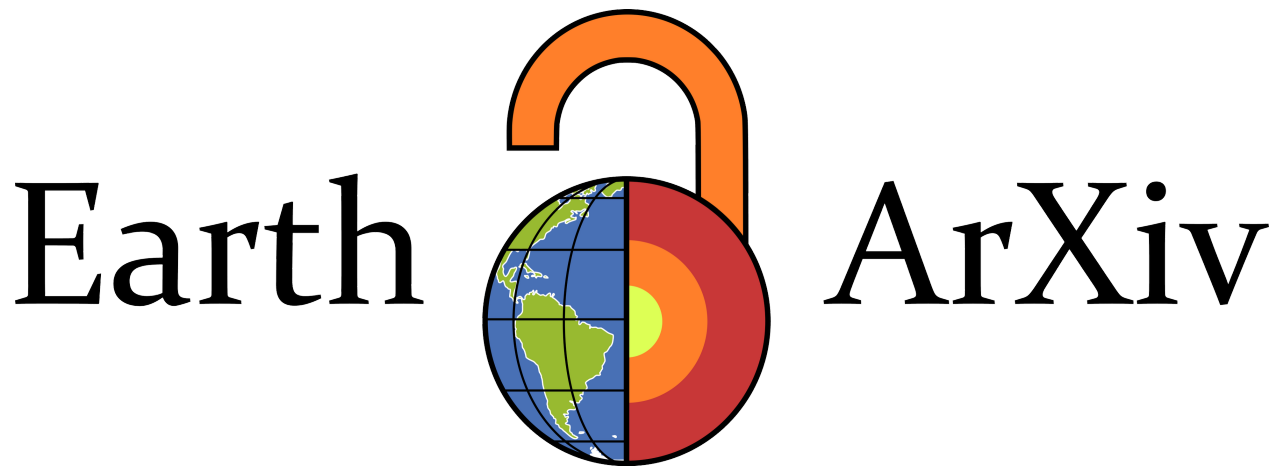




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Satellite Quantification of Methane Emissions from Individual Countries in Southeast Asia: Roles of Dry and Wet Seasons

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Abstract. Southeast Asia is a global methane (CH₄) hotspot, yet its emissions remain highly uncertain particularly regarding seasonal variability. Here we quantify methane emissions over ten Southeast Asian countries using TROPOMI satellite observations and analytical inversions at up to 0.25°×0.3125° resolution (~25km×25km), separately for the dry (October 2021-April 2022) and wet (May-September 2022) seasons. We find despite limited local retrievals during cloud-limited wet season, observations from downwind regions provide effective constraints, yielding considerable information. Our best estimates of annual total, anthropogenic, and natural emissions are 47.9(44.5-51.4), 27.8(26.4-29.2), and 20.1(18.1-22.3) Tg a⁻¹ respectively; parentheses indicate uncertainty ranges from the inversion ensemble. Anthropogenic emissions show a clear seasonal contrast not adequately represented in current inventories, increasing from 24.2 Tg a⁻¹ in the dry season to 32.8 Tg a⁻¹ in the wet season, largely due to rice, livestock,

and previously-overlooked oil and waste emissions. Annual rice and livestock emissions (10.8 and 5.8 Tg a⁻¹) exceed UNFCCC reports by 64% and 53%, with large discrepancies in Thailand, Viet Nam, Myanmar, and Indonesia, reflecting the use of outdated activity data and low emission factors. Our separate dry- and wet-season satellite inversions provide an improved basis for mitigation efforts in Southeast Asia under the Global Methane Pledge.

Keywords: methane emissions, satellite observations, top-down inversion, dry and wet season, Southeast Asia

1. Introduction

Methane (CH₄) is the second most important anthropogenic greenhouse gas after CO₂ with a lifetime of 9.1 ± 0.9 years (1). Its global warming potential is ~28 times that of an equivalent mass of CO₂ over a 100-year horizon (2). Average annual global methane concentrations increased by 284.7 ppb or 17.3% from 1984 to 2024 (3). Reducing methane emissions has been recognized as a priority mitigation under the Paris Climate Agreement (4). As of April 2026, 160 countries have signed the Global Methane Pledge, aiming to collectively reduce methane emissions by 30% below 2020 levels by 2030 (<https://www.globalmethanepledge.org/>).

Southeast Asia (including Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste and Viet Nam) is an important source region of methane emissions, contributing 9.6% of the global total, yet remains subject to high uncertainty (5). Based on the Global Carbon Project (GCP), it is estimated to have emitted 64 (42-93) Tg a⁻¹ out of a global total of 669 (512-849) Tg a⁻¹ for the 2010-2019 decade. Major methane sources in Southeast Asia include natural wetlands, rice cultivation, and waste (landfills and wastewater treatment), contributing 37.5%, 14.1% and 9.4% of total regional emissions respectively.

According to the latest national emission inventory submitted by the governments to the United Nations Framework Convention on Climate Change (UNFCCC), Indonesia (2022, the

latest inventory year), Viet Nam (2013) and Thailand (2022) are the largest emitters in Southeast Asia. Anthropogenic emissions from the three countries were reported at 8.9, 4.0 and 3.2 Tg a⁻¹, together accounting for 69.4% of total anthropogenic emissions in this region. These UNFCCC-reported emission inventories are primarily based on bottom-up approaches that combine activity data with emission factors (EFs) for each activity, and in some cases are further informed by source-specific information. There are however large uncertainties associated with these bottom-up methods (6). For example, East et al. (7) constrained global methane emissions for 2023 by inversion of TROPOspheric Monitoring Instrument (TROPOMI) observations in combination with point source information, and found that UNFCCC-reported emissions are largely underestimated in this region; for instance, national emissions reported for Thailand and Cambodia are underestimated by 65% and 87% respectively.

Southeast Asia is strongly influenced by a monsoon climate, resulting in distinct dry and wet seasons, typically spanning October to April, and May to September respectively (Figure 1). Methane emissions from seasonally-varying sectors, including wetlands, rice, livestock, and waste are highly sensitive to the monsoon climate, adding additional uncertainty into emission estimates. Current bottom-up emission inventories fail to describe accurately the seasonal variability of these methane emissions. East et al. (8) found that the GEOS-Chem simulations driven by traditional inventories cannot reproduce the sharp increase of atmospheric methane mixing ratios observed in July over the Northern Hemisphere (3), most likely resulting from the incorrect seasonal distribution of wetland emissions. Chen et al. (9) used 30-m Landsat retrievals to derive monthly methane emissions from rice paddies across Asia for 2022 and found that rice emission peak months differ largely across Southeast Asia, which is however uniformly set to be August by the widely used anthropogenic emission inventory Emissions Database for Global Atmospheric Research (EDGAR) (10). Yu et al. (11) suggested an over 45% upward correction to the traditional inventory over India and Southeast Asia during the summer monsoon season (July-October) for 2018-2019. This correction is likely related to monsoon-enhanced precipitation that increases methane emissions from rice, manure, landfills and sewers. Recent studies have indeed highlighted the previously-ignored seasonality in waste

methane emissions (12-14).

Satellite observations of atmospheric methane in the shortwave infrared (SWIR) enable top-down constraints that are critical for evaluating bottom-up inventories and reducing uncertainty. Satellite observations can be exploited through inversion with an atmospheric transport model linking surface emissions to atmospheric concentrations, with the bottom-up inventory as prior information (6, 15). TROPOMI (2018 - present) provides global continuous daily mapping of atmospheric methane at $7 \text{ km} \times 5.5 \text{ km}$ ($7 \times 7 \text{ km}$ before August 2019) nadir resolution (16), with improved coverage compared to previous satellite instruments (17-18). Recent studies have employed TROPOMI observations to perform inverse modeling of methane emissions for the Middle East and North Africa (19), East Asia (20-22) and the Americas (23-26). These studies however often focus on best optimizing annual-mean emissions, while the emission seasonality is imposed from the prior knowledge rather than being optimized. This limitation can bias emission estimation, particularly in regions such as Southeast Asia where emissions show large seasonality.

Limited data coverage in the wet tropics due to persistent cloudiness however has posed a long-standing challenge for satellite inversions (27). The number of available TROPOMI retrievals in the wet season (34,444) is only 5% that of the dry season (657,625) over Southeast Asia in 2022 (Figure 1). Satellite observations at downwind regions, however, might provide a useful, alternate constraint by capturing signals transported from upwind sources, which has not been sufficiently examined in recent satellite inversions. In this study, we leverage satellite observations in downwind regions, which potentially contain information of upwind methane emissions, to constrain emissions across Southeast Asia in the wet tropics.

Here we use TROPOMI observations to quantify methane emissions over Southeast Asia (Figure 1), conducted separately for the dry (October 2021–April 2022) and wet (May–September 2022) seasons. Emissions are estimated at a spatial resolution up to $0.25^\circ \times 0.3125^\circ$, with attribution to different source sectors. Using two seasons is a trade-off between maximizing observational constraints and the need to capture seasonal emission variability. We purposely extend our inversion domain to include South China, which lies downwind of Southeast Asia during the wet season (Figure 1b). We use an analytical approach to Bayesian

inference of methane emissions (6), which has the advantage of providing closed-form error statistics and hence information content as part of the solution, and allows to perform an ensemble of sensitivity inversions with minimal additional computational cost. Our objectives are threefold:

(1) to examine the extent to which satellite retrievals can be used to constrain dry- and wet-season emissions;

(2) to investigate the contributions of dry and wet seasons to regional total emissions;

(3) to attribute emissions to individual countries and major sectors, and compare these results with UNFCCC reporting to inform climate policy.

2. Data and Methods

We perform the inversions of TROPOMI data for the dry and wet seasons respectively from October 2021 to September 2022 over Southeast Asia (11° S - 29° N, 90° E - 141° E) at up to $0.25^{\circ} \times 0.3125^{\circ}$ resolution. Here the dry and wet seasons are delineated based on the climatological seasonality of mainland Southeast Asia (28), and therefore may not fully capture conditions in maritime Southeast Asia (mainly Indonesia, Malaysia, and the Philippines), where precipitation seasonality is weaker and influenced by different monsoonal dynamics. This is sufficiently accounted for in our subsequent analyses. Doing so is a trade-off between achieving effective observational constraint and resolving emission seasonality, as TROPOMI observations generally do not provide sufficient information to constrain emissions at finer timescales over this region (Sect. 3.1). In this section we describe in detail the TROPOMI data (Sect. 2.1), the prior emission estimates (Sect. 2.2), the forward GEOS-Chem model (Sect. 2.3), the analytical inversion method and sector attribution (Sect. 2.4), and inversion ensemble and uncertainty estimate (Sect. 2.5).

2.1. TROPOMI observations

TROPOMI was launched on board the polar sun-synchronous Sentinel-5 Precursor satellite and monitors greenhouse gases and air pollutants at ~13:30LT (Equator over pass) (18). It provides global daily coverage at a $7\text{ km} \times 5.5\text{ km}$ (nadir) spatial resolution (17). In this study, we use the blended TROPOMI + GOSAT XCH_4 product (29) and filter out low-quality retrievals ($'qa_value' < 0.5$). This blended product applies a machine learning model to correct the TROPOMI operational v02.04.00 data with Greenhouse gases Observing SATellite (GOSAT) observations as a reference, which are 250 times sparser than TROPOMI but less affected by artifacts. The machine learning model is trained using co-located TROPOMI and GOSAT observations during 2018-2020 to predict the TROPOMI-GOSAT XCH_4 difference based on predictor variables from the TROPOMI retrieval. This blended TROPOMI + GOSAT XCH_4 product shows reductions in variable bias and single-retrieval precision with the ground-based Total Carbon Column Observing Network (TCCON) observations relative to the original TROPOMI product (29). The blended dataset therefore combines extensive observational coverage and high sampling density with low retrieval bias. We further exclude satellite retrievals over the oceans following Chen et al. (19).

2.2. Prior estimates

Figure 2 shows the prior estimates of annual-mean emissions from different sectors over the inversion domain and Table 1 gives the regional totals during the dry and wet seasons over Southeast Asia. Emissions are expressed in units of Tg a^{-1} throughout the text to facilitate comparison. Emissions from oil, gas and coal are spatially distributed onto the $0.25^\circ \times 0.3125^\circ$ GEOS-Chem grid based on infrastructure data compiled in the Global Fuel Exploitation Inventory (GFEIv3) (30). Monthly Global Rice Paddy Inventory (GRPI) (9) is used for rice emissions, and the EDGARv8 inventory (31) is used for other anthropogenic emissions. The Global Fire Emissions Database version 4s (GFED4) (32) is used for monthly biomass burning emissions; we consider these emissions as an anthropogenic sector, as they are largely associated with deforestation and degradation in Southeast Asia.

Natural sources in each inversion include Lund-Potsdam-Jena Earth Observation

Simulator Dynamic Global Vegetation Model driven by MERRA-2 meteorology (LPJ MERRA-2) (33) for monthly wetlands emission, termites from Fung et al. (34), and seeps from Etiope et al. (35) scaled to a global emission of 2 Tg a^{-1} based on Hmiel et al. (36).

2.3. GEOS-Chem chemical transport model

We use the chemical transport model GEOS-Chem (v13.0.0; <https://doi.org/10.5281/zenodo.4618180>) as the forward model to simulate atmospheric methane concentrations in the inversion. The model is driven by Goddard Earth Observing System-Forward Processing (GEOS-FP) reanalysis meteorological fields with a temporal resolution of 1 h for surface variables and boundary layer height, and 3 h for others provided by NASA Global Modeling and Assimilation Office (GMAO) (37). Each simulation for the dry and wet seasons respectively is conducted over the study domain of Figure 1 at $0.25^\circ \times 0.3125^\circ$ horizontal resolution with 47 vertical layers. We use a nested GEOS-Chem model in Southeast Asia region and 3h dynamic boundary conditions from a global archive of smoothed TROPOMI fields, which are generated by correcting a $2^\circ \times 2.5^\circ$ GEOS-Chem simulation with TROPOMI satellite observations (38-39). We apply the TROPOMI averaging kernel vectors and prior vertical profiles (39) to the GEOS-Chem vertical profiles of methane dry-air mixing ratios to derive simulated $X\text{CH}_4$ for comparison with TROPOMI observations.

2.4. Analytical inversion

The emission inversions for the dry and wet seasons are performed on the $0.25^\circ \times 0.3125^\circ$ grid, with boundary condition vertical profiles also being part of the optimization. The available satellite observations do not provide sufficient information to constrain emissions on each grid in Southeast Asia, attempting this would result in substantial smoothing errors (40-41). Therefore, we adopt the Gaussian mixture model (GMM) approach of Turner and Jacob (40) to construct emission patterns that can be effectively constrained by TROPOMI. The GMM functions are chosen to preserve native resolution ($0.25^\circ \times 0.3125^\circ$, the original spatial

resolution of the GEOS-Chem model) in areas with strong, localized sources, while aggregating regions with low, uniform emissions. In practice, methane emissions at $0.25^\circ \times 0.3125^\circ$ resolution are mapped onto a set of P Gaussian components, where P represents the selected similarity criteria. We use 600 Gaussian functions for each emission inversion following Chen et al. (19-20). The inversion optimizes the amplitude of each Gaussian. We also optimize 4 boundary conditions (north, south, west and east of the domain edges) with a prior error standard deviation of 10 ppb, which adds up to a total of $600 + 4 = 604$ state vector elements.

The analytical Bayesian inversion optimizes the state vector $\mathbf{x}$ assuming normal error probability density functions (PDFs) by minimizing the cost function $J(\mathbf{x})$ (15):

$$J(\mathbf{x}) = (\mathbf{x} - \mathbf{x}_a)^T \mathbf{S}_a^{-1} (\mathbf{x} - \mathbf{x}_a) + \gamma (\mathbf{y} - \mathbf{K}\mathbf{x})^T \mathbf{S}_0^{-1} (\mathbf{y} - \mathbf{K}\mathbf{x}) \quad (1)$$

Where $\mathbf{x}$ is the state vector, $\mathbf{x}_a$ is the prior estimate for $\mathbf{x}$ and $\mathbf{S}_a$ is the prior error covariance matrix. $\mathbf{S}_0$ is the observation error covariance matrix which includes the error from instrument and the forward model. We calculate the variance terms from the statistics of the residual errors ($\varepsilon_0 = \mathbf{y} - \mathbf{F}(\mathbf{x}_a) - \overline{\mathbf{y} - \mathbf{F}(\mathbf{x}_a)}$) (42) and use them as the diagonal elements of $\mathbf{S}_0$. The regularization parameter γ is used to avoid assigning excessive weight to the observations and balance the impacts of $\mathbf{S}_a$ and $\mathbf{S}_0$ on the cost function $J(\mathbf{x})$. We achieve the optimal value of γ following Lu et al. (43), which ensures $(\hat{\mathbf{x}} - \mathbf{x}_a)^T \mathbf{S}_a^{-1} (\hat{\mathbf{x}} - \mathbf{x}_a)$ being approximately $n \pm \sqrt{2n}$, the expected value (± 1 standard deviation) from the Chi-square distribution with n degrees of freedom. The optimal posterior estimate $\hat{\mathbf{x}}$ is introduced in Eq. (2). Here we obtain γ of 0.05 for the dry season and 0.22 for the wet season. $\mathbf{K} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}}$ is the Jacobian matrix that represents the sensitivity of observations $\mathbf{y}$ to $\mathbf{x}$.

Minimizing the Bayesian cost function by setting $dJ(\mathbf{x})/d\mathbf{x} = 0$ yields analytical solutions for the posterior estimate of the state vector $\hat{\mathbf{x}}$ and its corresponding error covariance matrix $\hat{\mathbf{S}}$:

$$\hat{\mathbf{x}} = \mathbf{x}_a + (\gamma \mathbf{K}^T \mathbf{S}_0^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \gamma \mathbf{K}^T \mathbf{S}_0^{-1} (\mathbf{y} - \mathbf{K}\mathbf{x}_a) \quad (2)$$

$$\hat{\mathbf{S}} = (\gamma \mathbf{K}^T \mathbf{S}_0^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \quad (3)$$

The averaging kernel (AK) matrix $\mathbf{A}$, which describes the sensitivity of the posterior estimate to the true state, is calculated from the posterior error covariance matrix:

$$\mathbf{A} = \mathbf{I} - \hat{\mathbf{S}}\mathbf{S}_a^{-1} \quad (4)$$

The trace of $\mathbf{A}$ is often referred to as the degrees of freedom for signal (DOFS) (44), which quantifies the number of independent pieces of information on $\mathbf{x}$ constrained by observations. We refer to the diagonal terms of $\mathbf{A}$ as averaging kernel sensitivities, which represent the ability of the observations to independently constrain the individual elements of the state vector in each inversion.

The GMM generates 600 state vector elements that can be readily mapped on the native $0.25^\circ \times 0.3125^\circ$ grid. We select 600 Gaussian functions following previous studies (20, 40), considering the need to retain major spatial features of prior emissions while balancing aggregation and smoothing errors (40). We here further aggregate the gridded emissions into sectors and countries. This reduction in the state vector dimension is achieved by a summation matrix $\mathbf{W}$, which represents the linear transformation from the full state vector to a reduced state vector while preserving the information contained in the posterior error covariance matrix. Here, $\mathbf{W}_1$ is a $(p \times n)$ matrix that connects the individual elements of the state vector (n) to the p GEOS-Chem grid cells. For country level, we define $\mathbf{W}_c$ as a $(c \times p)$ binary matrix, with rows representing the c countries and columns representing the p GEOS-Chem grid cells. For sector level, $\mathbf{W}_s$ is an $(s \times p)$ matrix, with rows representing the s emission sectors and elements corresponding to the dry- or wet-season emissions of each sector in each grid cell (20). The weighting matrix is calculated as $\mathbf{W} = \mathbf{W}_i \mathbf{W}_1$, where $\mathbf{W}_i$ represents either $\mathbf{W}_c$ or $\mathbf{W}_s$. The resulting matrix is weighted by emissions and normalized so that the elements in each row sum to one.

The posterior estimate of the reduced state vector ($\mathbf{x}_{\text{red}}$), the posterior error covariance and averaging kernel matrices are computed as

$$\hat{\mathbf{x}}_{\text{red}} = \mathbf{W}\hat{\mathbf{x}} \quad (5)$$

$$\hat{\mathbf{S}}_{\text{red}} = \mathbf{W}\hat{\mathbf{S}}\mathbf{W}^T \quad (6)$$

$$\mathbf{A}_{\text{red}} = \mathbf{WAW}^* \quad (7)$$

where $\mathbf{W}^* = (\mathbf{W}^T \mathbf{W})^{-1} \mathbf{W}^T$ is the Moore-Penrose pseudoinverse (45).

249

250 **2.5. Inversion ensemble and uncertainty estimate**

251 Our base inversions for the dry and wet seasons in this study make assumptions on the
 252 values of inversion parameters including $\mathbf{S}_a$ and γ . But there is uncertainty in these choices
 253 and we therefore conduct an ensemble of sensitivity inversions by varying different parameters.
 254 The inversion ensemble includes (1) using 5 and 20 ppb for the prior error standard deviation
 255 in the boundary condition elements instead of 10 ppb, (2) giving 25% and 75% for the prior
 256 error standard deviation instead of 50%, (3) for the regularization factor γ , using 0.04 and 0.06
 257 for the dry season instead of 0.05, and 0.32 and 0.12 for the wet season instead of 0.22. The
 258 combination of these perturbations results in an inversion ensemble of 27 members for each of
 259 dry- and wet-season emission optimizations.

260

261 **3. Results and discussion**

262 **3.1. Evaluation of posterior emission estimates**

263 Figure 3 shows the prior emission, posterior emission and posterior–prior emission ratios
 264 for the dry and wet seasons respectively on the $0.25^\circ \times 0.3125^\circ$ grid. Figure 3 also shows the
 265 spatial distribution of the averaging kernel sensitivities during the dry and wet seasons, which
 266 indicate the ability of TROPOMI observations to constrain emissions independently of the prior
 267 estimates (0: not at all; 1: fully). We obtain considerable information content for wet-season
 268 emissions, with a DOFS value of 48, comparable to that in the dry season (DOFS = 69). DOFS
 269 quantifies the independent information provided by the observations for constraining the state
 270 vector. Despite reduced satellite coverage (34,444 in the wet season relative to 657,625 in the
 271 dry season), wet-season DOFS remains comparable to the dry season because methane emitted
 272 from upwind source regions is transported to downwind areas with denser observations (Figure
 273 1). Furthermore, sensitivity experiments involving emission perturbations in individual

countries show that the concentration enhancements can be detected by TROPOMI in downwind observations (see details in Sect. 3.2 and Figure 4). This wet-season information content obtained here also suggests that conducting inversions at finer temporal scales (monthly or weekly) would likely lead to large smoothing errors due to insufficient observational constraints.

GEOS-Chem simulations using posterior emissions indicate an improved fit to the TROPOMI observations relative to the prior simulations for both dry and wet seasons (Figure 1). The mean bias (MB) over the inversion domain decreases from -10.7 to -0.1 ppb in the dry season and from -4.6 to 0.6 ppb in the wet season. The root mean square error (RMSE) decreases from 20.4 to 15.4 ppb in the dry season and from 23.4 to 19.9 ppb in the wet season. The limited improvement of RMSEs is likely due to the observational errors (15 ± 3 ppb; see Sect. 2.4).

We also use monthly *in situ* surface observations from the GLOBALVIEWplus CH₄ ObsPack v7.0 database compiled by the National Oceanic and Atmospheric Administration (NOAA) Global Monitoring Laboratory (46) to evaluate the posterior estimates independently through the year of 2022. There are four surface sites in the inversion region between October 2021 and September 2022, all of which are in remote locations (Table 2). The overall MB across the four sites decreases from -22.8 to -13.0 ppb and the RMSE decreases from 28.2 to 16.2 ppb. The limited reduction in RMSE is likely due to the forward model transport error, which Lu et al. (43) estimated to be ~ 20 ppb globally.

3.2. Utility of satellite observations to constrain methane emissions by country and sector

Despite large differences in the number of satellite retrievals, we achieved AK values of 0.71 and 0.61 for the dry and wet seasons respectively (Table 1), indicating the satellite's comparable ability to constrain the dry and wet seasons. Furthermore, at country level, similar AK between the dry and wet seasons are found in Malaysia, Viet Nam, and Thailand (Table 3). We conduct a sensitivity test by perturbing country-level emissions during the wet season and run through GEOS-Chem, to see if TROPOMI is able to capture the emission pulse. For each

country, methane emissions are uniformly increased by 50% relative to the prior estimate, with emissions elsewhere kept unchanged. The resulting differences in XCH_4 , simulated by GEOS-Chem, are presented as enhancements relative to the baseline simulation during the wet season. Figure 4 shows the spatial distribution of XCH_4 enhancements ($\frac{\partial y}{\partial x}$). We do not show results of Singapore and Timor-Leste due to their small areas. We find that the relatively high DOFS achieved by Thailand, Viet Nam, and Myanmar, is largely due to the downwind observations. For example, Myanmar is influenced by the prevailing southwest wind (Figure 1b), and we find the emission perturbation leads to pronounced XCH_4 enhancements in the downwind areas including Thailand and southern China, where observations are dense (Figure 1d). We also find a stronger constraint in the wet season than the dry season over the Philippines (AK of 0.54, and 0.11, respectively), further indicating the usefulness of leveraging downwind observations during the wet season. During the wet season, the transport of emissions from the Philippines contribute to the XCH_4 enhancements of its downwind areas over Laos, Viet Nam and Cambodia (Figure 4). Similar patterns are evident in other individual countries as listed in Figure 4. These sensitivity tests indicate that satellite observations in downwind regions can be used to effectively improve the constraint on emissions in Southeast Asian countries during the wet season. Future inversion studies could benefit from including downwind regions to better constrain emissions in the source regions of interest.

We further examine the utility of satellite observations to attribute emissions to sectors for the dry and wet seasons. Figure 5 shows the respective error correlations between sectors (0: perfect separation; ± 1 : no separation). We are able to separate sectors for both periods. For both dry and wet seasons, most of the posterior error correlation coefficients (r) are smaller than 0.2, meaning successful separation. For example, the error correlation between biomass burning and other sectors is -0.25 - 0.29 for the dry season and -0.25 - 0.23 for the wet season. Furthermore, oil and gas emissions can be effectively separated because their prior estimates differ spatially, with oil sector concentrated in a few areas over Thailand, Indonesia, and offshore regions, while gas emissions are more widely distributed across Southeast Asia (Figures S1 and S2). However, the ‘other anthropogenic’ sector, largely related to urban emissions, shows high error correlations with wastewater and landfills sectors ($r = 0.77$ - 0.81 for the dry season and $r = 0.73$ -

0.81 for the wet season). Landfills and wastewater, two major methane sources in Southeast Asia (47), are also difficult to separate ($r = 0.98$ for the dry season and $r = 0.97$ for the wet season) due to their collocation, which is also found in studies over China and north America (20, 26); we therefore combine the two sectors as waste emissions for analysis. Specifically, we find that rice and wetlands cannot be effectively separated in the wet-season inversion ($r = 0.61$), mainly due to their spatial overlap in Viet Nam and southern Thailand (Figure S2).

3.3. Emission from individual countries and sectors

Table 1 shows the region-wide emissions over Southeast Asia for the dry and wet seasons, and Table 3 further summarizes the total and sectoral emissions, as well as averaging kernel sensitivities for each of the 10 individual countries in Southeast Asia, except Singapore (total emission is too low). Emissions are expressed in units of Tg a^{-1} throughout the text to facilitate comparison. For the dry season, the total posterior emissions (41.3 (39.0-44.5) Tg a^{-1}) are similar to the prior emissions (40.3 Tg a^{-1}), but they reflect a compensating pattern of anthropogenic and natural sectors (mainly rice and wetlands) (Table 1). Our estimates of anthropogenic and natural emissions are 24.2 (23.6-25.5) and 17.1 (15.3-19.0) Tg a^{-1} , respectively, in comparison to the prior emissions of 25.3 and 14.9 Tg a^{-1} . The averaging kernel sensitivities for the regional total and anthropogenic posterior emission estimates are 0.71 and 0.76, indicating that these estimates are largely determined by the TROPOMI observations. The sensitivity to observations is 0.32 for the natural posterior estimates, likely reflecting the low dry-season wetlands emission (20) (Table 1).

In contrast, the total posterior emissions (57.2 (52.3-61.2) Tg a^{-1}) in the wet season are 20% higher than the prior estimates (49.9 Tg a^{-1}), mainly resulting from upward corrections for wetlands (+3.49 Tg a^{-1} , +17%), livestock (+1.39 Tg a^{-1} , +27%), oil (+0.49 Tg a^{-1} , +36%) and termites (+0.15 Tg a^{-1} , +22%) (Table 1). Our best estimate of anthropogenic and natural emissions over the whole of Southeast Asia during the wet season are 32.8 (30.4-34.4) and 24.4 (21.9-26.8) Tg a^{-1} , respectively, both higher than the prior estimates of 29.2 and 20.8 Tg a^{-1} . The averaging kernel sensitivities for the total, anthropogenic, and natural posterior emission

estimates are 0.61, 0.63, and 0.50, suggesting an effective constraint of TROPOMI observations (Table 1).

The total, anthropogenic, and natural posterior emissions during the wet season are higher than those during the dry season (Figure 6). Wetlands are the largest source for both dry and wet seasons (16.3 (14.6-18.1) and 23.5 (21.1-25.8) Tg a⁻¹), followed by rice (7.6 (7.6-7.9) and 15.2 (14.2-15.6) Tg a⁻¹), and waste (6.7 (6.6-7.0) and 6.8 (6.8-7.0) Tg a⁻¹) (Table 1). Figure 6b gives the contributions from main sectors of posterior emissions in the dry and wet seasons. Wetlands, rice, and livestock emissions are higher in the wet season, whereas biomass burning emissions are as expected higher in the dry season. Table 3 shows that larger dry-season biomass burning emissions mainly occur in Cambodia and Myanmar, and are largely associated with deforestation, degradation, and savanna burning rather than agricultural residual burning, according to the GFED4 analysis (32, 48). Indeed, Tang et al. (49) also found strong fire Carbon Monoxide emissions over this region.

Waste emissions are comparable between the dry and wet seasons, but this reflects compensating emission patterns between countries. Woolley Maisch et al. (47) also found that strong waste emissions in Southeast Asia are detectable from stationary, mobile, and satellite measurements and persist over time. Specifically, we estimate higher dry-season emissions in Indonesia, Malaysia, and the Philippines, but higher wet-season emissions for the remaining countries in the region (Table 3). Again because the dry and wet seasons are delineated based on the climatology of mainland Southeast Asia in our work (Sect. 2), the higher dry-season waste emissions in Indonesia, Malaysia, and the Philippines likely reflect the different seasonal precipitation patterns of these maritime Southeast Asia countries. Palm oil wastewater treatment contributes highly to regional methane emissions, where Indonesia and Malaysia alone accounts for 82.5% of global palm oil productions in 2022 (<https://www.fas.usda.gov/data/production/4243000>). Most palm oil mills adopt conventional open-pond treatment systems to treat palm oil mill effluent (POME). During anaerobic digestion, substantial methane emissions are produced (50-52). Meanwhile, the peak harvesting season for palm oil production in Indonesia and Malaysia occur during the dry season (October for Indonesia and November for Malaysia)

(<https://www.fas.usda.gov/data/production/4243000>), which may further contribute to the observed seasonal pattern. The averaging kernel sensitivity is however low (0.11) for the dry season in the Philippines (Table 3), indicating limited confidence of our inversion.

Our annual region-wide estimate of wetlands (19.3 Tg a^{-1}) and rice emissions (10.8 Tg a^{-1}) are both within the uncertainty ranges from the GCP estimates ($16.0\text{--}38.0 \text{ Tg a}^{-1}$ for wetlands emission and $8.0\text{--}12.0 \text{ Tg a}^{-1}$ for rice emission) (5). The Southeast Asian regions defined in GCP (Figure S3) are slightly different from our work here. Our estimate of livestock emissions (5.8 Tg a^{-1}) is larger than GCP ($3.0\text{--}5.0 \text{ Tg a}^{-1}$). This is because most global datasets used in GCP are still based on the 2006 Intergovernmental Panel on Climate Change (IPCC) Tier 1 approach, whose EFs have been found too low (53–55). For example, Chang et al. (53) estimated livestock methane emission by using mixed Tier 1 and 2 (2019 Mixed Tiers), and Tier 1 (2019 T1) methods from the latest IPCC Guidelines (2019 IPCC Refinement) (56) and most of enteric fermentation EFs from these two methods in East and Southeast Asia are higher than those from 2006 Tier 1 method (e.g., dairy cows EF is 90, 78 and 68 kg methane per head for 2019 Mixed Tiers, 2019 T1 and 2006 T1, respectively). Zhang et al. (55) also yielded higher livestock methane emission estimates over Southeast Asia for 2019 (5.1 Tg a^{-1}) based on Tier 2 method from the 2019 IPCC Refinement.

We also compare our estimate of annual emissions to the UNFCCC reports (Figure 7). We collect the latest reported national emissions by sector in individual countries from the most recently available national communications (NCs) and biennial transparency reports (BTR) (<https://unfccc.int/first-biennial-transparency-reports>), which are more updated than the UNFCCC portal values (https://di.unfccc.int/detailed_data_by_party). The latest UNFCCC inventory year by individual countries is listed in Figure S4. Compared to the rice estimates from the UNFCCC reports (6.6 Tg a^{-1}), we find our annual region-wide posterior rice emission is much higher (10.8 Tg a^{-1} ; Figure 7). Most of our national rice estimates are larger than UNFCCC, especially from Thailand ($+2.1 \text{ Tg a}^{-1}$), Viet Nam ($+1.1 \text{ Tg a}^{-1}$), Myanmar ($+0.51 \text{ Tg a}^{-1}$) and Cambodia ($+0.50 \text{ Tg a}^{-1}$). The latest inventory year for Viet Nam is 2013 (Figure S4), which is likely outdated and in part explains our larger estimate relative to UNFCCC. Indeed, Chen et al. (9) used measurement-based EF and also estimated higher rice emissions in Viet

Nam ($5.7 \pm 1.0 \text{ Tg a}^{-1}$) than 1.8 Tg a^{-1} in the UNFCCC report. Furthermore, Vo et al. (57) conducted a meta-analysis of field studies in Viet Nam and found an EF more than twice the IPCC default, due to the reliable irrigation systems that sustain water supply to paddies.

Our annual livestock emission estimate over Southeast Asia (5.8 Tg a^{-1}) is also larger than UNFCCC-based estimates (3.8 Tg a^{-1}) (Figure 7), but emissions in individual countries are either higher or lower. Our lower estimate for Thailand (-0.38 Tg a^{-1}) and Cambodia (-0.10 Tg a^{-1}) likely result from an overestimate of UNFCCC activity data (e.g., manure loaded) or EFs from 2006 IPCC Tier 2 approach (58). We find larger estimates mainly in Myanmar ($+1.5 \text{ Tg a}^{-1}$) and Indonesia ($+0.40 \text{ Tg a}^{-1}$), which may be attributed to the outdated inventories used by UNFCCC (the year of 2005, Figure S4) in Myanmar and an underestimate of EFs used in the UNFCCC reports. For example, the revised EFs of dairy cow enteric fermentation in Southeast Asia from Wolf et al. (54) ($153.2 \text{ kg CH}_4 \text{ animal}^{-1} \text{ year}^{-1}$) were much higher than those given by the 2006 IPCC ($68 \text{ kg CH}_4 \text{ animal}^{-1} \text{ year}^{-1}$), linked to the increasing dairy cow body mass and productivity.

3.4. Major emitting countries and comparison to previous studies

We compare our posterior anthropogenic emissions from the top three emitting countries in Southeast Asia (Indonesia, Thailand and Viet Nam, accounting for 64.5% of annual anthropogenic emissions in Southeast Asia) to the prior estimates (EDGARv8, GRPI and GFEIv3) and to previous global TROPOMI inversions of East et al. (7) and Shen et al. (59). East et al. (7) estimated methane emissions in 161 countries of the world and sectors for 2023 at up to 25 km resolution with prior emissions from the UNFCCC reports. Part of their prior emissions use the outdated UNFCCC reports (e.g. the year of 2000 for Indonesia, and the year of 2013 for Thailand and Viet Nam), which might affect the inversion results. Shen et al. (59) conducted the inversion at up to 50 km resolution between May 2018 and February 2020 by using a prior estimate of GFEI v2 (60) and they only focus on coal, and oil/gas sectors.

Compared to the prior estimate, our total anthropogenic emissions estimate in Indonesia is higher in the dry season and is similar in the wet season. And our annual anthropogenic

estimate (8.0 Tg a^{-1}) is lower than East et al. (7) ($8.2\text{-}11.1 \text{ Tg a}^{-1}$). We find that the dominant sector in Indonesia is the waste. Our annual waste estimate (2.9 Tg a^{-1}) is smaller than East et al. (7) ($4.6\text{-}6.1 \text{ Tg a}^{-1}$) and the EDGARv8 (3.0 Tg a^{-1} , our prior estimate). East et al. (7) obtained prior estimate (7.5 Tg a^{-1}) from UNFCCC report in 2000, which is outdated and much higher than our prior estimate. In oil/gas sector, our posterior emission (0.91 Tg a^{-1}) is within the uncertainty ranges of East et al. (7) ($0.8\text{-}1.2 \text{ Tg a}^{-1}$) and Shen et al. (59) ($0.38\text{-}0.93 \text{ Tg a}^{-1}$), but is larger than the GFEIv3 (0.54 Tg a^{-1} , our prior estimate), likely due to underreported methane emissions from offshore oil and gas platforms (61) and neglected abandoned oil and gas wells (62). For coal, our annual estimate (0.14 Tg a^{-1}) is similar to the GFEIv3 (0.12 Tg a^{-1}) and on the low end of Shen et al. (59) ($0.11\text{-}2.7 \text{ Tg a}^{-1}$) and East et al. (7) ($0.1\text{-}0.2 \text{ Tg a}^{-1}$).

Our estimate of total anthropogenic emissions in Thailand is consistent with the prior estimate in the dry season but is higher in the wet season. Rice emissions are the largest sector in both dry and wet seasons. We estimate larger annual rice emissions (3.3 Tg a^{-1}) than East et al. (7) ($2.1\text{-}3.0 \text{ Tg a}^{-1}$) and the GRPI (2.4 Tg a^{-1} , our prior estimate). In oil/gas sector, our emissions estimate (0.47 Tg a^{-1}) is on high end of the uncertainty ranges from Shen et al. (59) ($0.12\text{-}0.59 \text{ Tg a}^{-1}$), but is in the middle of East et al. (7) ($0.6\text{-}0.8 \text{ Tg a}^{-1}$) and the GFEIv3 (0.43 Tg a^{-1}). However, none of these previous studies describe emission seasonality in the oil/gas sector, which has been highlighted in recent findings over the US (63-64). Indeed, our results suggest higher posterior oil/gas emissions in the wet season than the dry season (Table 3), possibly related to higher electricity consumption for cooling in Southeast Asia (65).

Compared to the prior estimate, our posterior anthropogenic emissions in Viet Nam are much lower in the dry season but are comparable in the wet season. This is mainly because of rice emissions, the largest sector in Viet Nam. Our posterior rice emissions (2.1 Tg a^{-1}) are lower than prior estimate (3.8 Tg a^{-1}) in the dry season (Table 3). The country-uniform EF used in the GRPI ($3.6 \text{ kg ha}^{-1} \text{ d}^{-1}$) is likely overestimated for the dry season. For example, the Ministry of Natural Resources and Environment of Viet Nam (66) reported that EF in Northern region is only $1.61 \text{ kg ha}^{-1} \text{ d}^{-1}$ for the winter-spring rice crop, approximately half of that for the summer and autumn (67). For oil/gas, our estimate (0.31 Tg a^{-1}) is within the uncertainty ranges of both East et al. (7) ($0.2\text{-}0.4 \text{ Tg a}^{-1}$) and Shen et al. (59) ($0.12\text{-}0.56 \text{ Tg a}^{-1}$), but lower than the GFEIv3

(0.45 Tg a⁻¹).

4. Implications for satellite inversion and methane inventory improvements

Our results show that satellite observations can provide effective constraints on methane emissions during the cloud-limited wet season in Southeast Asia. Although the number of available wet-season TROPOMI retrievals is only 5% of that in the dry season, the wet-season inversion retains substantial information content because methane enhancements transported from Southeast Asia can be observed over downwind regions with better satellite coverage. Including these downwind regions in regional inversion domains therefore offers a practical approach for improving satellite-based emission estimates in cloudy tropical regions. The availability of TROPOMI observations within a single year is however limited, particularly during the cloudy wet season. Combining multi-year observations (68) with the use of downwind observations, as employed here, would be a promising approach to further strengthen observational constraints on methane emissions.

Separately optimizing dry- and wet-season emissions also reveals a pronounced seasonal contrast that is not adequately represented by current inventories. Wet-season anthropogenic emissions are higher than dry-season emissions, driven primarily by rice (+7.6 Tg a⁻¹) and livestock (+1.4 Tg a⁻¹). Our annualized rice and livestock estimates exceed the latest national reports submitted to the UNFCCC by 64% and 53%, respectively (Figure 7), with major discrepancies in Thailand, Viet Nam, Myanmar, and Indonesia; these differences likely reflect underestimated emission factors, and outdated or incomplete activity data (e.g., rice production, cattle amount).

Shindell et al (69) identified rice, oil/gas, and waste as key methane mitigation sectors in Southeast Asia, and our results show that these sectors exhibit clear seasonal variability. Failure to represent this variability affects national emission totals and the identification of mitigation priorities. For rice cultivation, improved crop and water management can help reduce methane emissions, while better management of organic waste and methane recovery from landfills provide additional mitigation opportunities (70). For palm oil wastewater, methane emissions

from POME can be mitigated by covering conventional anaerobic ponds and capturing the resulting biogas for electricity generation or heat production (71-72). Improving biogas collection and utilization at palm oil mills in Indonesia and Malaysia can therefore provide an opportunity to reduce methane emissions from the palm oil industry. By resolving seasonal differences in sectoral methane emissions (Figure 7), our inversions provide a basis for identifying inventory discrepancies and informing sector-specific mitigation priorities across Southeast Asia.

Author Contributions

CX and ZC contributed to the study conceptualization. CX conducted the data and modeling analysis with contributions from SH, XW, XY, ML, SC, SA, and BD. CX and ZC wrote the paper with input from all authors.

Notes

The contact author has declared that none of the authors has any competing interests.

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