Response to Reviewer 2

Our comments are inset in blue colour following each point of the reviewers. The text quoted directly from the revised manuscript is set in italics. The line numbers cited in our response refer to the revised manuscript with no changes marked.

Guo et al presented (1990-2020) long-term, high-resolution emission inventory for mainland China. Building long-term methane emission inventory is hard work and the efforts by the authors are quite commendable. I also appreciate that the carbon community will have one more regional inventory to use/evaluate. A unique advantage of this work is the authors used statistical yearbook and remote sensing data to improve the temporal coverage.

Response: We sincerely appreciate the Reviewer's constructive suggestions. In the revised manuscript, we have significantly strengthened the revised manuscript by: 1) enhancing methodological descriptions on the usage of remote sensing products; 2) conducting comprehensive comparisons of CHN-CH4 with EDGAR v8, PKU-CH4 v2, and GFEI inventories; 3) performing extensive validation using 26 bottom-up estimates and 14 top-down inversions at both sectoral and national levels; and 4) thoroughly discussing uncertainty sources while refining all figures and clarifying text throughout.

1. My major concerns are on the spatial distributions. For the spatial distributions, the authors took them from existing inventories for some source sectors (FAO inventory for livestock, EDGAR inventory for coal, oil, gas, to some extent). Therefore, the authors found a better consistency with EDGAR than PKUv2, which is thus as expected. I was wondering if the authors can explicitly show maps between your results and EDGAR, and discuss in detail the extent to which your product has improved in spatial accuracy compared to existing inventories (e.g., EDGAR, as the authors stated in the Introduction, which is part of the motivation of this work). If the authors used spatial distribution from existing inventories, which are known to have spatial bias, the novelty of this work and the accuracy of this product demand more clarifications. I would suggest that the authors elaborate (in both text and figures) on this point. Doing so would improve the clarity and benefit the future readers and users of your product.

Response: In the revised manuscript, we enhanced the spatial analysis by incorporating existing inventories (GFEI, EDGAR, and PKU-CH4) for a comprehensive evaluation of CHN-CH4 (see

Figures 3 and 4 below). Among these, EDGAR shows the strongest spatial distribution agreement with CHN-CH4 (points clustered along the 1:1 line), while PKU-CH4 provides closer emission estimates. Spatially, CHN-CH4 displays higher emissions in North China (e.g., Shandong and Henan) but lower estimates in energy-intensive provinces (e.g., Shanxi and Sichuan), major rice-growing regions (e.g., Hunan and Jiangxi), and developed coastal areas (Figure 3). These discrepancies arise primarily from CHN-CH4's higher livestock emissions and lower estimates for coal mining, rice cultivation, and wastewater sectors. At the sectoral and national levels, we compiled 26 bottom-up estimates and 14 top-down inversions for comparison (Figure 5). The CHN-CH4 dataset reveals a clear increasing trend in total anthropogenic methane emissions from 1990 to 2020, though with moderate agreement to reference datasets. This divergence is largely driven by EDGAR's systematic overestimation, which exceeds CHN-CH4 by over 36% and PKU-CH4 by 30–40% (Peng et al., 2016), mainly due to overestimations for rice cultivation and wastewater. For other sectors, EDGAR's magnitude and variability align well with other inventories. We expanded the discussion of these findings in the revised manuscript and rewrote the Section 3.1, to better contextualize the inventory differences and their implications.

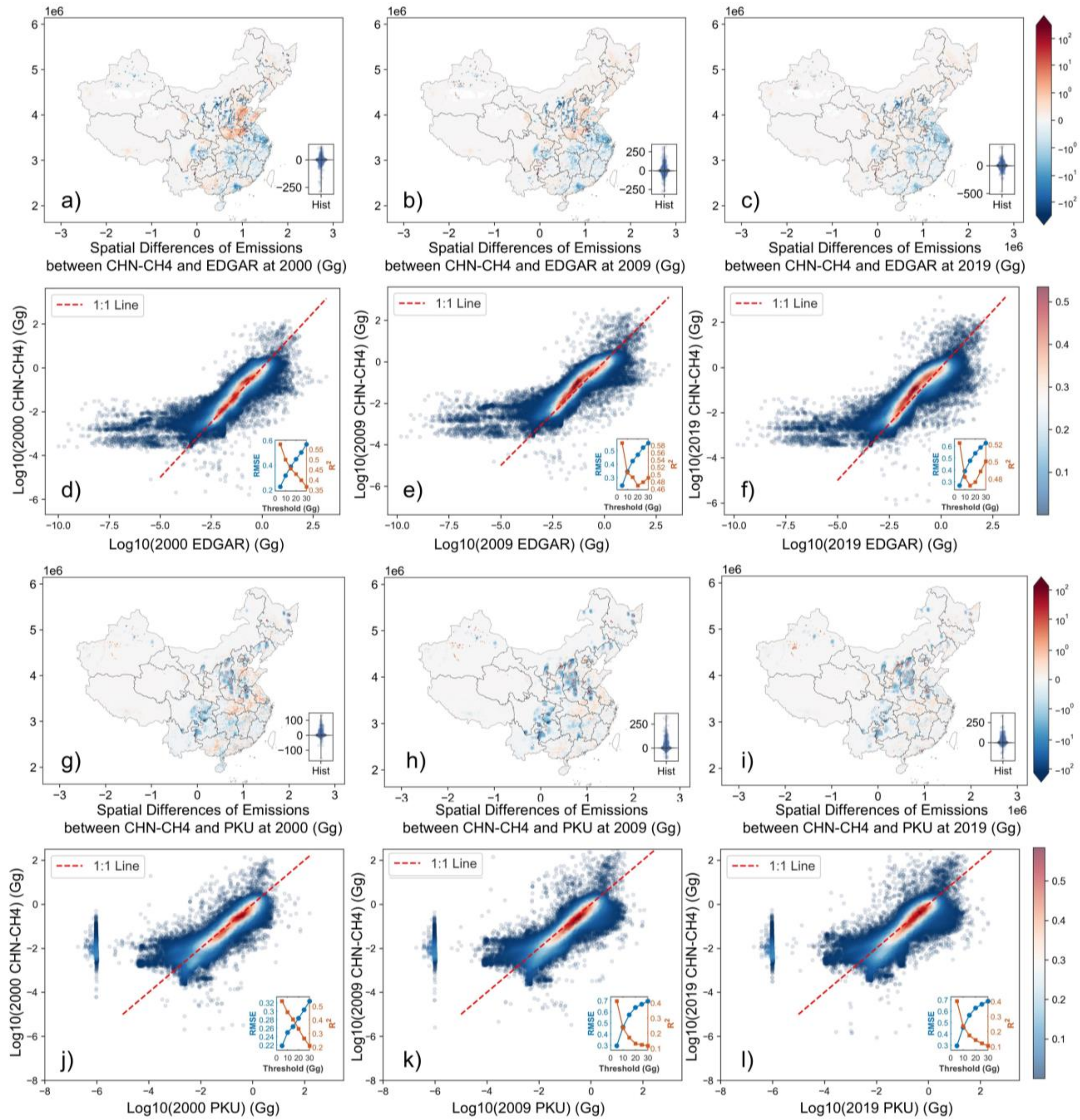

Figure 3. Pixel-level comparisons between CHN-CH4 and EDGAR/PKU-CH4. a-f) represent the comparison between CHN-CH4 and EDGAR v8, while g-l) represent the comparison between CHN-CH4 and PKU-CH4 v2 at year 2000, 2009, and 2019. 'Hist' in each spatial map represents the histogram of the differences between CHN-CH4 and EDGAR/PKU-CH4, with the unit Gg. The bottom-right subfigure in each log-log plot presents threshold-dependent performance metrics, demonstrating how $RMSE$ and R^2 vary when excluding grid cells over specific emission thresholds.

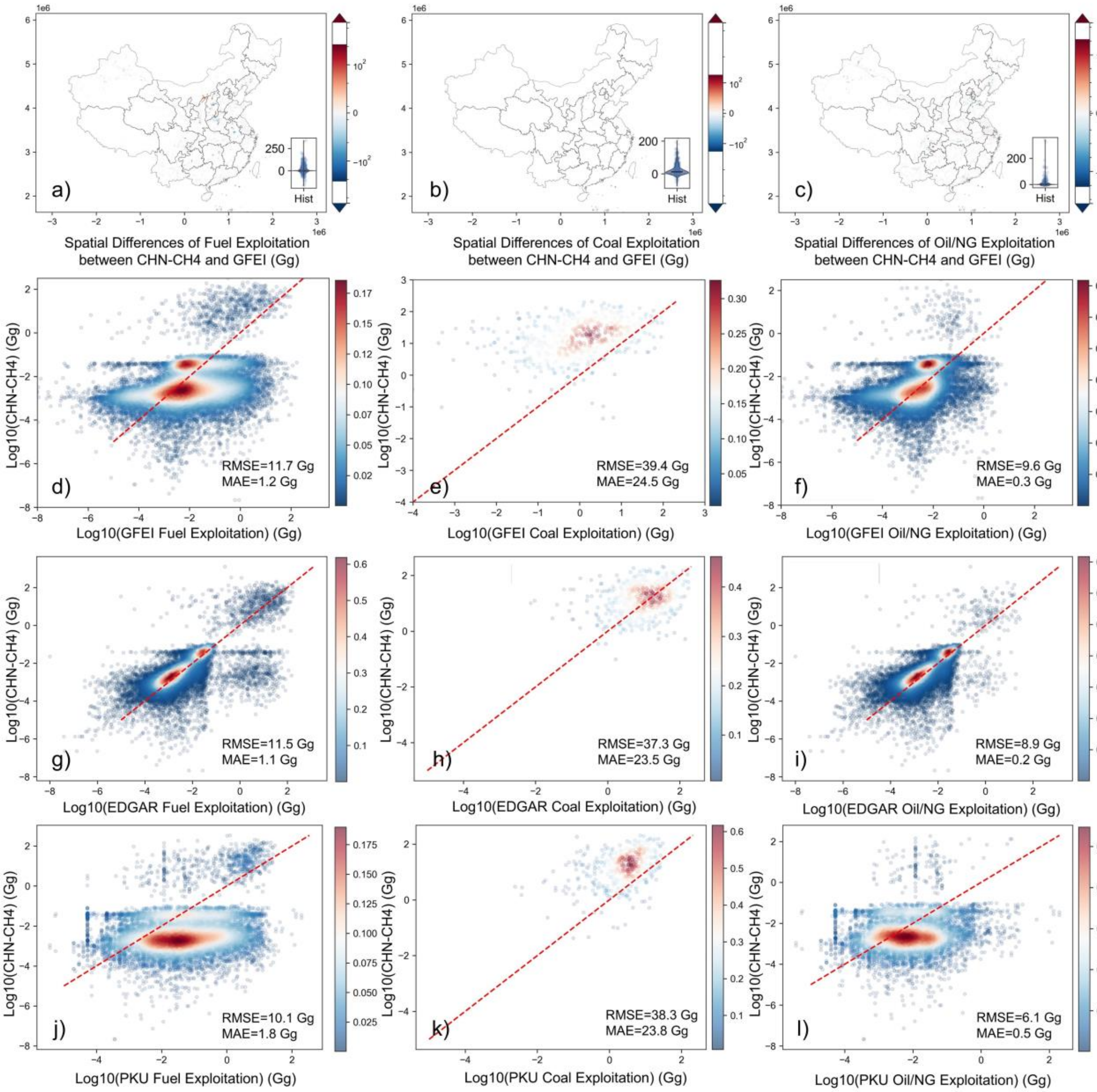

Figure 4. Pixel-level comparisons between CHN-CH4 and three inventories (GFEI, EDGAR, and PKU-CH4) in the energy sectors for 2019. a-c) show spatial differences between CHN-CH4 and GFEI. d-i) present log-log scatterplots of pixel-level emissions: CHN-CH4 versus GFEI (d–f), EDGAR (g–i), and PKU-CH4 (j-l), respectively.

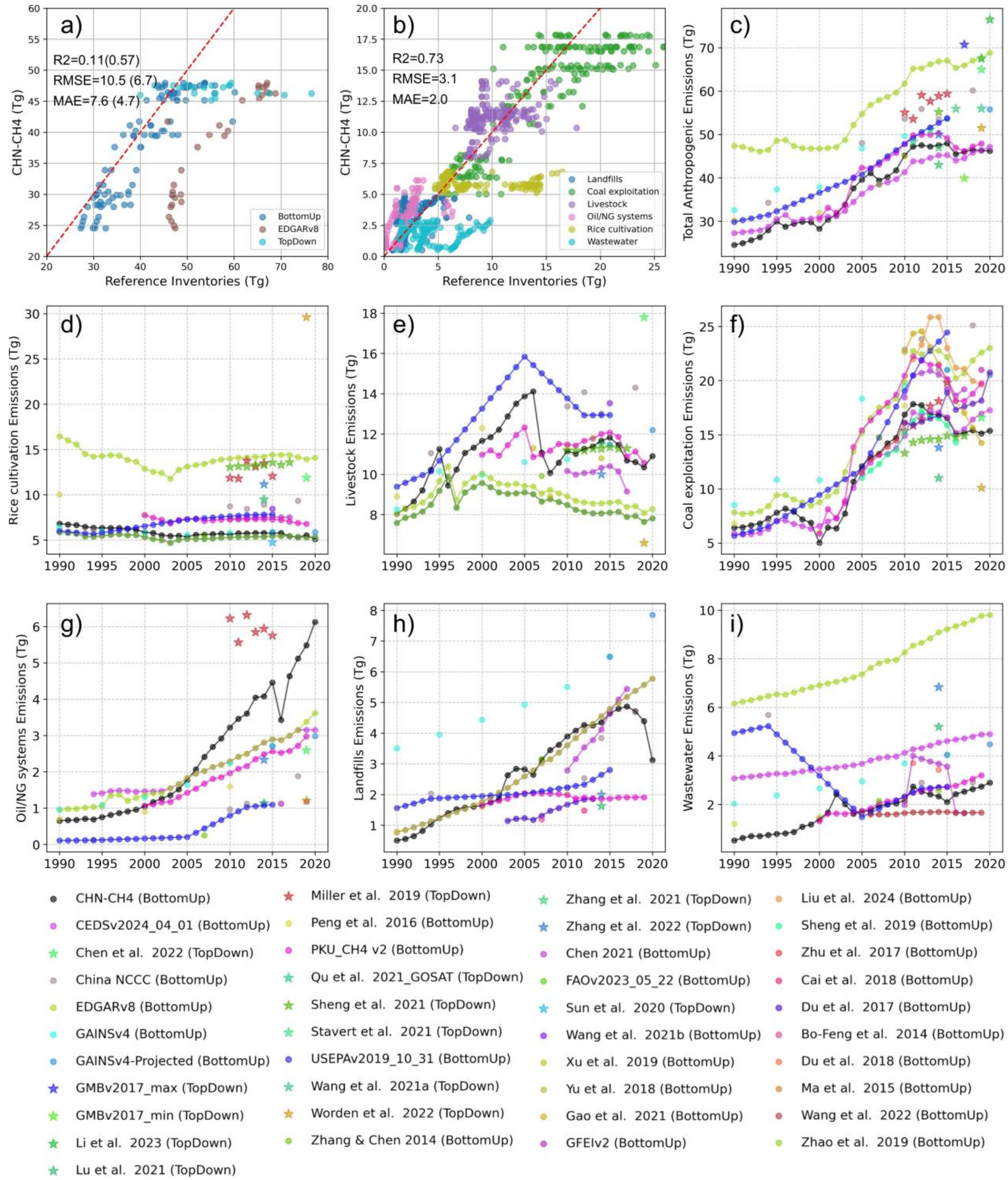

Figure 5. Sectoral and national comparisons between CHN-CH4 and reference inventories. a) National-level emission comparisons between CHN-CH4 and references, b) Combined sectoral emissions comparison across all inventory sources, c) Variations of total anthropogenic emissions of CHN-CH4 and references, and d-i) Individual sector-specific variations between

CHN-CH4 and the reference (rice cultivation, livestock, coal exploitation, Oil/NG systems, landfills, and wastewater, respectively). The red line is 1:1 line.

2. Another concern is the remote sensing dataset. The authors highlighted in the abstract and Fig. 1 that satellite remote sensing are substantially used in their work. But I failed to find such use in a clear way. For example, for rice paddies, the authors claimed that ‘Due to the limitations of existing satellite products, which do not cover the entire period from 1990 to 2020, we used two datasets for gridded rice cultivation areas annually: CCD-Rice for the period 1990-2016 (Shen et al., 2024) and ChinaCP for the 115 period 2017-2020 (Qiu et al., 2022).’ Therefore, satellite data is not used at least in rice paddy identification. Please clarify in detail how satellite remote sensing is used for the source sectors.

Response: In the revised manuscript, we added detailed descriptions of the two gridded rice paddy datasets used in our analysis. The CCD-Rice dataset (Shen et al., 2024) was derived from Landsat Collection 2 Level-2 Science Products at 30 m spatial resolution, utilizing shortwave infrared bands (B5 of Landsat 5/7 and B6 of Landsat 8). This dataset demonstrates high accuracy, with provincial-level distribution maps showing an average overall accuracy of 89.61% and strong coefficients of determination ($R^2 = 0.85$ for single-season rice and 0.78 for double-season rice) when validated against ground samples. The ChinaCP dataset (Qiu et al., 2022) was developed from MODIS imagery at 500 m resolution using phenology-based mapping algorithms. Validation against ground truth data revealed an overall accuracy of 89%, with excellent agreement to statistical data ($R^2 \geq 0.89$). We have incorporated this information in the revised manuscript (Lines 118-127) to provide readers with clear documentation of our data sources, their spatial resolutions, and validation metrics, ensuring full transparency regarding the foundational datasets used in our analysis. The updated text now reads (Lines 116-126):

Due to the limitations of existing satellite products, which do not cover the entire period from 1990 to 2020, we used two datasets for gridded rice cultivation areas annually: CCD-Rice for the period 1990-2016 (Shen et al., 2024) and ChinaCP for the period 2017-2020 (Qiu et al., 2022). The CCD-Rice dataset was derived from Landsat Collection 2 Level-2 Science Products at 30 m spatial resolution, with provincial-level distribution maps showing an average overall accuracy of 89.61% and strong coefficients of determination ($R^2 = 0.85$ for single-season rice and 0.78 for double-season rice). The ChinaCP dataset was developed from MODIS imagery at 500 m resolution using *phenology-based mapping algorithms. The validation against ground truth data revealed an overall accuracy of 89%, with excellent agreement to statistical data ($R^2 \geqslant 0.89$). The accuracy is further applied to evaluate the uncertainty caused by rice paddy area. These datasets were then resampled into 0.1° by 0.1° gridded maps*

Reference:

Shen, R., Peng, Q., Li, X., Chen, X., & Yuan, W. (2024). CCD-Rice: A long-term paddy rice distribution dataset in China at 30 m resolution. Earth System Science Data Discussions, 2024, 1-33. https://doi.org/10.5194/essd-2024-147

Qiu, B., Hu, X., Chen, C., Tang, Z., Yang, P., Zhu, X., ... & Jian, Z. (2022). Maps of cropping patterns in China during 2015–2021. Scientific data, 9(1), 479. https://doi.org/10.1038/s41597-022-01589-8

Minor comments.

3. Line 14: accumulative methane emissions are not very meaningful here. I suggest using the annual average instead.

Response: We revised this as suggested. Please see Line 14.

4. Line 29: livestock is part of agricultural activities. Re-phrase it here.

Response: In the updated version, we modified this sentence. Please see Line 29.

5. Sect. 2.2.1： I was curious if the authors included abandoned coal mines, as Qiang Liu et al., (2024), https://www.nature.com/articles/s41558-024-02004-3, highlighted the big role of it.

Response: The methane emissions from abandoned coal mines (AMM) are not included in our inventory, due to limited data availability on key parameters (e.g., residual gas ratios, site-specific decay rates, and geological conditions). We acknowledge the importance of distinguishing coal mine types (e.g., abandoned vs. active) in methane emission inventories. Recent studies, such as the Global Methane Tracker 2024 suggest that abandoned mines alone may contribute over 4.7 Mt CH_4/year in China, underscoring their significance in national budgets. Existing literature also highlights the underestimation of AMM emissions in China, particularly as current bottom-up estimates often fail to account for their increasing trends. In the revised manuscript, we expanded the discussions in Section 4, where we emphasize that future work should prioritize: 1) developing spatially resolved datasets of mine status and closure dates; 2) incorporating dynamic emission factors for abandoned mines; and 3) integrating these sources into gridded inventories We agree that this represents a critical gap requiring attention in subsequent inventory versions. Now Lines 484-491 read:

CHN-CH4 does not take the methane emissions from abandoned coal mines into consideration. Understanding its emissions and trends is critical for a low-carbon planet with more outdated mines closure. Current methodology still tends to use the default emissions factors, or the ratio of flooded or dry coal mines regionally/globally, which might bring large uncertainty. This sector warrants greater attention, particularly in developing spatially explicit mine status data and dynamic emission factors, given its substantial estimated emissions of 20.1 Tg annually from 2010–2019 (Gao et al., 2021). Existing literature also highlights the underestimation of AMM emissions in China, particularly as current bottom-up estimates often fail to account for their increasing trends (Liu et al., 2024).

6. Sect. 2.2.2： Can the authors elaborate on how you assign emission to midstream and downstream emissions? I believe it's missing from this section right now.

Response: We did not further subdivide this sector into upstream, midstream, and downstream processes, in the absence of spatial data on midstream and downstream emissions from oil and NG systems. Instead, we treated them as an aggregated source under IPCC subcategory 1B2 (Fugitive Emissions from Oil and Gas), adopting the methodologies from Schwietzke et al. (2014) and Peng et al. (2016). Our approach applied average emission factors for fugitive methane from China's oil and natural gas systems, encompassing emissions from venting, flaring, exploration, production, upgrading, transport, refining/processing, transmission, and storage. However, distinguishing emissions across upstream, midstream, and downstream processes is critical for identifying key emission sources, enabling targeted mitigation strategies rather than one-size-fits-all policies. We added one sentence in the Section 2.2.2 to clarify the methodology, and expanded the Section Uncertainties to address this limitation and outline future work to improve spatial allocation in emission inventories.

Reference:

Schwietzke, S., Griffin, W. M., Matthews, H. S., & Bruhwiler, L. M. (2014). Global bottom-up fossil fuel fugitive methane and ethane emissions inventory for atmospheric modeling. ACS Sustainable Chemistry & Engineering, 2(8), 1992-2001. https://doi.org/10.1021/sc500163h

Peng, S., Piao, S., Bousquet, P., Ciais, P., Li, B., Lin, X., ... & Zhou, F. (2016). Inventory of anthropogenic methane emissions in mainland China from 1980 to 2010. Atmospheric Chemistry and Physics, 16(22), 14545-14562. https://doi.org/10.5194/acp-16-14545-2016

Lines 115: I think we should consider uncertainties from both rice area and emission factors. Currently the authors only considered emission factor uncertainties, which is not comprehensive.

Response: The CCD-Rice and ChinaCP datasets exhibit average overall accuracies of 89.61% and 89%, respectively, based on the validation using ground observations. In the revised manuscript, we incorporated these accuracy values to estimate the uncertainties in rice paddy area mapping. For grid cell G in 2010, $A_{G,i}$ is the rice paddy area for season i (where $i \epsilon \{early, middle\ and\ late\}$). Considering the rice area uncertainty of 89.61% accuracy, the error bounds for each seasonal area can be expressed as:

$$\left[A_{G,i} - A_{G,i} * (1 - 89.61\%), A_{G,i} + A_{G,i} * (1 - 89.61\%)\right]$$
$$= [A_{G,i} * 0.8961, A_{G,i} * 1.1039]$$

To calculate the uncertainty in emissions from rice paddy areas, the upper and lower bound of the area can be incorporated into the following equation:

$$E(t) = \sum_{i} A_{G,i}(t) * EF_{R,i} * p_i$$

where $E(t)$ is the total emissions from rice cultivation, p is the rice growing period, $EF_{R,i}$ is the emission factor at region R. Based on this approach, we recalculated the uncertainties for the rice cultivation sector and subsequently for the total anthropogenic emissions. All relevant results in the manuscript have been reviewed and updated accordingly.