averaging. Therefore, regions appearing blank correspond mainly to areas where ODIAC lacks valid data, rather than to missing spatial information in the other inventories.

Revision:

Section 3.2.1, paragraph 1: *"…, while regions with limited nighttime lighting, including both sparsely populated areas and areas with high population but limited lighting, such as Western Sichuan, Inner Mongolia, and Xinjiang, are not captured. By contrast, the spatial gaps over western China in CAMS (Fig. 4d) mainly arise from the lack of aviation emissions. CAMS accounts for transport emissions from road, off-road, and ships but omits aviation. As shown in Figure S1, EDGAR, MEIC, and GEMS capture distinct emission bands along major flight corridors over western China, whereas CAMS only shows the road transport pattern, explaining the missing emissions over western China."*

Section 7, Figure S1:

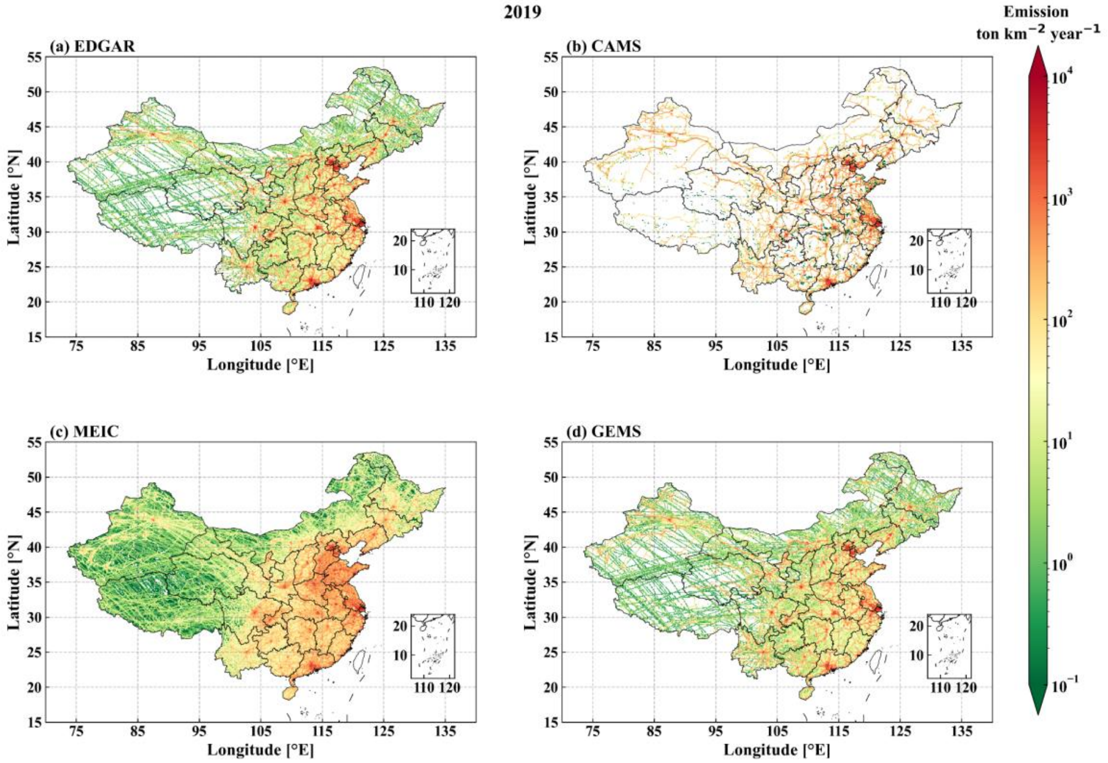
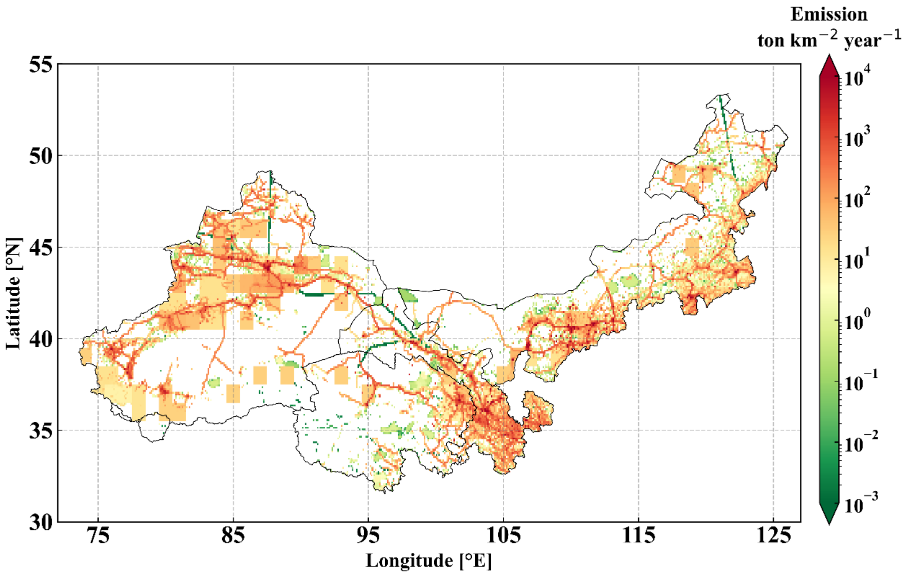


Figure S1. *Spatial distribution of CO_2 emissions from transport sector in 2019 across four inventories (EDGAR, CAMS, MEIC, and GEMS).*

7. Figure 5c. Why are there some squares with high values in the west and northeast China?

Response: We thank the reviewer for this insightful comment. As noted above, we only analyzed grid cells with valid values in both inventories. The squared patches visible in Fig. 5c mainly occur in Xinjiang, Qinghai, Gansu, and Inner Mongolia. To verify their origin, we extracted CAMS emissions for these provinces, as shown in the figure below. The results indicate that these squared patterns originate from the CAMS dataset itself.



CAMS emission distribution in selected provinces (Xinjiang, Qinghai, Gansu, and Inner Mongolia).

8. Figure 7. Why is the CEADs province data nearly ten times higher than other inventories in Shanxi Province?

Response: We thank the reviewer for this insightful comment. We examined CO_2 emissions from CEADs (sectors) and CEADs (provinces) for Shanxi and found that the large discrepancy mainly arises from differences in raw coal–related emissions, which is the dominant contributor to total emissions (Wei, 2022). As shown in the figure below, CO_2 emissions from raw coal in CEADs (provinces) are on average 664.71 Mt year^{-1} higher than those in CEADs (sectors), leading to an overall mean difference of 512.18 Mt year^{-1} between the two datasets. We have included this figure in the supplementary material and revised the manuscript to clarify the source of the discrepancy in Shanxi's CEADs emissions.

Revision:

(1) ***Section 3.3.1, paragraph 1:*** *"…In contrast, the CEADs (sectors) closely matches the other five independent inventories (ODIAC, EDGAR, MEIC, CAMS and GEMS), with its mean emissions deviating by no more than 3.84 Mt year^{-1} from the average of the five inventories. <u>The large discrepancy between CEADs (provinces) and CEADs (sectors) mainly originates from the much higher raw coal–related emissions in CEADs (provinces) (Fig. S3), as coal is the dominant contributor to total emissions (Wei, 2022).</u>"*

Section 7, Figure S3:

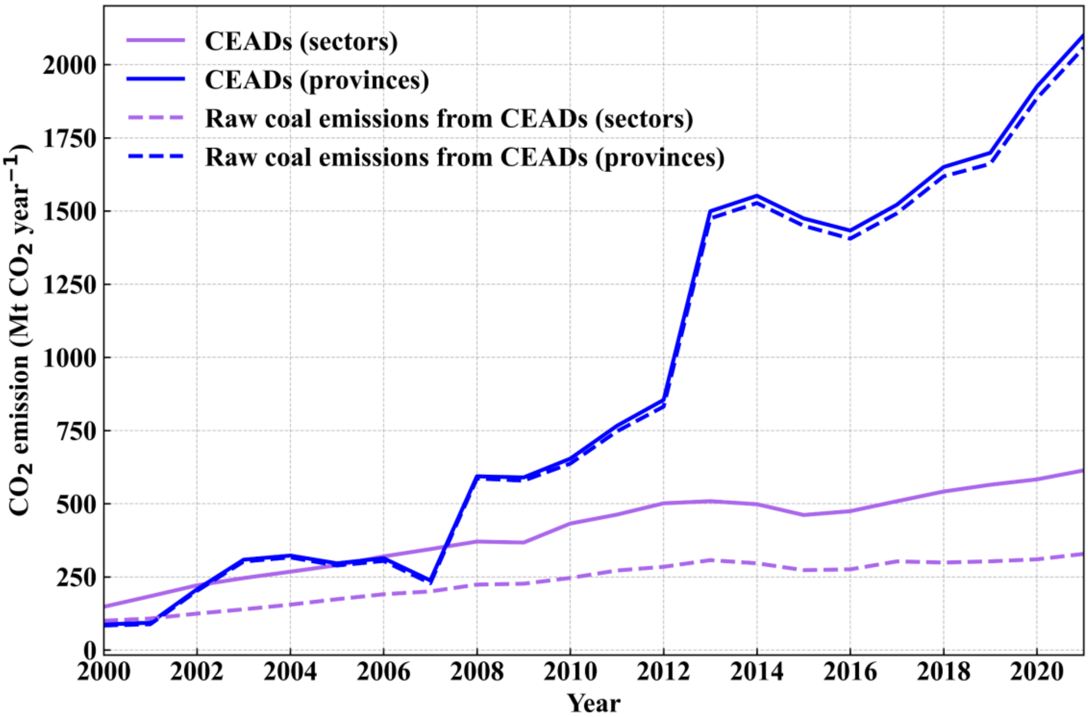


Figure S3. *Comparison of total CO_2 emissions and raw coal–related CO_2 emissions in Shanxi from CEADs (sectors) and CEADs (provinces) during 2000–2020. Solid lines represent total emissions, while dashed lines indicate emissions from raw coal combustion.*

Reference:

Wei, C.: Historical trend and drivers of China's CO2 emissions from 2000 to 2020, Environ Dev Sustain, 1–20, https://doi.org/10.1007/s10668-022-02811-8, 2022.

9. Figure 8. EAGAR and MEIC are the highest and lowest inventories for national CO_2 emissions, but these values varied at the provincial level. What are the key factors that affected these results? For example, CAMS had the highest values in Liaoning, Hubei provinces and Shanghai but the lowest in Hebei and Shandong provinces.

Response: We appreciate the reviewer's insightful question regarding the provincial variations among inventories. The inconsistency between EDGAR and MEIC at the national and provincial scales likely arises from their different downscaling methods. Differences in spatial proxies can significantly affect the spatial distribution of sectoral emissions, as illustrated by the contrasting transport emission patterns in EDGAR and MEIC (Section 3.2.2).

Although CAMS uses EDGAR emission data as its primary foundation, it also incorporates additional spatial proxies like CAMS-GLOB-Ship for sectoral allocation (Soulie et al., 2024). Consequently, CAMS may assign relatively higher emissions to provinces like Liaoning, Hubei, and Shanghai, while allocating lower values to Hebei and Shandong, depending on how industrial, transport, and energy-use proxies are spatially represented. Therefore, while inventories may show consistent national totals, differences in spatial proxy selection and downscaling methods can lead to noticeable discrepancies at the provincial scale.

Reference:

Soulie, A., Granier, C., Darras, S., Zilbermann, N., Doumbia, T., Guevara, M., Jalkanen, J.-P., Keita, S., Liousse, C., Crippa, M., Guizzardi, D., Hoesly, R., and Smith, S. J.: Global anthropogenic emissions (CAMS-GLOB-ANT) for the Copernicus Atmosphere Monitoring Service simulations of air quality forecasts and reanalyses, Earth Syst. Sci. Data, 16, 2261–2279, https://doi.org/10.5194/essd-16-2261-2024, 2024.

10. Figures S1&S2, Why do SD and CV for Hubei and Guangdong decrease sharply in 2023?

Response: Thank you for your attention on this detail. We carefully rechecked the original provincial emission data and confirmed that there are no calculation or processing errors. The sharp decrease in the CV of Hubei and Guangdong in 2023 mainly results from the reduced number of available inventories. Specifically, by 2023, only three inventories—EDGAR, MEIC, and CAMS—provided data, whereas ODIAC, CEADs, and GEMS had ended earlier (GEMS in 2019, CEADs in 2021, and ODIAC in 2022).

As shown in Figures 8c and 8e, ODIAC consistently reported the highest emissions in Guangdong and the lowest in Hubei. The absence of ODIAC in 2023 therefore reduces the spread among inventories, leading to markedly lower SD and CV values in these two provinces. To illustrate this data-coverage effect, we have added shading in Figure S5 to indicate the years after 2019, when the number of available inventories began to decline.

Revision:

Section 7, Figure S5:

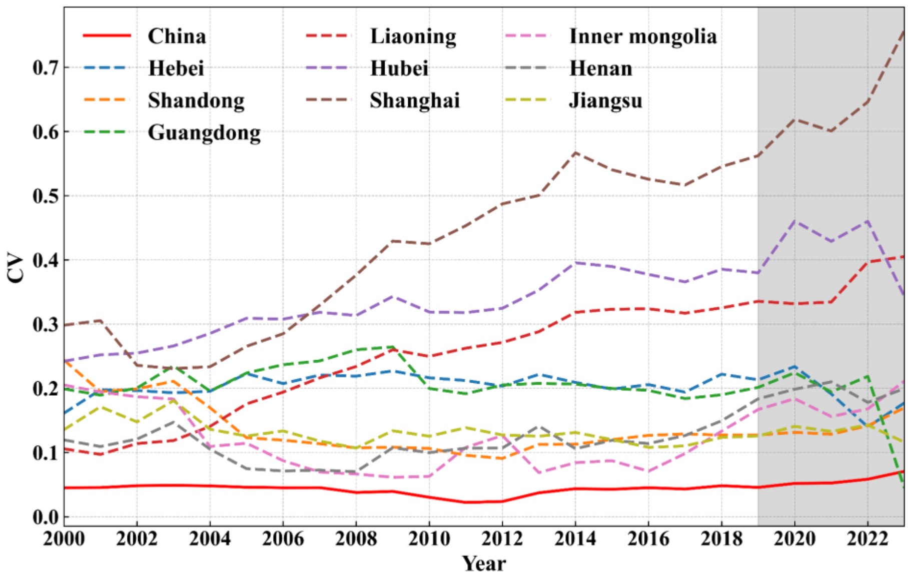


Figure S5. *Coefficient of variation (CV) of emissions at national level and for nine typical provinces during 2000-2023. <u>The shaded area represents the period after 2019, when the number of available emission inventories began to decrease (GEMS ended in 2019, CEADs in 2021, and ODIAC in 2022).</u>*

11. Table 1. Why can CAMS report the data in 2026 when it was published in 2023?

Response: We appreciate the reviewer's insightful comment. According to Soulie et al. (2024), CAMS uses EDGAR data as its primary input and applies the Community Emissions Data System (CEDS) to extrapolate emissions to recent years. In our analysis, CAMS v6.2 is based on EDGAR v7 (up to 2021) and extends the emissions estimates up to 2026. We have updated the Data and Methods section to clarify this point.

Revision:

Section 2.1, paragraph 4: "*CAMS is a global inventory developed as part of the Copernicus Atmosphere Monitoring Service project. It builds on EDGAR and integrates several complementary datasets, including the Community Emissions Data System (CEDS) <u>for the extrapolation of the emissions up to the current year</u>, the CAMS-GLOB-TEMPO <u>for monthly variability</u>, and the CAMS-GLOB-SHIP for ship emissions. …***"**

Reference:

Soulie, A., Granier, C., Darras, S., Zilbermann, N., Doumbia, T., Guevara, M., Jalkanen, J.-P., Keita, S., Liousse, C., Crippa, M., Guizzardi, D., Hoesly, R., and Smith, S. J.: Global anthropogenic emissions (CAMS-GLOB-ANT) for the Copernicus Atmosphere Monitoring Service simulations of air quality forecasts and reanalyses, Earth Syst. Sci. Data, 16, 2261–2279, https://doi.org/10.5194/essd-16-2261-2024, 2024.

12. Line 104. What does "BP plc" mean?

Response: We thank the reviewer for the question. "BP plc" refers to BP p.l.c., formerly known as British Petroleum. The company later adopted the abbreviation "BP" as its official name. It is a global energy company that publishes the BP Statistical Review of World Energy, which provides widely used energy activity data. This information has been added to the revised manuscript.

Revision:

Section 2.1, paragraph 1: *"…such as BP plc <u>(formerly the British Petroleum company p.l.c.)</u>, the United States Geological Survey (USGS), …"*