Response to Reviewer 2nd – Manuscript gmd-2025-268 "Towards an integrated inventory of anthropogenic emissions for China " by Zhang et al., 2025

We would like to thank the reviewer for the careful reading and suggestions to improve the clarity and quality of the manuscript. Below, we provide a detailed reply to each of the comments (Reviewers' comment/question in bold black, our reply in black, and new text in the manuscript in blue).

Comment 1. Recent efforts, such as HTAP v3.1 (https://essd.copernicus.org/preprints/essd-2024-601/), have also incorporated MEIC for China. It is suggested that the authors compare CINEI with HTAP v3.1 over China to highlight differences and improvements.

Comment 2. Similarly, MIX v2 has integrated MEIC emissions. What are the methodological advancements and advantages of CINEI relative to MIX v2?

We thank the reviewer for the detailed comments on the newly released HTAPv3.1 and MIXv2 emission dataset (Li et al., 2024; Guizzardi et al., 2025) and the suggestion to compare with the here developed inventory in order to further support the usefulness of it.

CINEI introduces methodological improvements and offers a more comprehensive coverage of emission sectors than MIXv2, especially with the inclusion of the agriculture and aviation sectors. In addition, CINEI's detailed NMVOC speciation enhances its suitability for global atmospheric modeling. When comparing the HTAPv3.1, MIXv2, and CINEI inventories, the main advantages of CINEI are:

(1) Broader emission sectors in CINEI, including aviation and domestic ships, are missing from the MIXv2 inventory (see Table 2 in Li et al., 2024). MIXv2 presents only seven broad sectors in gridded format and lacks the detailed 22 subsectors in time series, which are available in MEIC v1.4. As shown in Figures S10–S12, MIXv2 is limited in its ability to analyze subsector emission trends over time and complicates direct sector mapping with global inventories. For example, Table 2 in Li et al. (2024) provides a one-way mapping between MIXv2 and the IPCC code. In contrast, Figure S8 provides a two-way mapping, including one between the CINEI and the IPCC code and one between the existing inventories and the IPCC code. Therefore, the absence of specific sub-sectors complicates direct sector mapping with global inventories. For example, enteric fermentation (3A) is missing in MIXv2, while wastewater treatment and discharge (4D) is omitted in both MIXv2 and HTAP. These missing sub-sectors can be identified and addressed during the screening process.

(2) Updated NMVOC speciation profiles in CINEI that are fully compatible with the MOZART chemistry mechanism, which is widely adopted in air quality studies and regional chemistry and transport models (CTMs), such as the Weather Research and Forecasting (WRF) model coupled with Chemistry (WRF-Chem), the Community Earth System Model (CESM) and the Multi-Scale Infrastructure for Chemistry and Aerosols

(MUSICA) (Dai et al., 2023 and 2024; Mariscal et al., 2025; Tilmes et al., 2019). The MIXv2 inventory provides speciations such as CB05 and SPARC that are suitable for certain regional and chemistry models; while HTAPv3.1 currently lacks local profile updates for NMVOC species and the speciated NMVOC emissions in gridded format have not yet been completed (Guizzardi et al., 2025).

(3) Facilitation of widely used chemistry mechanisms for global climate models. CINEI's integration with the global CEDS inventory further enhances its applicability for climate change studies, including use within the Coupled Model Intercomparison Project (CMIP) framework (Feng et al., 2020). CINEI is compatible with the MOZART chemistry mechanism that is widely adopted in air quality studies and regional chemistry and transport models; This broad compatibility positions CINEI as a flexible and valuable resource for a wide range of modeling applications.

We have added a supplementary Figure S6 that shows a comparison of the interannual variation in NO_x, CO, and NMVOC emissions among CINEI, MIXv2, and HTAPv3.1. For the overlapping period (2010–2017), the inventories show minor discrepancies. On average, annual emissions in HTAPv3.1 are 2.1% higher than CINEI (ranging from -0.8% to +5.8% across different species), while MIXv2 emissions are consistently 3.2% lower (ranging from -1.6% to -6.1%). These differences mainly result from variations in sectoral aggregation methodologies. For instance, NO_x emissions in CINEI and HTAPv3.1 are higher than in MIXv2, with annual differences of 1.5 Tg (5%), mainly due to the omission of aviation (1.1 Tg) and agricultural soil emissions (0.3 Tg) in MIXv2. Annual CO emissions from agricultural waste burning in HTAPv3.1 are 5 Tg higher than in CINEI and MIXv2. Although both CINEI and MIXv2 provide speciated NMVOC emissions compatible with chemistry mechanisms, HTAP currently lacks local profile updates for NMVOC species.

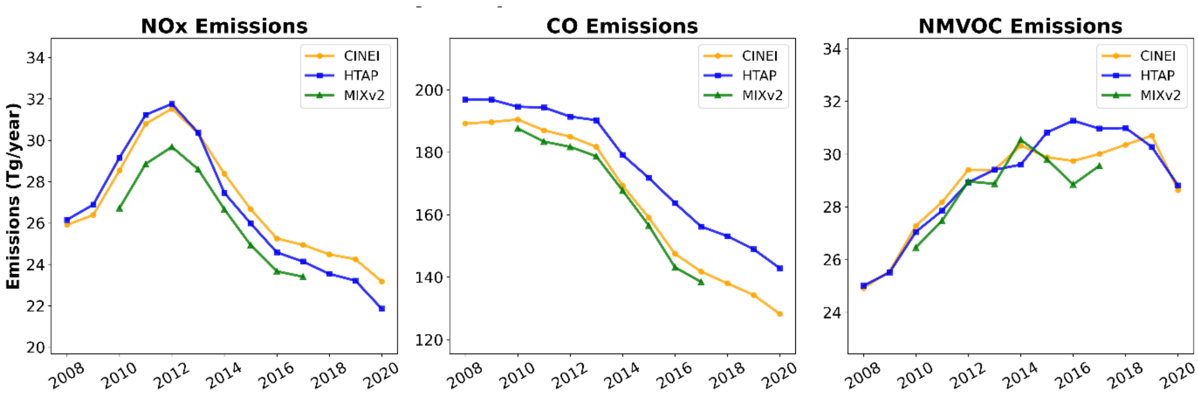


Figure S5. Interannual variability of total NOx (NO_2), CO and NMVOC emissions in China from the CINEI in orange (2008 to 2020) and MIXv2 in green (2010 to 2017), and HTAPv3.1 in blue (2008 to 2020).

We have also performed an additional experiment based on MIXv2 in the summer that showed an underestimation of NO_2 by 7 ppbv (NMB = -54%), CO by 0.5 ppmv (-85%), and O_3 by 14 ppbv (-34%) (Figure S29 and Table S22). The larger discrepancy likely resulted from missing aviation emissions and reactivity due to lumping together NMVOC species (Li et al., 2024). However, CINEI and HMEI both have consistent speciated NMVOC emission values that align with global inventories, resulting in more reliable model performance. Furthermore, modelling performance based on CINEI in July 2017 outperforms that based on MIXv2, as illustrated in Figure S25 and Table S23. The MIXv2-based runs substantially underestimated all three pollutants: NO_2 by 7 ppbv (-54%), CO by 0.5 ppmv (-85%), and O_3 by 14 ppbv (-34%). These underestimations likely result from (1) missing emission sectors such as aviation and agriculture, leading to lower NOx and CO emissions and (2) incomplete accounting for transported emissions from surrounding regions and the ocean. CINEI integrates China's emissions within the CEDS inventory, while MIXv2 uses other regional inventories (CAPSS for Korea and MOEJ for Japan). Additionally, MIXv2 inventory provides NMVOCs species as high-lumped species, which might lead to missing reactivity of NMVOCs species in WRF-Chem model.

This discussion is added in the supplementary material section S12.

In the revised manuscript we added the following text:

The 4th paragraph in section 1(Line 67) in the main text: Reference to Guizzardi et al., 2025 was added.

The 4th paragraph in section 2.1 (Line 129-138) in the main text:

Our final dataset-CINEI aims at methodological improvements and offers a more comprehensive coverage of emission sectors than MIXv2, especially with the inclusion of the agriculture and aviation sectors. In addition, CINEI's detailed NMVOC speciation that is fully compatible with the MOZART chemistry mechanism enhances its suitability for global atmospheric modeling and its versatility relative to other regional inventories, including MEIC, REAS, and MIXv2. Figure S6, showing a comparison of the interannual variation in NOx, CO, and NMVOC emissions over China among CINEI, MIXv2, and HTAPv3.1 inventories for the overlapping period (2010–2017), demonstrates only minor discrepancies among the inventories. Annual emissions in HTAPv3.1 are 2.1% higher than CINEI (ranging from -0.8% to +5.8% across different species), while MIXv2 emissions are consistently 3.2% lower (ranging from -1.6% to -6.1%) (see further discussion in ~~the~~ section S4 of SI).

Step 3 in section 2.2 (Line 233-234) in the main text: CINEI inventory with MOZART NMVOC speciation can be used in a wide range of air quality studies, as well as in regional and global chemistry and transport models (CTMs). Examples include the Weather Research and Forecasting (WRF) model coupled with Chemistry (WRF-Chem), the Community Earth System Model (CESM) and the Multiscale Infrastructure for Chemistry and Aerosols (MUSICA) (Dai et al., 2023; Mariscal et al., 2025; Danabasoglu et al., 2020). Such compatibility enhances the versatility of CINEI relative to other regional inventories, including MEIC, REAS, and MIXv2.

Supplement

New Figure S6 in Page 9 of SI: Comparison of the interannual variability of total NO_x (NO_2), CO and NMVOC emissions in China between HTAPv3.1, CINEI and MIXv2.

Added discussion text (following) as section S5 (Page 11) of SI:

When comparing the HTAPv3.1, MIXv2 and CINEI inventories, the main advantages of CINEI are:

(1) Broader emission sectors in CINEI, including aviation and domestic ships, are missing from the MIXv2 inventory (see Table 2 in Li et al., 2024). MIXv2 presents only seven broad sectors in gridded format and lacks the detailed 22 subsectors in time series, which are available in MEICv1.4. As shown in Figures S10–S12, MIXv2 is limited in its ability to analyse subsector emission trends over time and complicates direct sector mapping with global inventories. For example, Table 2 in Li et al. (2024) provides a one-way mapping between MIXv2 and the IPCC code. In contrast, Figure S8 provides a two-way mapping, including one between the CINEI and the IPCC code and one between the existing inventories and the IPCC code. Therefore, the absence of specific sub-sectors complicates direct sector mapping with global inventories. For example, enteric fermentation (3A) is missing in MIXv2, while wastewater treatment and discharge (4D) is omitted in both MIXv2 and HTAP. These missing sub-sectors can be identified and addressed during the screening process.

(2) updated NMVOC speciation profiles in CINEI that are fully compatible with the MOZART chemistry mechanism, which is widely adopted in air quality studies and regional chemistry and transport models (CTMs), such as the Weather Research and Forecasting (WRF) model coupled with Chemistry (WRF-Chem), the Community Earth System Model (CESM) and the Multi-Scale Infrastructure for Chemistry and Aerosols (MUSICA) (Dai et al., 2023 and 2024; Mariscal et al., 2025; Tilmes et al., 2019). The MIXv2 inventory provides speciations such as CB05 and SPARC that are suitable for certain regional and chemistry models; while HTAPv3.1 currently lacks local profile updates for NMVOC species and the speciated NMVOC emissions in gridded format have not yet been completed (Guizzardi et al., 2025).

(3) Facilitation of widely used chemistry mechanisms for global climate models. CINEI's integration with the global CEDS inventory further enhances its applicability for climate change studies, including use within the Coupled Model Intercomparison Project (CMIP) framework (Feng et al., 2020). CINEI is compatible with the MOZART chemistry mechanism that is widely adopted in air quality studies and regional chemistry and transport models; This broad compatibility positions CINEI as a flexible and valuable resource for a wide range of modeling applications.

Figure S6 shows a comparison of the interannual variation in NOx, CO, and NMVOC emissions among CINEI, MIXv2, and HTAPv3.1. For the overlapping period (2010–2017), the inventories show minor discrepancies. On average, annual emissions in HTAPv3.1 are 2.1% higher than CINEI (ranging from -0.8% to +5.8% across different species), while MIXv2 emissions are consistently 3.2% lower (ranging from -1.6% to -6.1%). These differences mainly result from variations in sectoral aggregation methodologies. For instance, NOx emissions in CINEI and HTAPv3.1 are higher than in MIXv2, with annual differences of 1.5 Tg (5%), mainly due to the omission of aviation (1.1 Tg) and agricultural soil emissions (0.31 Tg) in MIXv2. Annual CO emissions from agricultural waste burning in HTAPv3.1 are 5 Tg higher than in CINEI and MIXv2. Although both CINEI and MIXv2 provide speciated NMVOC emissions compatible with chemistry mechanisms, HTAP currently lacks local profile updates for NMVOC species.

Furthermore, an additional experiment was performed with the MIXv2 inventory for July 2017. The modeling setup, including input data, was kept consistent for both inventories, except for the anthropogenic emission data, as noted in the main manuscript. Due to limited availability of HPC resources, we were unable to perform simulations for January. A comparison of MIXv2 and CINEI modeling results for July 2017 (Figure S29 and Table S22) shows that CINEI delivers better performance than MIXv2 when compared to observations. In contrast, MIXv2 consistently underestimates concentrations: NO_2 by 7 ppbv (-54%), CO by 0.5 ppmv (-85%), and O_3 by 14 ppbv (-34%). These discrepancies can be attributed to several factors: (1) MIXv2 lacks important sectors, such as aviation and agriculture, which leads to lower NOx and CO emissions; (2) emissions from surrounding regions and the ocean are not fully accounted for, whereas CINEI integrates China's emissions within the broader CEDS inventory, while MIXv2 relies on CAPSS for Korea and MOEJ for Japan. (3) MIXv2 provides NMVOC emissions as broad, lumped categories, potentially missing key reactivity of NMVOCs required for accurate simulation in WRF-Chem.

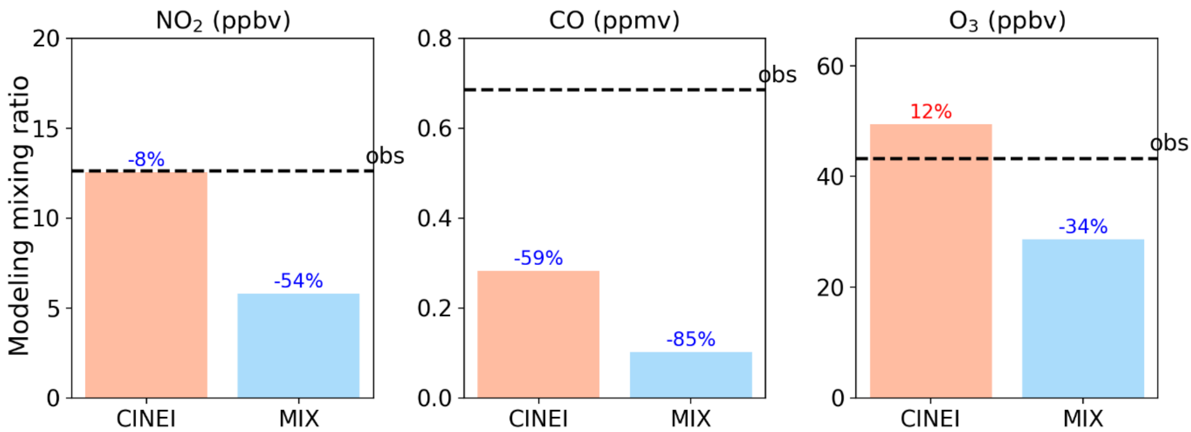


Figure S29. WRF-Chem simulated mixing ratios of O_3, NO_2, and CO for July 2017 (summer) and within the modeling domain using CINEI (in orange) and MIX (in blue). Individual columns show simulated mean mixing ratios in the model domain for each emission inventory used. The dashed blue lines show average observed mixing ratios calculated using the stations within the specified domain. The numbers on the columns are Normalized mean bias (NMB). Blue (red) number indicates underestimated (overestimated).

Table S22. Statistical metrics to evaluate modeling O_3, CO and NO_2 performance based on CINEI and

Metric	O3 (ppbv)		CO (ppmv)		NO2 (ppbv)	
	MIX	CINEI	MIX	CINEI	MIX	CINEI
Observed	43.24	43.24	0.68	0.68	12.61	12.61
Model	28.68	49.46	0.10	0.28	5.79	12.54
NMB (%)	-34	12	-85	-59	-54	-8
MFB (%)	-42	10	-149	-84	-88	-17
MNAE (%)	34	18	85	59	58	34
R	0.95	0.95	0.28	0.50	0.85	0.85

The first paragraph in section 2.3 (Line 278) in the main text: In addition, the MIXv2 inventory incorporates the MEICv1.4 inventory for Asia, which has high lumped speciation and missing aviation emissions. Its modeling performance with the same setup for July 2017 is discussed in the Supplement (figure S29 and Table S22).

The 3rd paragraph in section 3.4 (Line 482-487) in main text: An additional experiment based on MIXv2 in the summer showed an underestimation of NO_2 by 7 ppbv (NMB = -54%), CO by 0.5 ppmv (-85%), and O_3 by 14 ppbv (-34%) (Figure S29 and Table S22). The larger discrepancy of MIXv2 with observations likely resulted from missing aviation emissions and reactivity due to lumping together NMVOC species (Section S12). However, the speciated NMVOC emission values for both CINEI and HMEI are consistent and align with global inventories, resulting in more reliable model performance.

Section S13 (Line 384-390) in SI: Furthermore, modelling performance based on CINEI in July 2017 outperforms that based on MIXv2, as illustrated in Figure S29 and Table S22. The MIXv2-based runs substantially underestimated all three pollutants: NO_2 by 7 ppbv (-54%), CO by 0.5 ppmv (-85%), and O_3 by 14 ppbv (-34%). These underestimations likely result from (1) missing emission sectors such as aviation and agriculture, leading to lower NOx and CO emissions and (2) incomplete accounting for transported emissions from surrounding regions and the ocean. CINEI integrates China's emissions within the CEDS inventory, while MIXv2 uses other regional inventories (CAPSS for Korea and MOEJ for Japan). Additionally, MIXv2 inventory provides NMVOCs species as high-lumped species, which might lead to missing reactivity of NMVOCs species in WRF-Chem model.

Added Table S22 in SI.

Added Figure S29 in SI.

Comment 3. Table 2: When the same emission source exists in multiple global inventories, how is the choice made? For instance, international shipping emissions are available in CEDS, CAMS, and HTAP. Why is CAMS selected in this case? A clearer explanation of the selection principles is needed.

When the same sector appears in different global inventories, we compare the datasets and examine the sources and methodologies behind the emissions calculations. In the CINEI inventory, emissions data for each sector are selected based on two main criteria: (1) the sector must be as complete as possible in terms of included sub-sectors and chemical species (see 'Completion of sub-sectors and species' in Table 2); and (2) the underlying data used for emissions calculations must be high-quality and up to date (see 'Better underlying data' in Table 2). Below is a summary of how leading global inventories meet these criteria:

The HTAP v3 agricultural emissions are more complete than those of the other models and use more up-to-date underlying data. The HTAP agriculture sector includes subsectors such as manure management (NOx), agricultural soils (NOx) and field burning of agricultural residues (CO and some NMVOC species).

Waste emissions from CEDS are more complete than those from other sources. The HTAP waste sector includes the biological treatment of solid waste and the treatment and discharge of wastewater. The main relative species is CO. Emission data from CAMsv5.3 is adopted from EDGAR v5. We prioritize emission data from more complete sectors, and then make further selections based on whether the data is updated.

Shipping emissions are tracked mainly using Automatic Identification System (AIS) data, which combines terrestrial and satellite observations to provide detailed vessel activity. CAMS further refines shipping emissions and routes with the STEAM3 model (Johansson et al., 2017). However, inland shipping data in CAMS is less comprehensive because AIS coverage is limited on inland waterways. HTAP, which builds on EDGAR data, offers an independent sub-sector specifically for domestic (inland) shipping emissions.

Paragraphs 3rd, 4th, and 5th of Section 2.2 in the main text:

Table 2 lists the data sources for CINEI's sectoral emissions and the missing sectors in existing inventories. By following the IPCC sector definitions, we were able to identify sectors that were omitted from certain emission inventories (see Figure S8). We selected the emission sectors from different inventories based on three principles, in the following priority order: (1) whether the sectors included complete sources (sub-sector) and species, as indicated by "Completion of sub-sectors and species" in Table 2; (2) whether the sector used high-quality and updated underlying data for calculating emissions, as indicated by "Better underlying data" in Table 2; and (3) whether the emission estimations for the sectors considered the mitigation measures implemented in China (as discussed in Section S2), which is indicated by "incorporation of pollution mitigation measures" in Table 2.

For CINEI, we retained the emissions from the four existing sectors (transportation, residential, industry, and energy) that were utilized in MEIC, as these sectors adhere to the three principles.

As detailed in Section S2, MEICv1.4 employed local emission factors and activity data and included a parameter for abatement estimation (Section S2 and Table S1). The emission peak year is consistent with the year of mitigation implementation (see Section S7).

We integrated emissions from various global inventories for the four missing sectors to ensure comprehensive sectoral coverage and consistency between national and global emission inventories. Specifically, we used emissions from HTAP for aviation and domestic shipping. We opted for HTAP's data for domestic shipping because its inventory provides an independent sub-sector for inland shipping, whereas inland shipping emissions from CAMS are less complete due to the limited use and coverage of the Automatic Identification System (AIS) on inland waterways. We incorporated ocean shipping emissions from CAMS, which refines data using the Ship Traffic Emission Assessment Model (STEAM3), providing a more detailed representation of shipping routes and emissions (Johansson et al., 2017). For the agriculture and waste sectors, we utilized data from CEDS because its agricultural emissions are more comprehensive than those of MEIC (which only considers NH_3, and its waste emissions are more complete than those from sources from other inventories (Figure S6).

Updated Table 2 as shown below:

Table 2. Data sources of CINEI sectoral emissions and mapping with global emission inventories

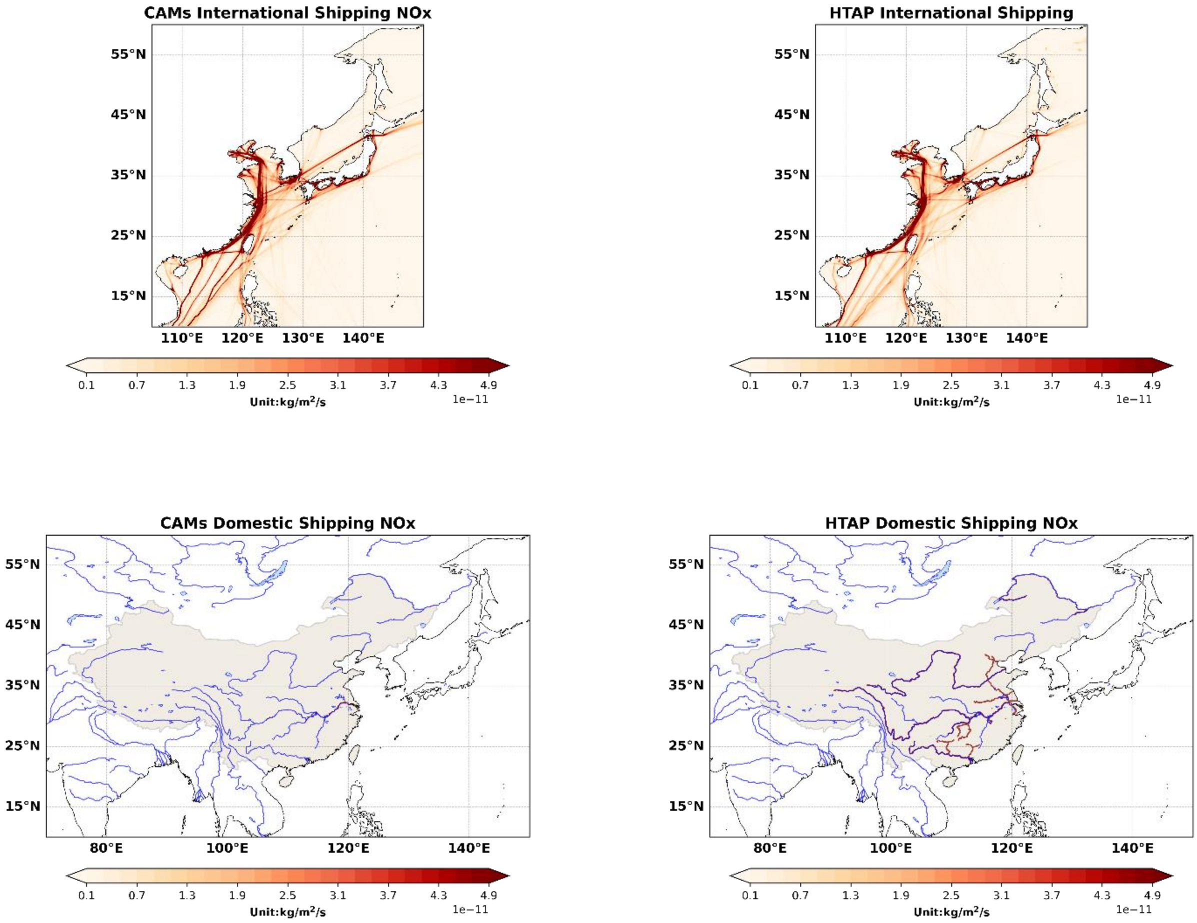
Sectors	If provided by existing inventories				CINEI Data Source	Selection Principles***
	MEIC	CEDS*	CAMS	HTAP*		
Power	✓	✓	✓**	✓	MEICv1.4	(1) (2) (3)
Industry	✓	✓	✓**	✓	MEICv1.4	(1) (2) (3)
Residential	✓	✓	✓	✓	MEICv1.4	(1) (2) (3)
Aviation	missing	missing	missing	✓	HTAPv3	(2)
Transportation	✓	✓	✓	✓	MEICv1.4	(1) (2) (3)
International Ships	missing	✓	✓	✓	CAMSv5.3	(2)
Domestic Ships	missing	missing	✓	✓	HTAPv3	(2)
Agriculture	✓**	✓	✓	✓	HTAPv3	(2)
Waste	missing	✓	✓	✓**	CEDSv2021	(2)

* As emissions from HTAP and CEDS are not extended to 2020, we use a linear regression of the emissions from 2008 to 2018 (2019) for HTAP (CEDS) and extrapolate to 2020 for CINEI.

** Indicates that the emissions inventory provides parts of the sectoral emissions but misses some subsectors suggested by the IPCC report. Details on IPCC subsectors and a comparison to each inventory are listed in Figure S6.

*** The selection principles are prioritized in the following order: (1) Completion of sub-sectors and species, (2) Better underlying data, and (3) Incorporation of mitigation.

Added Figure S7 in SI: Spatial distribution of international shipping and inland shipping of CAMs and HTAP.



Comment 4. What are the exact differences between HMEI and CINEI? Is it solely the inclusion of previously missing sectors (e.g., ships, aviation, waste, agriculture), or are there additional improvements in sectoral mapping, NMVOC speciation, or spatial harmonization?

We thank the reviewer for highlighting the differences between the HMEI and CINEI inventories. The primary distinction is that the MEIC inventory that the basis of the HMEI inventory for Mainland China does not cover certain sectors—specifically shipping, aviation, waste, and agriculture—while CINEI addresses these gaps by incorporating these additional sources. CINEI also improves NMVOC characterization by utilizing locally observed NMVOC profiles, ensuring that sector-specific compositions are more accurately represented. Furthermore, CINEI uses a uniform sector definition and a consistent spatial resolution of 0.25°, enhancing comparability and spatial detail.

The increase in total emissions in CINEI compared to HMEI is primarily due to the inclusion of these previously omitted sectors (see Figures 3d–f), resulting in average annual increases of 2.7 Tg NOx, 5.2 Tg CO, and 1.4 Tg NMVOCs. CINEI's use of local NMVOC profiles also leads to differences in the chemical composition of emissions, especially for sectors such as agriculture and waste, which contribute notable amounts of propene, ethene, formaldehyde, and acetaldehyde (see Figure 4b).

Section 2.2 (Line 266-268) in the main text: The difference between CINEI and HMEI lies in the new sectors (shipping, aviation, waste, and agriculture) added to CINEI, which increase total emissions. Speciated NMVOCs in CINEI are improved by applying locally observed NMVOC profiles. Furthermore, the additional emission sectors affect the composition of specific local emissions, which will be discussed in later sections.

2nd paragraph in section 3.1 (Line 320-322) in the main text: Compared to MEIC (harmonized inventories) for China, CINEI total emissions on annual average include the contributions of the ships sector to NOx emissions (2.7 Tg), the waste sector to CO emissions (5.2 Tg), and the agricultural sector to NMVOC emissions (1.4 Tg) (Fig. 3d-f).

2nd paragraph in section 3.2 (Line 383-386) in the main text: The agricultural sector is the main source for formaldehyde (52%) and acetaldehyde emissions (60%), related to the emissions along with crop burning (including the burning of rice and wheat straw, maize, etc.). Ignoring agricultural NMVOC emissions in anthropogenic emission inventories can lead to underestimated contributions of these species to ozone pollution. Ozone pollution may occur in areas with intensive local agricultural activity.

Comment 5. The CAMS dataset is extended from 2018 to 2022 using linear slopes from CEDS. How are uncertainties introduced by this extrapolation process quantified and propagated? More detailed treatment or discussion is recommended.

Table 3 summarizes the uncertainties associated with CAMS emissions for the main sectors. Overall, the CAMS extrapolation method introduces between 30% and 60% of uncertainty. The greatest uncertainties are found in the power sector, reaching 96% for CO emissions and 148% for NMVOC emissions. These unusually high values are likely due to systematic uncertainty regarding how CAMS defines the power and industry sectors. In comparison, uncertainties from bottom-up and top-down modeling approaches cited in the literature are lower, typically between 20% and 50%. To reduce uncertainties in future work, we recommend a combined approach that uses activity data, in-situ measurements, satellite observations, and CTM modeling. Section S3 and Table S3 will be added in the supplementary to explain how uncertainties in CAMS emissions due to the extrapolation method are evaluated.

Table S3. Comprehensive uncertainty table for CAMs Emissions Extrapolation Method: CO, NOx, and NMVOC by Sector

Species	Sector	Slopes (Tg/year)			Emission in base year (2018)			σ_model	σ_total
		CEDS	CINEI	σ_slope (%)	CAMs (Tg)	CINEI (Tg)	σ_bias (%)	(%)	(%)
CO	Transportation	-1.6021	-1.5969	0.3	14.83	23.67	45.9	39.0	60.2
	Residential	-2.1838	-2.2927	4.9	27.34	55.81	68.5	39.0	78.8
	Power	0.0692	0.1850	91.1	12.80	5.01	87.5	39.0	95.8
	Industry	-1.3966	-2.2350	46.2	75.49	47.67	45.2	39.0	59.7
NOx (NO2)*	Transportation	-0.0160	-0.1717	165.8	5.2	7.5	35.0	46.0	57.8
	Residential	-0.0229	-0.0267	15.5	1.0	0.8	17.3	46.0	49.2
	Power	-0.1439	-0.2977	69.7	6.3	4.0	44.1	46.0	63.7
	Industry	-0.0956	-0.1608	50.9	8.5	9.1	7.2	46.0	46.6
NMVOC†	Transportation	-0.2747	-0.2145	24.6	3.89	4.63	17.4	26.0	31.3
	Residential	-0.2069	-0.0941	74.9	3.05	4.67	42.1	26.0	49.5
	Power	0.1204	-0.0024	208.2	0.49	0.08	146.0	26.0	148.3
	Industry‡	-0.0046	0.5275	203.5	20.19	19.49	3.5	26.0	26.2

Notes:

* CAMs NOx (represented by NO) emissions scaled by factor 1.5

‡ Industry sector for NMVOC includes solvents (ind + slv)

- Slopes calculated from linear regression (2015-2019)
- Base year emissions in appropriate units for each species
- Uncertainties calculated using equations (2)-(4) from methodology
- Model uncertainties: CO (39%), NOx (46%), NMVOC (26%) from Li et al. (2024).

Add text in section 2.1 (Line 120) in the main text: The uncertainties of CAMs extrapolation method will also be discussed in Section 3.1.

2nd paragraph in section 3.1 (Line 323-325) in the main text: The uncertainties of the CAMs extrapolation method for the main sectors are estimated between 30% and 60% (see Section S5 and Table S3). One exception is the power sector where uncertainty exceeds 100%, likely due to the systematic uncertainty in the sector' definitions and mapping.

Section 4 (Line 540-543) in the main text: In a follow-up study, we will evaluate CINEI's representation of NOx-VOC photochemistry in CTM models and compare the results with observational data. We also plan to incorporate additional observational and modeling approaches to develop an updated version of the CINEI emissions dataset. This will help reduce uncertainties in the emission estimates and minimize modeling biases in CTM applications.

Main text Line 542: We will use more observational data, such as from TROPOMI and in-situ measurements, to constrain the total emissions for ozone precursors and NMVOC speciation.

Add Table S3 in SI:

Add a section S5 in SI:

1. Method to quantify the uncertainties on the projection of CAMs emission from 2018 onward.

For this study, CAMs emissions for the main sectors (industry, power, residential and transportation) from 2018 to 2020 are extrapolated using linear slopes ($slope_{spec,i}$) derived from CEDS for the period 2015 to 2019, with 2018 as the base year. The emissions for a given species (spec) and sector (i) in years 2019–2020 are calculated as:

$$E_{spec,year,i} = E_{spec,2018,i} + slope_{spec,i} \times (year - 2018) \quad (1)$$

Here, $slope_{CEDS,\ spec,i}$ is the slope of linear regression of annual total CEDS emissions for sector i and specific species (spec) from 2015 to 2019 and $slope_{CINEI,\ spec,i}$ is the slope of linear regression of annual total CINEI emissions. The uncertainty of the linear slope is calculated as the absolute difference between linear slopes of CINEI and CEDS from 2015 to 2019 with respect to their averages. The calculation is expressed as:

$$\sigma_{slope} = \frac{|slope_{CEDS,spec,i} - slope_{CINEI,spec,i}| \times 2}{slope_{CEDS,spec,i} + slope_{CINEI,spec,i}} \times 100 \quad (2)$$

The uncertainty of the bias is calculated as the absolute difference of CAMs and CINEI emissions with respect to their average in the base year.

$$\sigma_{bias2018} = \frac{|E_{CAMs,spec,2018,i} - E_{CINEI,spec,2018,i}| \times 2}{E_{CAMs,spec,2018,i} + E_{CINEI,spec,2018,i}} \times 100 \quad (3)$$

The uncertainty of the model (σ_{model}) originates from differences in approaches to calculate emissions, including top-down estimation (satellite estimation and inverse modeling) and bottom-up estimation (Miyazaki et al., 2017; Li et al., 2024; Liu et al., 2016a). This component is independent of the uncertainties of linear slope and base-year emission in bottom-up emission inventories. Adopted from Li et al. (2024), the standard deviation of all estimates on emission trends can be represented by 46% for NOx, 39% for CO, and 26% for NMVOC.

The propagation of uncertainty for three independent uncertainties is expressed as follows:

$$\sigma_{total,spec,i} = \sqrt{\sigma^2_{slope,spec,i} + \sigma^2_{model,spec,i} + \sigma^2_{bias,spec,i}} \quad (4)$$

References

Feng, L., Smith, S. J., Braun, C., Crippa, M., Gidden, M. J., Hoesly, R., Klimont, Z., van Marle, M., van den Berg, M., and van der Werf, G. R.: The generation of gridded emissions data for CMIP6, Geosci. Model Dev., 13, 461–482, https://doi.org/10.5194/gmd-13-461-2020, 2020.

Mariscal, N., Emmons, L. K., Jo, D. S., Xiong, Y., Judd, L. M., Janz, S. J., Chai, J., and Huang, Y.: Evaluation of Ozone and its Precursors using the Multi-Scale Infrastructure for Chemistry and Aerosols Version 0 (MUSICAv0) during the Michigan-Ontario Ozone Source Experiment (MOOSE), EGUsphere [preprint], https://doi.org/10.5194/egusphere-2025-228, 2025.

Li, M., Kurokawa, J., Zhang, Q., Woo, J.-H., Morikawa, T., Chatani, S., Lu, Z., Song, Y., Geng, G., Hu, H., Kim, J., Cooper, O. R., and McDonald, B. C.: MIXv2: a long-term mosaic emission inventory for Asia (2010–2017), Atmos. Chem. Phys., 24, 3925–3952, https://doi.org/10.5194/acp-24-3925-2024, 2024.

Guizzardi, D., Crippa, M., Butler, T., Keating, T., Wu, R., Kamiński, J. W., Kuenen, J., Kurokawa, J., Chatani, S., Morikawa, T., Pouliot, G., Racine, J., Moran, M. D., Klimont, Z., Manseau, P. M., Mashayekhi, R., Henderson, B. H., Smith, S. J., Hoesly, R., Muntean, M., Banja, M., Schaaf, E., Pagani, F., Woo, J.-H., Kim, J., Pisoni, E., Zhang, J., Niemi, D., Sassi, M., Duhamel, A., Ansari, T., Foley, K., Geng, G., Chen, Y., and Zhang, Q.: The HTAP_v3.1 emission mosaic: merging regional and global monthly emissions (2000–2020) to support air quality modelling and policies, Earth Syst. Sci. Data Discuss. [preprint], https://doi.org/10.5194/essd-2024-601, in review, 2025.