



Evaluating When and Where TROPOMI XCH₄ Uncertainties Yield Consistent Flux Estimation over East, South, and Central Asia

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Abstract. Satellite remote sensing of methane (CH₄) offers the potential to monitor emissions across large scales, but skepticism remains among regulators, policymakers, and the scientific community of both the precision and accuracy of such estimations due to unquantified observational uncertainties. Using 500 perturbation experiments with four error distributions applied to TROPOMI XCH₄ over East, South, and Central Asia, we systematically assess where and when divergence-based emission estimates are reliable. We show that the shape of the uncertainty distribution - not just its magnitude - governs error propagation and thus effects the stability of derived fluxes. Furthermore we show that uncertainty propagates over both space and time, indicating that purely local accounting may lead to an underestimate of uncertainty. Coal-dominated industrial grids retain trustworthy signals (30% retention of valid perturbations), whereas agricultural and mixed-use grids retain only 16%, indicating that current filtering practices are insufficient for these land types. These results provide a practical, uncertainty-aware filter for satellite-derived methane emissions, directly supporting the Global Methane Pledge and national greenhouse gas inventories by identifying where satellite data can be trusted (coal-dominated regions)



and where additional caution or alternative approaches are needed. The process is data-neutral and can
30 be extended to other satellite platforms and adopted by other regions around the globe.

1. Introduction

Methane (CH_4) is a potent greenhouse gas with a global warming potential significantly higher than that
of carbon dioxide over a short-term period (Kuylensstierna et al., 2021). Its emissions originate from
various sources, including natural processes (Zhang et al., 2023), agricultural activities (Smith et al., 2021),
35 fossil fuel extraction (Tibrewal et al., 2024), and waste management (Zhu et al., 2023), with trends driven
and modified by anthropogenic emissions (Skeie et al., 2023). Reducing methane emissions has become
a crucial strategy in the global effort to mitigate climate change, primarily due to its substantial
contribution to the enhanced greenhouse effect (Intergovernmental Panel On Climate Change, 2014) and
its relatively short atmospheric lifetime (Li et al., 2022; Rigby et al., 2017) compared to carbon dioxide.
40 Moreover, methane reduction also offers co-benefits such as improved air quality (Mar et al., 2022) and
decreased agricultural damage (Shindell et al., 2019). Therefore, understanding the sources and pathways
of methane emissions, and implementing effective reduction measures, are important for achieving
sustainable development goals and safeguarding the global environment.

The Tropospheric Monitoring Instrument (TROPOMI) is a state-of-the-art satellite instrument
45 designed to monitor trace gases and aerosols in the Earth's atmosphere. It is the primary payload aboard
the Copernicus Sentinel-5 Precursor satellite, which was launched in October 2017, and has been widely
used for methane quantification (Hu et al., 2018, 2016). A number of inverse studies have used TROPOMI
observations to quantify methane emissions globally, for specific regions and sectors (Balasus et al., 2023;
Li et al., 2024; Liang et al., 2023; Liu et al., 2021; M. Liu et al., 2024; Schneising et al., 2019; Tsuruta
50 et al., 2023; Vanselow et al., 2024; Varon et al., 2023). Several methods have been applied using
TROPOMI data to quantify methane emissions, such as analytical inversion methods (Hemati et al., 2024;
Shen et al., 2023), data assimilation (Tsuruta et al., 2023), divergence-based (Liu et al., 2021), machine
learning (Schuit et al., 2023), and tracer gas ratio scaling methods (Plant et al., 2022). The formulation of
effective policies relies crucially on the availability of accurate data, including satellite observations, the
55 locations of emissions, and their magnitudes (Conrad et al., 2023). So it is essential to examine the impact
of data uncertainties on the outcomes.



The source of data errors for satellite-based CH₄ stem from limits imposed by aliasing of surface albedo errors (Lorente et al., 2021), scattering-induced surface reflectance errors (Lorente et al., 2023), errors in surface altitude (Hachmeister et al., 2022), weather conditions such cloud coverage (Frankenberg et al., 2024) and aerosols (Yu et al., 2024), among other factors (Jacob et al., 2016). During the retrieval process, satellites strive to minimize the influence of abovementioned factors. Currently, the majority of studies select high-quality data based on product specifications. To address potential residual errors, correction factors are introduced to further enhance the accuracy and reliability of the data (Buchwitz et al., 2017). Nevertheless, when such additional observations are not available or are unknown to address the correction factors, some literatures will rely on reanalysis datasets (Gautier et al., 2024; Z. Liu et al., 2024). However, these are based on known uncertainties in the data, and if uncertainties remain or not fully accounted for, then errors will continue to propagate between the data, resulting in inaccurate emission estimates.

Emissions vary greatly across regions, with the largest totals in China and South Asia. Uncertainties in emissions are again largest for China (Kuylenstierna et al., 2021). In addition, China's topography and emission sources are complex, especially its coal sector (Zhang et al., 2025). This study presents a set of perturbation experiments designed to investigate the impact of TROPOMI data uncertainty on atmospheric remotely sensed emission products based on the divergence operator, which can effectively integrate the joint gradient information of both wind fields and concentration fields. Random errors of physically realistic ranges have been considered based on several different uncertainty distributions. When, where, and whether consistent emission fluxes are produced when explicitly considering the uncertainty was examined based on grid and county level. As a result, this work additionally quantifies when and where emissions estimations can be expected to be untrustworthy.

2. Materials and methods

2.1 Satellite datasets

The TROPOMI instrument operates in a sun-synchronous, low Earth orbit that provides daily global information on concentrations of trace gases and others. We use the column-averaged dry air methane ratio (XCH₄) measurements after accounting for the surface albedo effect (European Space Agency, 2021). The product provided by the Netherlands Institute for Space Research (Hu et al., 2016) simultaneously



85 retrieves the methane column and aerosol information in order to account for the influence of aerosol
scattering. This work uses the Level-2 OFFL data stream with bias-corrected XCH₄ with qa_value > 0.5.
The bias-corrected XCH₄ is resampled across a standard latitude/longitude grid of 0.25°×0.25° using an
area-weighted average. The data span 1 January 2019 to 31 December 2023 over the domain 10°N-60°N,
70°E-140°E.

90 2.2 Wind fields datasets

Wind fields include u- and v-direction wind from ECMWF ERA-5 reanalysis(Copernicus Climate
Change Service, 2018) at different pressure levels. The pressure levels were chosen based on the 60 Arc-
Second Resolution geoid height(NOAA National Centers for Environmental Information, 2022), which
was coarsened to a resolution of 0.25°×0.25° with the median value of the 60arc data within each 0.25-
95 degree grid used to represent the value of that grid. In this study, wind pressures were considered over
the range from 350hpa to 975hpa (18 levels) along with 10m and 100m wind. Based on the relationship
between pressure and altitude, we calculated the pressure values for each grid and selected the wind from
the nearest pressure level within the pressure range of the wind fields.

2.3 Consistent flux evaluate method

100 The continuity equation expresses mass conservation within an elemental volume of fluid. For a chemical
species i with concentration measured by its mass density, the continuity equation is expressed in an
Eulerian framework as

$$\partial \rho_i / \partial t + \nabla \cdot (\rho_i w) = s_i \quad (1)$$

Where $w = (u, v)^T$ is the 2-D wind velocity vector, $\nabla \cdot (\rho_i w)$ is the flux divergence, which represents
105 the transport term, and s_i is the net local source of the species(Brasseur and Jacob, 2017).

The divergence of a vector is the sum of the partial derivatives of its components with respect to their
individual coordinates ($\nabla \cdot F = (\partial F^x / \partial x + \partial F^y / \partial y)$). The divergence theorem relates the flux outward
through the surrounding surface of a closed volume to the total divergence inside(Hautala, 2020). The
divergence operator thus was used to assess how the uncertainty in the satellite observation data would
110 impact computation of emissions.

Initially, the divergence ($\nabla \cdot (\omega * VCH_4)$, hereafter referred as Div, unit in $\mu\text{g m}^{-2} \text{s}^{-1}$) was calculated.
Subsequently, for each grid point, random errors with a mean of zero and a range of $\pm x\%$ of the grid



value were introduced, resulting in a set of 500 perturbed instances which should be identical to VCH_4 value plus white noise uncertainty of $x\%$. The selected distributions (Normal, Uniform, Beta, Lognormal) of random errors were chosen to represent diverse statistical properties - symmetric, asymmetric - which encompass a broader range of potential true error mechanisms inherent in satellite remote sensing data. The divergence was then computed for each of these perturbed instances ($\nabla \cdot (\omega * VCH_4')$, hereafter referred as Div'). If the emissions are true and stable, then the relative error of divergence ($(Div' - Div)/Div$) should not exceed the magnitude of the perturbation applied, $x\%$. Therefore, the absolute value of $|(Div' - Div)/Div|$ was chosen as a metric (referred as relative change ratio, RCR), with grids that fulfilled $|(Div' - Div)/Div| < x\%$ deemed valid. This condition was applied on a grid-by-grid and day-by-day basis. For the grids with half or more perturbations valid, they are referred as Grid0.5. The selected criterion is intended as a robustness metric rather than a formal uncertainty estimate. If small perturbations in XCH_4 produce disproportionately large changes in the derived divergence field, the resulting flux estimate is considered unstable with respect to observational uncertainty. The requirement that at least 50% of perturbation realizations satisfy the criterion provides a pragmatic balance between sensitivity and robustness, enabling identification of regions where divergence-derived emissions remain relatively insensitive to plausible retrieval noise. A schematic representation of the workflow for this study is depicted in Figure 1.

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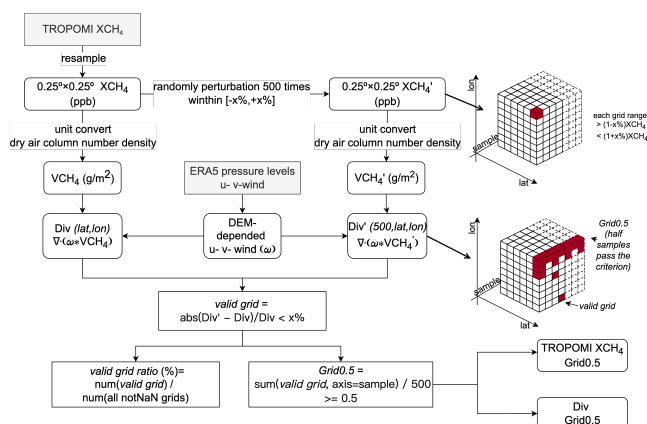


Figure 1: Flowchart of this work



3. Results and discussion

3.1 Sensitivity of Valid Grid to Different Setup

Div was computed using a series of stochastic perturbations varying in percentage of XCH₄ observations, specifically [-10%, +10%], [-5%, +5%], [-1%, +1%], to account for white noise uncertainty of each given magnitude, following the details described in the methodology. First, it was found that the valid grid ratio on a grid-by-grid basis did not change significantly under different perturbation ratios, but rather was sensitive to the distribution of the perturbation (see Table S1). Besides, a number of different ranges of wind fields was also considered, specifically 10m, 100m, and at various pressure levels (350–975hpa). Considering that the Lognormal distribution has the lowest valid grid ratio, consistent with the fact that the total uncertainty is a complex function of multiple terms including concentration, and factors impacting both scattering and absorption which are more likely to form a skewed or uniform distribution when acting in tandem (Cohen and Prinn, 2011), it was not shown in the main text (refer to Table S1 for details).



Figure 2: The valid grid ratio and its maximum over different distributions and wind fields: (a) applying different observational error distributions, and (b) using different wind field levels.

As shown in Figure 2(a), the valid grid ratio changes when the distribution of $x\%$ is altered, with a beta distribution ($a=2$, $b=5$) yielding the highest valid grid ratio. This beta distribution is right-skewed, which means a majority of the sampled perturbations will be of relatively small yet non-zero magnitude, while



larger perturbations are less probable. From Figure 2, it can be seen that the probabilistic distribution of input uncertainties, not just their maximum magnitude (see Figure S2), fundamentally governs error propagation and the overall reliability of derived geophysical quantities in atmospheric remote sensing.

155 Figure 2(b) compares the same metric for pressure levels, 10m and 100m wind fields, with all curves following the same temporal trend as Figure 2(a). The 100m wind field consistently exhibits lower valid percentages (0.52%), while the performance of pressure level winds (51.7%) is slightly better than that of 10m winds (47.8%). This suggests a differential sensitivity to uncertainty propagation across various atmospheric layers. Pressure level winds represent a broader atmospheric layer, in contrast, 10m and

160 100m winds are highly sensitive to localized boundary layer processes and surface conditions, which may not be representative at the scales of the satellite observations used in this work. The comparison of the valid grid ratio across different meteorological wind fields shows that the spatiotemporal coverage of credible TROPOMI-derived emission estimates remains broadly consistent regardless of the specific wind product used. There is the issue of the vertical distribution of emissions in mountainous areas or

165 areas with complex source types, in which case wind speed and direction too close the surface may not represent the wind where the emissions have occurred(Cohen et al., 2011). Therefore, for subsequent analysis in this work, we use reanalysis winds at various atmospheric heights consistent with motion in the lower parts of the troposphere, as being representative of the dispersion impacting fresh emissions which have mixed in-situ to the spatial scales used.

170 Notably, there is inter-annual oscillation in the valid grid ratio from 2019-2024, consistently across years and for different wind fields/x% distributions, in part due to changes in various earth cycles including the Asian Monsoon start time, El-nino, and the Indian Ocean Dipole. This implies an annual “dip” in the valid grid ratio around Central Asia in late spring/early summer, followed by a recovery and subsequent decline into the next year. It could be affected by Asian Monsoon Systems and ENSO (El Nino-Southern

175 Oscillation), since changes in these phenomena can directly impact atmospheric circulation, fire emissions, dust emission and suspension, and subsequent transport of moisture, smoke, and dust in Asia, thereby altering the strength and spatial structure of divergence fields. This wavy pattern strongly suggests that Asia’s unique climate and atmospheric dynamics directly influence the robustness of emissions calculations. To more accurately assess the reliability of divergence products, the uncertainty

180 quantification framework needs to incorporate not only seasonal variability but also this significant inter-annual oscillation. The global variation of this trend deserves further study.



3.2 Characterization of the Spatio-Temporal Distribution of Grid0.5

Considering that pressure wind and beta distribution can bring the maximum valid grid ratio, subsequent analysis obeys a beta distribution ($a=2$, $b=5$) and wind fields range of 350~975hpa. Meanwhile, the uncertainty for cloud and AOD are both larger than 1%(Filonchyk and Hurynovich, 2020), and these errors must be taken into consideration before any uncertainty in CH_4 can be taken into consideration, so the analysis in the main text takes the error range of 5%.

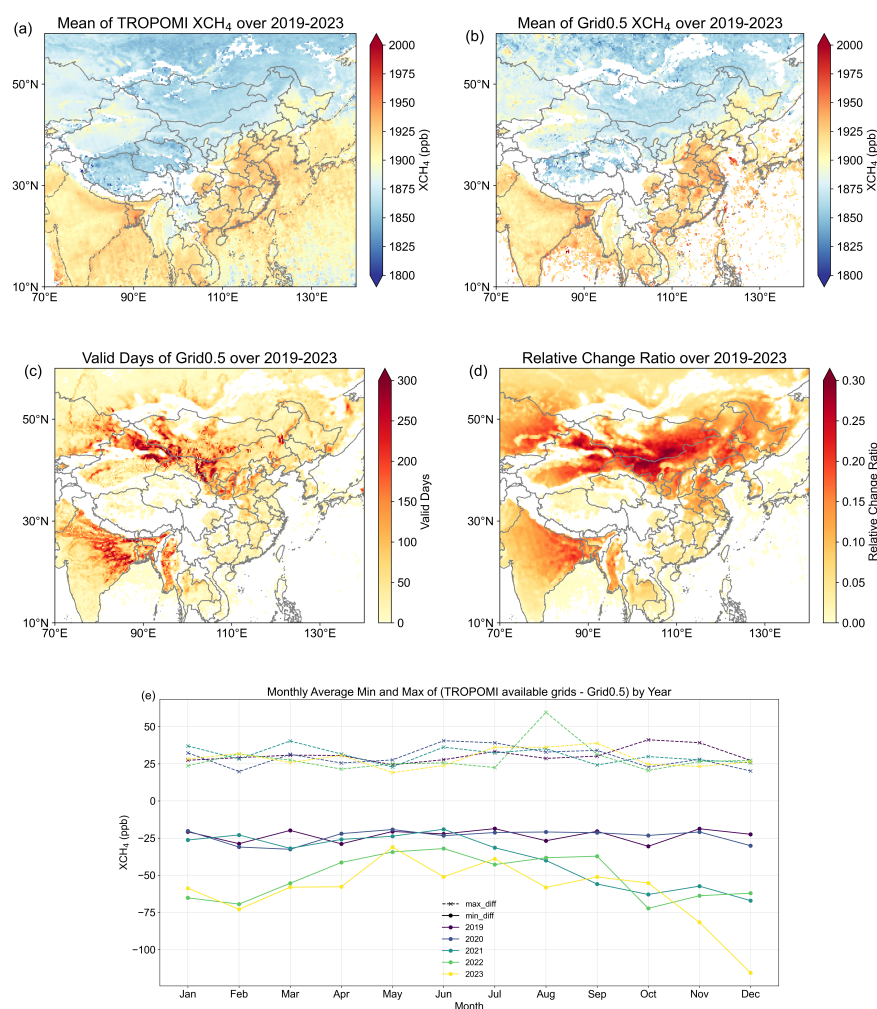


Figure 3: Mean of TROPOMI(a) and Grid0.5(b) XCH_4 over 2019-2023, valid days of Grid0.5 over 2019-2023(c), relative change ratio of XCH_4 (exclude $<5^{\text{th}}$, $>95^{\text{th}}$ along temporal dimension) over 2019-2023(d), and Monthly Average Min and Max between TROPOMI and Grid0.5 by year(e).



Figure 3(a) and Figure 3(b) represent the TROPOMI XCH₄ without perturbations (ref as TROPOMI available grids) and each TROPOMI grid has half of the perturbation data per day that meets the $|(Div'-Div)/Div| < 5\%$ condition's XCH₄ (ref as Grid0.5) over 2019-2023 (see Figure S4 for annual spatial distribution). The spatial coverage of TROPOMI in the study area, as depicted in Figure 3(a), is relatively comprehensive, with the exception of the southwestern region of China, which lack data. The spatial distribution of Grid0.5 significantly differs over ocean surfaces, showing more spatial gaps. Oceanic regions are typically characterized by different atmospheric and surface conditions compared to land. This finding indicates that XCH₄ over oceanic regions are less frequently associated with robust divergence operator. On the other hand, over land, the data is more robust to small random perturbations, and the high-low pattern of XCH₄ remains largely unchanged (higher observations in the south, lower observations in the north). Notably, most of the locations of strong emission sources (such as coal mining) are retained, indicating that this filtering method is not random (see Text S1).

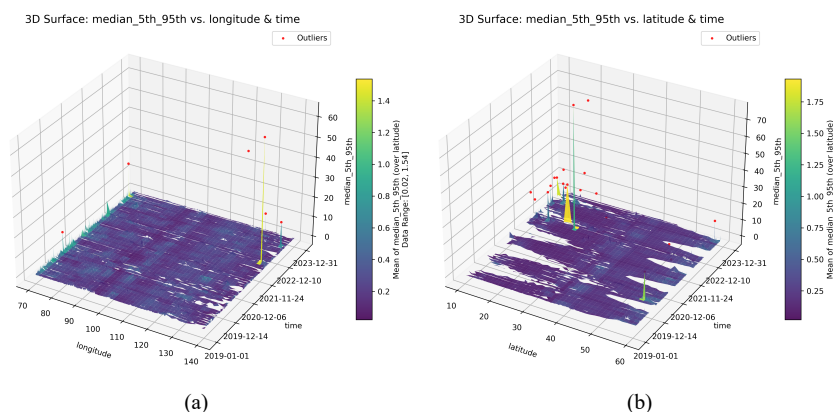
Figure 3(c) and Figure 3(d) show the number of valid days and the spatial distribution of relative change ratio. The maximum number of valid days is 487 days (out of a total period of 2019-01-01 to 2023-12-31, total days of 1731 days), with an average of 26.8 days, which is quite low. This suggests that the condition $|(Div'-Div)/Div| < 5\%$ is a relatively stringent criterion for valid grid determination. This highlights the inherent sensitivity of divergence operator to even small (5%) perturbations. The higher valid days over northwest China and northeast India point to regions where the divergence signals are generally very strong and stable. First, both regions contain large amounts of coal mines and therefore should have a relatively stable sources of methane emissions (more details refer to Supplement). Second, Northwest China is generally arid and has few clouds as well as a relatively stable spatial aerosol distribution, which minimizes the temporal and spatial variation of their induced spectral interference and signal noise in the TROPOMI 2.3 μ m absorption band. Third, while northeast India is influenced by strong intra-annual variations associated with monsoonal flow, within some of the phases of the monsoon flow, the cloud and aerosol levels are relatively low, and the wind is relatively coherent in areas not impacted by mountains and coasts. Strong, coherent atmospheric signals in these regions might be less susceptible to a 5% random perturbation, thus maintaining the desired relative change threshold. The spatial mean of relative change ratio is 1.06, however, when excluding the lowest and highest outlying data points (i.e., below the 5th and above the 95th percentile along the temporal dimension), the spatial mean is 0.05, which means the relative change ratio is heavy-tailed. When these extremes are not

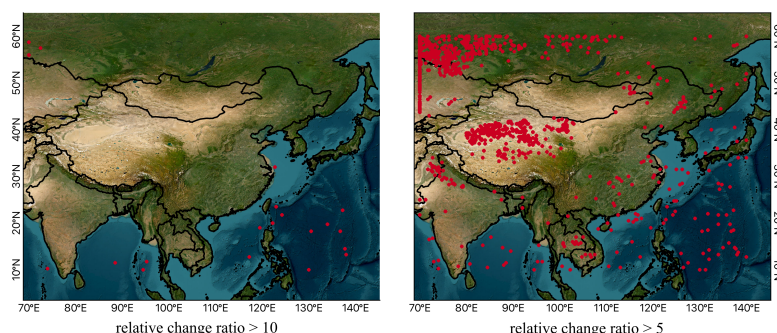


excluded, the spatial distribution of relative change ratio is disorganized (see Figure S2). The impact of elevation roughness (see Text S2) and TROPOMI retrieval versions (see Text S3) was also taken into account.

Figure 3(e) shows the difference between the extreme values of TROPOMI available grids and Grid0.5 within the study area, where $\text{max-diff} = \text{TROPOMI available grids spatial maximum} - \text{Grid0.5 spatial maximum}$ and min-diff vice versa. The max-diff is always positive, around 25 ppb monthly, while the min-diff is always negative, around -25 ppb (or smaller). This means that divergence-based filter affects the spatial XCH_4 extreme values, i.e. divergence-based filter preferentially removes all outliers (both low and high) XCH_4 values. This could suggest that extremely high XCH_4 concentrations are often associated with factors including time-varying emissions sources or unusual atmospheric dynamical conditions, both of which are not well sampled and/or are more susceptible to noise. It could also suggest that while high AOD is filtered, uncertainties persist due to unconsidered aerosol absorption and reliance on reanalysis data for co-absorbing CO and water vapor, especially in industrial areas. This could also suggest that regions where XCH_4 has low concentration or strong local sinks are also highly sensitive in divergence calculations (Zheng et al., 2026). After July 2021, the amplitude of these differences increases, sometimes exceeding 50 ppb. Worth noting is, since 2021-07-01, TROPOMI XCH_4 retrievals (v02.02.00) updates the CH_4 cross section, the a-posteriori bias corrected CH_4 is independent of any reference data, and has newly improved L1b input.

3.3 Characterization of the Spatio-Temporal Distribution of Relative Change Ratio





(c)

Figure 4: 3D surface analysis of relative change ratio (excluding the lowest and highest 5th value), where red points highlight the relative change ratio > 10(a, b, left c) and 5(right c).

Figure 4 visualized the sensitivity of relative change ratio among spatio and temporal. From Figure 4(a), it can be seen that the main surface across the longitude (70°E-140°E) and time (1 January 2019 to 31 December 2023) domain remains low. This indicates that in the vast majority of the spatio-temporal domain, the divergence exhibits strong robustness against the 5% uncertainty. However, there are a small number of red outliers (median 5th and 95th of relative change ratio > 10). These isolated points denote specific longitude-time coordinates where a minor perturbation in the input data ($\pm 5\%$) leads to a massive relative change in the calculated divergence. The outliers appear sporadically in time but show a tendency to occurs from late-2020 to 2023 period, primarily distributed in the mid-to-high longitude range. Similar to the longitude plot, the core surface over the latitude (10°N-60°N) and time plane also maintains a very low relative change ratio, confirming the overall high robustness of the divergence calculation. In the latitude range of approximately 10°N~25 °N, particularly around 2022 and 2023, there are pronounced localized peaks. Different from longitude plot, the outliers in latitude plot exhibit a clearer clustering pattern.

Interestingly, these outliers appeared for a total of 20 days, concentrated from February to September, of which a quarter of the outliers occurred in June (5 days), followed by May (4 days), April (3 days), February, March, and July (2 days), and 1 day each in August and September.

Figure 4(c) visualized the geographic location of all grid cells where the relative change ratio exceeds specific thresholds (>10 and >5). The locations where relative change ratio > 10 (left) are sparse and scattered, consisting of 3 grids over the land and 7 grids over ocean. While lowering the threshold to 5(right) results in a substantial increase in the number and density of sensitive grids. The relative change



ratio > 5 grids cluster into distinct geographical regions: northern continental land and southern/maritime clusters. Four spatially dense clusters of unstable emissions are observed, where even minor absolute changes in divergence due to data perturbation are magnified dramatically. These unstable regions spatially coincide with areas frequently affected by wildfire activity, dust transport, snow and ice cover, or strong anthropogenic emissions. However, attribution of the observed sensitivity to specific physical mechanisms is beyond the scope of this study and requires dedicated investigation. For subsequent modeling or physical interpretation, the data quality and uncertainty budget for these continental interiors and the maritime clusters must be rigorously scrutinized, and error metrics based on absolute change should be considered alongside the relative change ratio to provide a complete error assessment.

3.4 The Relationship between Relative Change Ratio and City Type

The classification of county-level administrative units in this study was initially conducted based on industrial structure data derived from the *China Statistical Yearbook (County Level)* (China Statistical Yearbook 2023). Specifically, we categorized the sample counties into four primary functional types, i.e., Agricultural, Industrial, Service/Comprehensice, and Balanced, by calculating the respective proportions of the primary, secondary, and tertiary industry added values relative to the regional Gross Demestic Product (GDP). To account for the specific developmental trajectories of resource-dependent regions, we further redined this classification by identifying Coal-based Cities. This identification was performed by academic literature and the National Sustainable Development Plan for Resource-Based Cities (State Council Gazette Issue No. 35 Serial No. 1466 (December 20, 2013); Yi and Su, 2025; Yu et al., 2018). Consequently, coal-based counties were isolated as a distinct category to investigate the unique impact of extractive industries on regional dynamics. Following the typological classification, Box-and-Whisker plots were employed to visualize the distribution of the Relative Change Ratio (RCR) across the different categories (Figure 5).

The first observation is that while every city (county) has some values filtered out in order to enter the trustworthy emissions perturbation smaller than or equal to the XCH_4 perturbation (TW), that coal cities are the only subtype in which the total number of cities did not decrease. However, over all of the other types, we observe that there is a 13%-24% decrease in the total number of cities which pass TW. This means that statistics which analyze country wide or global wide sectors may be introducing biases in all major sectors except for coal. The second observation is that for the subset of grids at $0.25^\circ \times 0.25^\circ$ as well



as remaining individual cities which pass TW, that the overall mean RCR is 6% lower for coal than the other industrial types. This implies that inverse modeling using TROPOMI data is likely to have both a higher error and more bias when inverting types of cities including agricultural, industrial, service, and mixed, as compared to coal based cities. This means that current studies need to take great care when assessing how small changes in non-coal (and possibly oil and gas, which are more similar to coal, but not studied herein) are actually really changing, since the reliability has both a larger uncertainty and a bias.

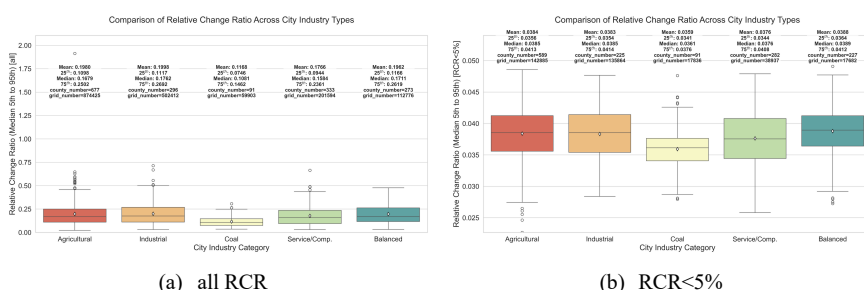


Figure 5: Distribution of Relative Change Ratio (RCR) across various city industry types. Where left shows all spatial-temporal grid, while right shows only RCR<5%.

The substantial reduction in the number of grids (70%-84%) across all categories indicate that the inherent spatial and temporal noise present at the grid-scale. Coal-based grids have the least reduction (70%), while agricultural and balanced types have the most reduction (84%). This indicates that the emission scenarios of coal-type cities have higher spatial homogeneity and continuity, whereas agricultural-type and balanced-type areas are more noisy in terms of micro-fluctuations due to fragmentation of farmland, multi-crop rotations, or interlacing of urban functional zones, which leads to greater noise, making it difficult to satisfy the requirement of stability with high precision (<5%).

4. Conclusions

This study selected multiple distributions of random errors to represent diverse statistical properties induced by uncertainties across various physical properties contributing to uncertainty - concentration, scattering, and absorption - which encompass a broader range of potential true error mechanisms inherent in satellite remote sensing data. This is supported by recent work from (Sicsik-Paré et al., 2026) demonstrating that three different versions of TROPOMI derived CH₄ can vary by 20 to 50 ppb on a



grid-by-grid basis. The experimental results provide compelling evidence that the probabilistic distribution of input uncertainties, not just their maximum magnitude, fundamentally governs error propagation and the overall reliability of derived geophysical quantities in atmospheric remote sensing. This is similar to findings from Cohen and Prinn (2011) and Cohen (2014) with respect to air pollution that such uncertainty shapes can make substantial differences on emissions of Black Carbon. The relatively high RCR retention rate of the coal-type grid (30% retention vs. 16% for the other types) implies that industrialized, large-scale production patterns provide a stronger, more stable signal signature that is spatially more resistant to disturbance than natural landscapes (Agricultural) or complex functional areas (Balanced). This scientific point has been raised by (Lu et al., 2025; Zheng et al., 2026), indicating that uncertainty in background subtraction on both the emitting grid as well as those around the emitting grid can lead to calculating very large spurious emissions.

This finding underscores the need for thorough characterization and realistic modeling of observation uncertainties to improve the accuracy and confidence in atmospheric analyses. One particularly important aspect of these findings is that they provides a quantitative basis for interpreting TROPOMI-derived methane fluxes, including from both top-down model-based approaches and more simplified approaches, and demonstrate that particularly in coal-dominated regions, such approaches should generally be robust, while in other types of regions, the approaches may not be as robust, and should be examined far more carefully than the community is currently doing. It also provides a means by which current TROPOMI-derived methane fluxes can be filtered to increase their reliability in terms of policy-relevant analysis, and opening the door to examine in which geospatial regions additional work will be needed to improve reliability. The findings have direct implications for methane emission studies based on TROPOMI observations. While divergence-based approaches appear relatively robust in regions characterized by strong and persistent emission sources, particularly coal-dominated regions, caution is warranted in areas exhibiting high sensitivity to observational perturbations. Future inversion and flux estimation studies should explicitly account for the distribution and propagation of retrieval uncertainties, rather than relying solely on nominal uncertainty magnitudes.

One limitation of this work stems from the gaps that are present in the observed products, which can lead to smearing of signals or completely missing other signals. A second limitation is due to the fact that there are occasional long-range transport events which may advect real emissions further than observed by the gradient term, and therefore are not identified. A third limitation is that this work has not



considered the sub-grid variability induced by substantial but smaller spatially diverse clouds and aerosols, which may lead to a geospatial variation in the uncertainty which is not detected at the resolution
345 analyzed here. Other limitations may occur from different inversion techniques and instrument errors across different profiles. This work can be rapidly adopted in different geographical regions, and hope that such adaptation to different strong fossil fuel source types, will help provide both insight, as well as additional value in areas dominated by other sources.

Data Availability

350 TROPOMI Level 2 Methane Total Column products are available at <https://browser.dataspace.copernicus.eu/>. The wind data at different pressure levels are from the European Centre for Medium-Range Weather Forecasts ERA-5 reanalysis products, available at <https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5>. The 60 Arc-Second Resolution geoid height product is available at <https://www.ncei.noaa.gov/products/etopo-global-relief-model>.

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Supplement link

Supplementary information The online version contains supplementary material available at doi.org.

Author contributions

Wei Hu: conceptualization, methodology, data curation, formal analysis, writing - original draft, review
360 and editing. **Jason Blake Cohen:** conceptualization, methodology, scientific interpretation, writing - review and editing. **Lingxiao Lu, Bo Zheng, and Pravash Tiwari:** conceptualization, methodology. **Simone Lolli, Andrea Garzelli:** writing - review and editing. **Jun Li:** funding acquisition. **Kai Qin:** conceptualization, writing - review and editing.

Competing interests

365 Jason Blake Cohen is a member of the editorial board of Atmospheric Chemistry and Physics.



Acknowledgments

We thank Dr. Robert Field (UNEP-IMEO) for discussions and support.

Financial support

This research was supported by the Shanxi Province Science and Technology Cooperation and Exchange
370 Special Program [Grant Number 202304041101026] and Jiangsu Provincial Department of Science and
Technology Science Project (BZ2024060). This research was enabled by support from the International
Methane Emissions Observatory to Reduce Short-Lived Climate Pollutants (CCD25-MB7876).

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