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# The 2019 Methane Budget And Uncertainties At 1 Degree Resolution And Each Country Through Bayesian Integration Of GOSAT Total Column Methane Data And A Priori Inventory Estimates

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**Abstract**: We present 2019 global methane ($CH_4$) emissions and uncertainties, by sector, at 1-degree and country-scale resolution based on a Bayesian integration of satellite data and inventories. Globally, we find that agricultural and fire emissions are 227 +/- 19 Tg $CH_4$/yr, waste is 50 +/- 7 Tg $CH_4$/yr , anthropogenic fossil emissions are 82 +/- 12 Tg $CH_4$/yr, and natural wetland/aquatic emissions are 180 +/- 10 Tg $CH_4$/yr. These estimates are intended as a pilot dataset for the Global Stock Take in support of the Paris Agreement. However, differences between the emissions reported here and widely-used bottom-up inventories should be used as a starting point for further research because of potential systematic errors of these satellite based emissions estimates. ***Calculation of emissions and uncertainties:*** We first apply a standard optimal estimation (OE) approach to quantify $CH_4$ fluxes using Greenhouse Gases Observing Satellite (GOSAT) total column $CH_4$ concentrations and the GEOS-Chem global chemistry transport model. Second, we use a new Bayesian algorithm that projects these posterior fluxes to

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emissions by sector to 1 degree and country-scale resolution. This algorithm can also quantify uncertainties from measurement as well as smoothing error, which is due to the spatial resolution of the top-down estimate combined with the assumed structure in the prior emission uncertainties. ***Detailed Results:*** We find that total emissions for approximately 58 countries can be resolved with this observing system based on the degrees-of-freedom for signal (DOFS) metric that can be calculated with our Bayesian flux estimation approach. We find the top five emitting countries (Brazil, China, India, Russia, USA) emit about half of the global anthropogenic budget, similar to our choice of prior emissions. However, posterior emissions for these countries are mostly from agriculture, waste and fires (~129 Tg $CH_4$/yr) with ~45 Tg $CH_4$/yr from fossil emissions, as compared to prior inventory estimates of ~88 and 60 Tg $CH_4$/yr respectively, primarily because the satellite observed concentrations are larger than expected in regions with substantive livestock activity. Differences are outside of 1-sigma uncertainties between prior and posterior for Brazil, India, and Russia but are consistent for China and the USA. The new Bayesian algorithm to quantify emissions from fluxes also allows us to "swap priors" if better informed or alternative priors and/or their covariances are available for testing. For example, recent bottom-up results supposes greatly increased values for wetland/aquatic emissions while isotopic evidence indicates larger fossil emissions, relative to prior inventories. Swapping in priors that reflect these increased emissions results in posterior wetland emissions or fossil emissions that are inconsistent (differences greater than calculated uncertainties) with these increased bottom-up estimates, primarily because constraints related to the methane sink only allow total emissions across all sectors of ~560 Tg $CH_4$/yr and because the satellite based estimate well constrains the spatially distinct fossil and wetland emissions. Given that this observing system consisting of GOSAT data and the GEOS-Chem model can resolve much of the different sectoral and country-wide emissions, with ~402 DOFS for the whole globe, our results indicate additional research is needed to identify the causes of discrepancies between these top-down and bottom-up results for many of the emission sectors reported here. In particular, the impact of systematic errors in the methane retrievals and transport model employed should be assessed where differences exist. However, our results also suggest that significant attention must be provided to the location and magnitude of emissions used for priors in top-down inversions; for example, poorly characterized prior emissions in one region and/or sector can affect top-down estimates in another because of the limited spatial resolution of these

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top-down estimates. Satellites such as the Tropospheric Monitoring Instrument (TROPOMI) and those in formulation such as the Copernicus $CO_2$M, Methane-Sat, or Carbon Mapper offer the promise of much higher resolution fluxes relative to GOSAT assuming they can provide data with comparable or better accuracy, improving the accuracy of emissions by reducing smoothing error. Fluxes calculated from other sources can also in principal be incorporated in the Bayesian estimation framework demonstrated here for the purpose of reducing uncertainty and improving the spatial resolution and sectoral attribution of subsequent methane emissions estimates.

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# 1.0 Introduction

## *1.1 Atmospheric Methane Background*

Atmospheric methane ($CH_4$) is the second most important anthropogenic greenhouse gas behind carbon dioxide ($CO_2$) and a contributor to poor surface air quality as it is an ozone precursor. Atmospheric methane has increased by nearly a factor 3 over its pre-industrial values largely due to anthropogenic emissions (e.g. Dlugokencky *et al*. 2011; Ciais *et al*. 2013, and refs therein). Over the last two decades, methane has been increasing but for reasons that are still being assessed, although recent studies provide evidence that it is due to a combination of fossil and agricultural emissions with some role due to variations in the atmospheric sink of methane (e.g. Schaefer *et al*. 2016; Worden *et al*. 2017; Turner *et al*. 2019; Zhang *et al*. 2021). However, it is unclear which regions and which sectors are the cause of changes in atmospheric methane over the last twenty years because of substantial uncertainties in all components of the methane budget (Kirchke *et al*. 2013, Janssens *et al*. 2019; Sanuois *et al*. 2020) from the global (Table 1) to local scale (Section 2). Methane has a relatively short lifetime of approximately 9 years making it an attractive target for emissions reduction as a decline in emissions will have a rapid impact on net radiative forcing and corresponding atmospheric heating (e.g. Shindell *et al*. 2009;

| **Sector** | **Prior** ($Tg\ CH_4$/yr) | **Posterior** ($Tg\ CH_4$/yr) |
|---|---|---|
| Wetlands / Aquatic | 199.8+/-52.8 | 179.8+/-10.0 |
| Seeps | 32.0+/-6.2 | 22.5+/-3.8 |
| Livestock | 87.6+/-17.2 | 146.1 +/-10.3 |
| Rice | 36.9+/-12.9 | 67.6 +/-6.8 |
| Fires | 15.1+/-2.5 | 13.3+/-2.2 |
| Waste | 57.7+/-11.9 | 49.6+/-7.1 |
| Oil | 41.6+/-9.7 | 28.8 +/-4.7 |
| Gas | 24.5+/-4.7 | 28.0 +/-3.6 |
| Coal | 31.4+/-9.8 | 25.3 +/-3.9 |
| Total | 526+/-128 | 561 +/-52 |

Table 1: Prior emissions and uncertainties are generated from various inventories or models (Section 2.3). Posterior emissions represent projection of satellite based fluxes back to emissions while accounting for the prior emissions distribution and covariances (Section 2.2). We conservatively assume uncertainties are 100% correlated so that the total reported prior and posterior uncertainties are the sum of the individual uncertainties.

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Ganeson *et al*. 2019; Turner *et al*. 2019). Hence there is significant interest in accurately quantifying methane emissions for identifying those emissions that can be efficiently reduced.

### *1.2 Global Stock Take*

As part of the effort to reduce methane emissions and corresponding risk related to changes in climate, the Paris Agreement resulted in a framework by which countries provide an accounting of their emissions. A "Global Stock Take" (GST) to track progress in emission reductions is conducted at five-year intervals, beginning 2023. To support the first GST, Parties to the Paris Agreement are compiling inventories of GHG emissions and removals to inform their progress. Inventories are generally estimated using "bottom-up'' approaches, in which emission estimates are generally based on activity data and emission factors. These bottom-up methods can provide precise and accurate emission estimates when the activity data are well quantified and emission factors are well understood. However, substantial uncertainties exist for emissions in many parts of the globe where these measurements are not rigorously made or tested across multiple sites. Even regions and emissions that are thought to be well measured can have significant differences between independent assessments and official reports; for example, Alvarez *et al*. (2018) demonstrates that 2015 oil and gas emissions are under estimated by the United States Environmental Protection Agency by about 60%. These differences, if they are representative for emissions across the globe indicate a need for an independent assessment of emissions and their uncertainties to better evaluate if reported changes in emissions are in fact occurring or if changes in the natural carbon cycle through wetlands and the methane sink are substantively affecting atmospheric methane burden. Top down estimates of methane emissions using atmospheric measurements provide an independent way of testing these inventories as observed methane concentrations are compared against expected concentrations that result from reported inventories. The objective of this paper is to demonstrate the use of satellite observations for testing and updating emissions by sector for use with the Global Stock Take. While these top-down atmospheric methane budgets cannot replace the detailed activity reports used to generate bottom-up inventories, they can be combined with those bottom-up products to produce a more complete and transparent assessment of progress toward greenhouse gas emission reduction targets. They can also help determine if the natural part of the methane budget is becoming a strong component of atmospheric methane increases. As discussed next, an

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important component of this assessment is the evaluation of uncertainties from both bottom-up inventories and in top-down approaches.

### *1.3 Overview of Bottom-Up Emissions And Uncertainties*

Bottom-up uncertainties are calculated for the methane budget by comparison between independent methods or sources, evaluating multiple estimates from a single source, comparison between models and remote sensing data, and expert opinion. For example, Saunois *et al.* (2020) uses a range of results from different studies to quantify uncertainty in the different sectors of the methane budget. However, these uncertainties are likely underestimated as they suggest that total anthropogenic agricultural emissions, for example, are known to 10% or better, whereas comparisons between different global inventories (e.g., Janssens-Maenhout *et al.* 2019) suggest a much larger range of estimates for the global totals (e.g., 129 to 219 Tg $CH_4$/yr for agriculture, and 129 to 164 Tg $CH_4$/yr for fossil emissions). Uncertainties in national or regional total emissions are even more challenging to estimate such that expert opinion is used: Janssens-Maenhout *et al.* (2019) suggests that Annex 1 (developed) countries have approximately 15% uncertainty in reported fossil emissions whereas Annex 2 countries have ~30% uncertainties, essentially asserting that less informed inventories have double the uncertainty of better informed emissions. Wetland emissions, which comprise ~30-45 % of the methane budget also show significant differences of up to 40% across wetland models (e.g. Melton *et al.* 2013; Poulter *et al.* 2017, Ma *et al.* 2021), depending on region. An example of how these uncertainties are projected to the total methane budget for each of the main sectors is presented in Table 1 using the prior emissions and their uncertainties for the analysis discussed in this paper (Section 2.3).

However, recent studies challenge even these estimates of emission uncertainties; emissions for lakes and rivers could be as large or larger than wetlands, with correspondingly larger uncertainties of 50% or more (Saunois *et al.* 2020; Rosentreter *et al.* 2021). Primarily because of this extra term from lakes and rivers, the total budget from bottom-up inventories discussed in Saunois *et al.* (2020) ranges from 583 – 861 Tg $CH_4$/yr. Contrasting with this much larger than expected biogenic source is isotopic evidence that suggests fossil emissions are also much larger than expected, 160 +/- 40 Tg $CH_4$/yr (Schweitzke *et al.* 2017). These larger than

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expected values from aquatic and fossil sources are challenging to reconcile with existing bottom up estimates and with global estimates from the top down which are primarily constrained by the methane sink. For example, the methane sink must approximately balance total methane emissions, leading to total emissions of 560 +/- 60 Tg $CH_4$/yr (e.g., Prather *et al*. 2012). Consequently much larger values in either aquatic emissions or fossil emissions must be balanced by much lower emissions in other sectors indicating that either our knowledge of the processes controlling different components of the methane sink are fundamentally wrong or one or both of these inflated emissions is incorrect, that is, well outside calculated uncertainties.

### *1.4 Use of Remote Sensing For Quantifying Emissions and Uncertainties*

Top-down approaches using in situ or remote sensing measurements of atmospheric methane can be used to evaluate and update bottom-up emissions (or inventories) by first projecting bottom up emissions through a chemical transport model to atmospheric concentrations and then comparing these modeled concentrations to observations (e.g.

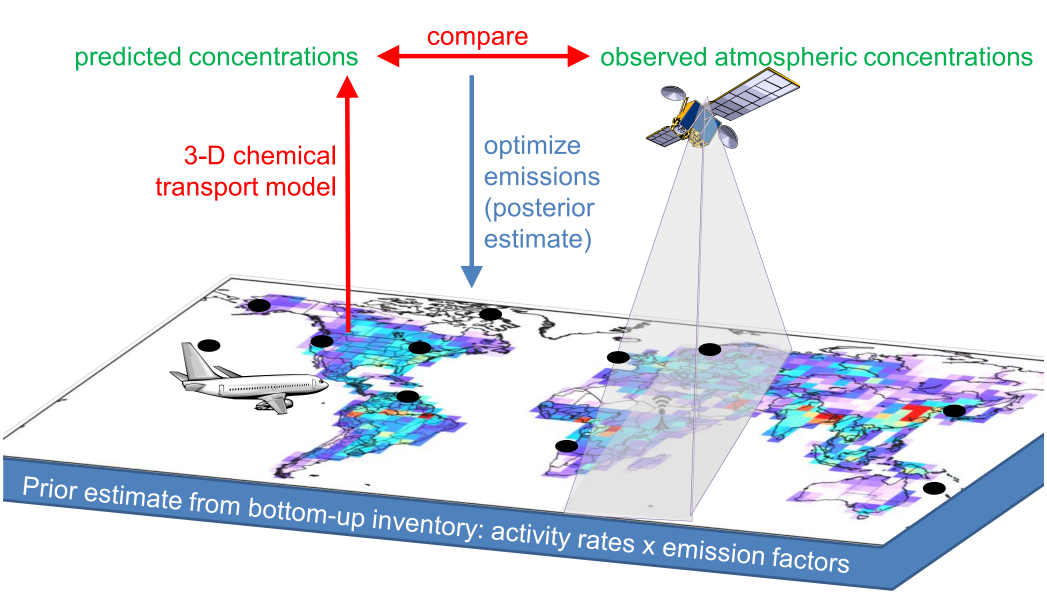


Figure 1: Schematic describing how observed atmospheric concentration data are used with a global chemistry transport model to quantify methane fluxes.

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Frankenberg *et al*. 2005; Bergamaschi *et al*. 2013, Qu *et al*. 2021 and refs therein). An inverse method is utilized to update the net flux (or total emissions and surface sinks) within a chosen grid scale based on the mismatch between modeled and observed concentrations (Figure 1). When the top-down quantified flux can be uniquely associated with a single source, these tests of bottom-up inventories provide information about biases in the reported emission (e.g, Duren *et al*. 2019, Varon *et al*. 2019, Pandey *et al*. 2019) which can be used to either update the emissions or provide evidence that additional research is needed to improve the process knowledge used to construct the emissions. However, top-down fluxes have other uncertainties that must be accounted for when comparing to bottom-up inventories, these include 1) systematic and random uncertainties in the data, 2) smoothing error related to uncertainty in the prior emissions combined with the spatial resolution of the top-down estimate, and 3) systematic errors in the model that relates observed methane concentrations to fluxes.

Top-down approaches can typically quantify the precision of the fluxes as it is directly related to the uncertainties of the observations and the prior knowledge of the flux distribution. However, the accuracy of the top-down fluxes related to data and model is more challenging to quantify and recent results suggest that these errors can be substantive. For example, Qu *et al*. (2021) demonstrates that systematic differences between total column $CH_4$ concentrations from TROPOMI and GOSAT satellite data can lead to substantial differences when used to constrain top-down fluxes. For example, there is almost a 100% difference between estimated livestock emissions in Brazil when comparing TROPOMI versus GOSAT based fluxes, which Qu *et al*. (2021) attributes to biases in the TROPOMI total column data due to surface albedo variations over Brazil. Similarly, Mcnorton *et al*. (2020) finds that model errors can be as large or larger as uncertainties in the data, which could lead to almost a doubling of the expected uncertainty in top-down fluxes.

Smoothing error, is also challenging to quantify for top-down estimates. This uncertainty depends on the spatial and temporal resolution of the top-down estimate combined with the prior uncertainty of the emissions (Rodgers 2000). As typical top-down estimates do not quantify the terms needed to quantify smoothing error, smoothing error is not usually represented in top-down error budgets. However, this term can be the largest of the error sources, as discussed further in Section 2.1, especially if the *a priori* uncertainties for emissions are poorly characterized. Our Bayesian, optimal estimation approach (Rodgers 2000) described here allows

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us to either remove the effect of smoothing error in comparisons between top-down fluxes and wetland models such as demonstrated in Ma *et al*. (2021) or to explicitly quantify it for sectoral emissions (Section 2.2 and 2.3).

Related to the problem of calculating smoothing error is that many top-down fluxes are projected back to emissions by assuming that all emissions within a grid can be uniformly scaled by the ratio of posterior to prior flux (e.g., Maasakkers *et al*. 2019 and references therein). This method, while computationally expedient, diverts from the Bayesian assumptions used with top-down inversions, potentially adding poorly characterized uncertainty and potentially unphysical biases (Cusworth *et al*. 2021) to the emissions estimates, because it does not account for the structure of the errors or their correlations and instead assumes that different types of emissions within a grid cell (e.g. fires, fossil, livestock, wetlands) are 100% correlated. Shen *et al*. (2021) addresses this problem by weighting the posterior emissions estimate by their prior uncertainty. Our approach used here is derived in Cusworth *et al*. (2021) and summarized in Section 2.2, addresses this problem by accounting for the structure of the errors, following a Bayesian methodology from the start of the problem (calculation of fluxes using observations) to the end (calculation of emissions from fluxes).

## 2.0 Approach for Quantifying "Top Down" Emissions Using Satellite Data

Our emission quantification approach is described in this section. First optimal estimation is used (Section 2.1) to quantify methane fluxes on a 2x2.5 grid using the GEOS-Chem global chemistry transport model with GOSAT satellite data for the year 2019. For our purposes of emissions attribution, this first inverse step must report the prior as well as the posterior flux error covariance (or Hessian) matrices *(*Zhang *et al*. 2021*,* Qu *et al*. 202*1)*. The posterior error covariance (or Hessian) can be computationally challenging to calculate so is typically not reported with variational or adjoint based top-down estimates and instead ensemble approaches are used to approximate flux uncertainties (e.g. Janadarnan *et al*. 2020). However in our approach, this first step uses analytic Jacobians derived from the GEOS-Chem model that relate emissions to concentrations and hence has been traditionally computationally expensive as compared to ensemble or adjoint based inversion methods, but does allow for a straightforward calculation of the Hessian. The second step (Section 2.2) uses the prior fluxes, the corresponding constraint and Hessian covariance matrices, and priors and prior covariances for emissions by

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sector, to linearly project the fluxes to emissions by sector at 1 degree resolution while accounting for the prior uncertainty distributions, correlations in the posterior covariance, and varying spatial resolution. This step can use different prior emissions and prior covariances from that of the flux inversion as the information from the flux inversion is preserved (Rodgers and Connor 2003). Critical to this second step is that prior uncertainties and their correlations are provided for the emissions for the desired sector and spatial resolution (Section 2.3).

### *2.1 Top Down Flux Estimates*

We estimate top-down fluxes based on the approach described in Zhang *et al*. (2021) and Qu *et al*. (2021). We optimize a state vector that consists of (1) 2019 methane emissions from all sectors on a global 2°×2.5° grid (4020 elements); and (2) tropospheric OH concentrations in northern and southern hemispheres (2 elements). We assume the seasonal variations of methane emissions to be correct in the prior inventory and apply posterior/prior ratio equally to all months in each grid cell. The optimization of annual hemispheric OH concentrations avoids propagating biases in the simulated interhemispheric OH gradient to the solution for methane emissions (Zhang et al., 2018). We solve this Bayesian problem analytically, which yields a best posterior estimate for the state vector, the posterior error covariance matrix, and the averaging kernel matrix. Unlike in Zhang *et al*. (2021) and Qu *et al*. (2021), wetland fluxes are not treated as separate elements in the state vector as we found that introduced uncertainties into the sectoral attribution because the wetland flux areas used in Qu *et al*. (2021) could overlap the different regions (Table 2) used in our approach to mitigate computational complexity.

The inverse problem is regularized by prior estimates for the state vector, which are compiled from multiple bottom-up studies. The EDGAR v4.3.2 global emission inventory for 2012 (Janssens-Maenhout et al., 2017) is used as default for anthropogenic emissions, superseded in the U.S. by Maasakkers et al. (2016) and for the fossil fuel exploitation sector by Scarpelli et al. (2020). Seasonalities of emissions from manure management and rice cultivation are specified following Maasakkers et al. (2016) and B. Zhang et al. (2016), respectively. Monthly wetland emissions in 2019 are from the WetCHARTS v1.3.1 18-member ensemble mean (Bloom et al., 2017). Daily global emissions from open fires are taken from GFEDv4s (van der Werf et al., 2017). Global geological emissions for the flux inversion are set to be 2 Tg $a^{-1}$ based on Hmiel et al. (2020) with the spatial distribution from Etiope et al. (2019). Termite emissions are

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from Fung et al. (1991). The prior estimates for the hemispheric tropospheric OH concentrations are based on a GEOS-Chem full chemistry simulation (Wecht et al., 2014).

The GEOS-Chem CTM v12.5.0 (10.5281/zenodo.3403111) is used as forward model for the inversion. The simulation is driven by MERRA-2 meteorological fields (Gelaro et al., 2017) from the NASA Global Modeling and Assimilation Office (GMAO) with 2º×2.5º horizontal resolution and 47 vertical layers (~ 30 layers in the troposphere). We excluded observations poleward of 60°, where low Sun angles and extensive cloud cover make the retrieval more difficult, and stratospheric CTM bias can affect the inversion (Turner *et al.*, 2015).

The posterior estimate as defined by Bayesian inference assuming Gaussian error statistics is obtained by minimizing the cost function *J(x)*:

$$J(x) = (\mathbf{x} - \mathbf{x}_{\mathrm{A}})^{\mathrm{T}} \mathbf{S}_{\mathbf{A}}{}^{-1} (\mathbf{x} - \mathbf{x}_{\mathrm{A}}) + \gamma (\mathbf{y} - \mathbf{K}\mathbf{x})^{\mathrm{T}} \mathbf{S}_{\mathbf{y}}{}^{-1} (\mathbf{y} - \mathbf{K}\mathbf{x}), \qquad (1)$$

where **K** is the Jacobian matrix describing the sensitivity of the observations to the state vector as simulated by GEOS-Chem. The vector $\boldsymbol{x}_{\mathrm{A}}$ is the prior flux estimate. $\mathbf{S_A}$ is the *a priori* covariance matrix for this inversion and is a diagonal matrix that is constructed by assuming 50% prior error standard deviation for emissions on the 2°×2.5° grid and 10% prior error standard deviation for hemispheric annual mean OH concentrations. $\mathbf{S_y}$ is the observational error covariance matrix. Diagonal elements of $\mathbf{S_y}$ are calculated using the residual error method (Heald et al., 2004) as the variance of the residual difference between observations and the GEOS-Chem prior simulation on the 2°×2.5° grid after subtracting the mean difference. We use a regularization parameter $\gamma$ (Hansen et al., 1999; Y. Zhang et al., 2018, 2020; Maasakkers et al., 2019; Lu et al., 2021) to account for the off-diagonal structure missing in $\mathbf{S_y}$. Based on the corner of the L-curve (Hansen et al., 1999) and the expected chi-square distribution of the cost function (Lu et al., 2021), we choose $\gamma = 0.5$ (Qu et al., 2021).

Assuming that the problem for quantifying methane fluxes from observed concentrations is linear, or only moderately non-linear, then the fluxes, $\hat{\mathbf{x}}$, can be related to observed methane concentrations using the following equation: (Rodgers 2000):

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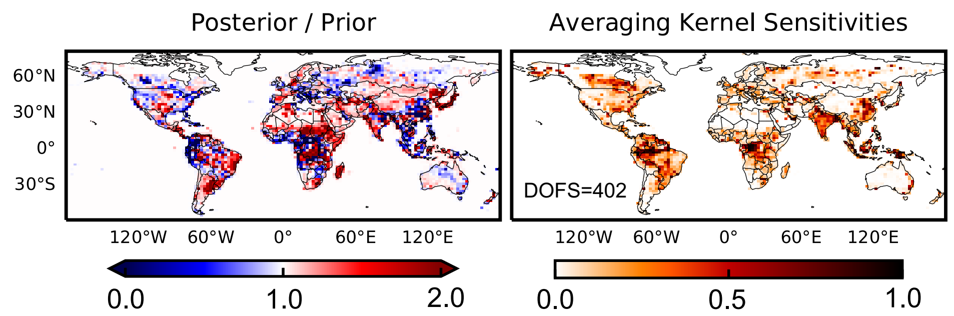


Figure 2. (left panel) Corrections to prior estimates of methane emissions on the 2°×2.5° grid and corresponding averaging kernel sensitivities. (right panel) The averaging kernel sensitivities are the diagonal elements of the averaging kernel matrix for the inversion. The trace of the averaging kernel matrix defines the degrees of freedom for signal (DOFS) for the inversion, shown in the inset.

$$\hat{\mathbf{x}} = \mathbf{x}_{\mathrm{A}} + \hat{\mathbf{S}}\mathbf{K}^{T}\mathbf{S}_{\mathrm{y}}{}^{-1}(\boldsymbol{y} - \mathbf{K}\mathbf{x}_{\mathrm{A}}) \qquad (2)$$

The posterior error covariance matrix $\hat{\mathbf{S}}$ is given by:

$$\hat{\mathbf{S}} = (\mathbf{K}^{T}\mathbf{S}_{\mathrm{y}}{}^{-1}\mathbf{K} + \mathbf{S}_{\mathrm{A}}{}^{-1})^{-1}. \qquad (3)$$

This top-down flux inversion also provides the spatial resolution matrix or Averaging Kernel Matrix **A,** which defines the sensitivity of the solution to the true state:

$$\mathbf{A} = \mathbf{I} - \hat{\mathbf{S}}\mathbf{S}_{\mathrm{A}}{}^{-1}, \qquad (4)$$

Summing the diagonal elements of the averaging kernel for a given region provides the Degrees of Freedom for Signal (or DOFS), a useful metric for the sensitivity of the observing system to the underlying fluxes as it describes the sensitivity of the estimated fluxes to the actual distribution of fluxes (Rodgers 2000). Figure 2 (right panel) shows the averaging kernel sensitivities (or diagonal elements of the averaging kernel matrix) of the inversions. The averaging kernel sensitivities are highest over major anthropogenic source regions, where the

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methane emissions are the largest and the observations have a good ability to determine the posterior solution independently of the prior estimate. The inversion has ~402 DOFS for methane emissions, meaning that it contains 402 independent pieces of information on the distribution of methane emissions. Although our flux inversion is based on the top-down setup described in Qu *et al*. (2021), this value is larger than the DOFS reported in Qu et al. (2021) because that estimate separates wetlands from non-wetlands in the inversion scheme whereas the flux estimate used here does not. The posterior / prior ratios for the 2019 inversion in Figure 2 (left panel) show consistent upward adjustments in the south-central US, Venezuela, and the Middle East and downward adjustments in the western US and North China Plain, consistent with Qu et al. (2021) and Zhang et al. (2021).

If the matrix $\mathbf{S_A}$ in equations 1 and 3 represents the actual *a priori* uncertainty corresponding to the *a priori* $\mathbf{x_A}$, then the posterior error covariance describes the total error for the estimate (Rodgers 2000). In practice, the matrix $\mathbf{S_A}$ represents a "constraint matrix" that is either a best guess for uncertainties of fluxes (e.g., assumed here to be 50%) within a grid and/or it is constructed to ensure the inversion converges, typically because systematic errors in the data and/or the model or numerical instabilities make it challenging to find a global minimum in the cost function as shown in Equation 1 (Bowman *et al*. 2006). In the case where $\mathbf{S_A}$ represents a constraint matrix, the total posterior error becomes:

$$\mathbf{S_{tot}} = (\mathbf{I} - \mathbf{A})\mathbf{S_A^{true}}(\mathbf{I} - \mathbf{A})^{\mathbf{T}} + \hat{\mathbf{S}}\mathbf{K}^{\mathbf{T}}\mathbf{S_y}^{-1}\mathbf{K}\hat{\mathbf{S}} \quad \mathbf{(5)}$$

Where the $\mathbf{S_A^{true}}$ is the *a priori* uncertainties for the estimate. In practice, $\mathbf{S_A^{true}}$ can be challenging to calculate due to lack of information about the emissions or fluxes and may not even be invertible because of correlations within the matrix. However, we use a set of informed inventories and models to generate a prior covariance for methane emissions as described in the next section. As discussed Worden *et al*. (2004), the smoothing error in the estimate is the first term on the right side, the error due to measurement uncertainty is the second/middle term, and the last term is that due to systematic errors in the model. While the variables in Equation 5 are representative here of the top-down flux estimate, the formulation can be generalized for any estimate to support interpretation of the results. For example, in a system with perfect resolution the averaging kernel matrix becomes the identity matrix and the smoothing error becomes zero,

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hence the reason that improving the spatial resolution reduces the smoothing error, an important goal which can be realized with the increased observation density of up-coming satellites such as CO2M, methane-sat, and Carbon Mapper. Equation 5 also demonstrates that poorly characterized prior uncertainties in one region affect an estimate in another regions because of cross-terms in the averaging kernel matrix **A**. This aspect of top-down inversions must therefore be accounted for when interpreting the seasonality and magnitude of top-down fluxes (e.g. Ma *et al*. 2021).

Systematic errors can be included by adding the following term: $\mathbf{\hat{S}K_{sys}^{T}S_{sys}}^{\mathbf{-1}}\mathbf{K_{sys}^{T}\hat{S}}$, where $\mathbf{K}_{sys}$ is the Jacobian that describes the sensitivity of the modeled concentrations to different parameters in the model that relate emissions to concentrations and $\mathbf{S}_{sys}$ is a matrix containing uncertainties for the model or data parameters. In this manuscript we do not explicitly calculate systematic errors for the fluxes. We are currently studying how to empirically evaluate systematic errors in the flux estimate, following the approach in Jiang *et al*. (2015) for use in quantifying uncertainties in methane fluxes and emissions.

**Evaluation of Top-Down Flux Estimates:** The combination of model (GEOS-chem) and data (GOSAT) used to quantify methane fluxes have been evaluated previously by comparing prior and posterior model concentrations to independent data. Maasakkers et al (2019) finds that posterior methane concentrations have correlations ($R^2$) of 0.76, 0.81, and 0.91 with data from surface sites, aircraft, and total column data respectively. These correlations are essentially the same as those for the GEOS-chem prior concentrations, likely because these measurements are taken in background regions away from sources. These comparisons between posterior concentrations with independent data sets demonstrate that the GEOS-Chem model with GOSAT data has skill in quantifying atmospheric methane concentrations and that assimilating GOSAT data into GEOS-Chem for the purpose of quantifying fluxes is at least as skillful as using prior information when looking at background regions away from emissions sources. Changes in fluxes based on GOSAT data are therefore driven entirely by differences in satellite observed concentrations over source regions.

### *2.2 Projecting Fluxes To Emissions And Their Uncertainties*

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The derivation that describes how to project top-down fluxes back to emissions by sector at arbitrary resolution is described in Cusworth *et al*. (2021) and summarized in this section. For policy-relevance and $CH_4$ budget quantification, we wish to optimize emissions ($\mathbf{z}$) using atmospheric observations, i.e., we want to compute the explicit posterior representation without re-simulation of an atmospheric transport model. The relationship we use between emissions $\mathbf{z}$ and fluxes $\mathbf{x}$ is simple aggregation (the total flux within a grid box is the sum of emissions), and can be represented by matrix $\mathbf{M}$:

$$\mathbf{x} = \mathbf{M}\mathbf{z}. \quad (6)$$

The solution for projecting fluxes back to emissions takes the form (Cusworth *et al*. 2021):

$$\hat{\mathbf{z}} = \mathbf{z}_A + \hat{\mathbf{Z}}\mathbf{M}^T\hat{\mathbf{S}}^{-1}\left[\left(\mathbf{I} - \hat{\mathbf{S}}\mathbf{S}_A^{-1}\right)(\mathbf{x}_A - \mathbf{M}\mathbf{z}_A) + (\hat{\mathbf{x}} - \mathbf{x}_A)\right] \quad (7)$$

where the ($\hat{\mathbf{z}}$) is the posterior emissions vector with error covariance ($\hat{\mathbf{Z}}$) and $\mathbf{I}$ is the identity matrix, The posterior emission error covariance matrix $\hat{\mathbf{Z}}$ is calculated explicitly given $\mathbf{M}$, $\mathbf{S}_A$, $\hat{\mathbf{S}}$, and prior emissions error covariance matrix $\mathbf{Z}_A$:

$$\hat{\mathbf{Z}} = \left(\mathbf{M}^T\left(\hat{\mathbf{S}}^{-1} - \mathbf{S}_A^{-1}\right)\mathbf{M} + \mathbf{Z}_A^{-1}\right)^{-1} = \left(\mathbf{M}^T(\mathbf{K}^T\mathbf{S}_y{}^{-1}\mathbf{K})\mathbf{M} + \mathbf{Z}_A^{-1}\right)^{-1} \quad (8)$$

This solution depends on the top-down flux inversion providing the inversion characterization products (i.e., the flux prior $\mathbf{x}_A$ and flux constraint matrix $\mathbf{S}_A$ and the flux Hessian $\hat{\mathbf{S}}$). Note that here we must use the Hessian as described in Equation 3, not the total posterior covariance as described by Equation 5 (Cusworth *et al*. 2021). To quantify the set of sectoral emissions $\hat{\mathbf{z}}$, a corresponding prior emissions $\mathbf{z}_A$, and covariance matrix $\mathbf{Z}_A$, must be provided at the desired spatial grid; in this study we choose a 1 degree lon/lat grid. Note that the emissions and their prior uncertainties used to generate prior fluxes for the top-down flux inversion ($\mathbf{x}_A$) can be different from those used to project the top-down fluxes back to sectoral emissions for linear or moderately non-linear problems (e.g. Rodgers and Connor 2003; Bowman *et al*. 2006) as the

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information from the measurement is preserved in the $\mathbf{K}^T\mathbf{S_y}^{-1}\mathbf{K}$ term which is contained in $\hat{\mathbf{S}}^{-1} - \mathbf{S}_\mathrm{A}^{-1}$ as shown in Equation 8. This means that $\mathbf{Mz_A}$ can be different from $\mathbf{x_A}$, and their corresponding covariances, as long as the inversion problem is linear or only moderately nonlinear (Bowman *et al*. 2006; Cusworth *et al*. 2021). However, the interpretation of fluxes will be different if these matrices ($\mathbf{S_A}$ and $\mathbf{Z_A}$) are inconsistent (e.g. Shen *et al*. 2021), that is $\mathbf{S_A} \neq \mathbf{MZ_AM^T}$.

The uncertainty for any given element of the state vector **z** is generally given by the square root of the diagonal element of the total error covariance and includes the effects of the limited spatial resolution of the top-down flux and how this projects uncertainties from one grid box and sector into another grid box and sector as discussed in the previous section. For example, the estimate for the emissions for some emissions sector "*i*" at some lon/lat grid box "*j*" is given by (Rodgers and Connor 2003; Worden *et al*. 2004):

$$\hat{z}_{ij} = z_a^{ij} + A_{ij,ij}\left(z_{ij} - z_a^{ij}\right) + \mathbf{A}_{\boldsymbol{ij,xy}}\left(\mathbf{z_{xy}} - \mathbf{z_a^{xy}}\right) + \delta_{ij} \tag{9}$$

Where the italicized variables in Equation 9 are scalar representations of the variables in Equations 7 and 8, the index "*x*" represents all sectors and the index "*y*" represents all other lat/lon elements and matrices and vectors are boldfaced. Note that the paired indices *x* and *y* exclude the paired indices *i* and *j*. The variable "$z_{xy}$" represents the "true" value corresponding to the estimate "$\hat{z}_{ij}$" and the variable $\delta_{ij}$ represents the error due to random noise (we exclude systematic error here to simplify the math but Equation 9 can be expanded to include this term). Of course we do not actually know the true value and its errors but Equation 9 allows us to represent them in a manner than allows us to calculate their statistics. The total error for $\hat{z}_{ij}$, equivalent to an element of the total error in Equation 8, is:

$$E\left|\left|\hat{z}_{ij} - z_{xy}\right|\right| = \left(1 - A_{ij}\right)Z_a^{ij}\left(1 - A_{ij}\right)^T + \mathbf{A}_{ij,xy}\mathbf{Z}_{\boldsymbol{a}}^{xy}\mathbf{A}_{\boldsymbol{ij,xy}}^{\mathbf{T}} + S_{ij}^n \tag{10}$$

Where the E|| || term describes the expectation operator for calculating the statistics of the quantity of interest (Bowman *et al*. 2006). The diagonal elements of the total error covariance therefore include the effect of the limited spatial resolution through the second term on the right

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hand side of Equation 10, which projects prior uncertainties from one region and sector (x,y) into the region and sector of interest (i,j). The last term is the covariance due to measurement noise. As the spatial resolution increases, the averaging kernel matrix becomes an identify matrix; in this limit the first and second terms on the right side converge to zero such that the total error is due to noise (last term in Equation 10) and any residual systematic errors (not shown in Equation 10 but discussed in the previous section). Improving the spatial resolution of the methane emissions estimate therefore improves the accuracy.

In order to calculate the uncertainty for an aggregation of the elements of the state vector **z** (e.g. the coal sector for a country), instead of an individual element, we must sum the desired set of elements [$z_i$] that represent this sector and region. The uncertainty for this sum (squared) is then:

$$\sigma_{ij}^2 = \mathbf{h}\hat{\mathbf{Z}}_{ij}\mathbf{h}^T \tag{11}$$

where **h** is a vector that is the same length as [$z_{ij}$], with values of one in each element and $\hat{\mathbf{Z}}_{ij}$ is the square sub-matrix of the covariance matrix $\mathbf{Z}$ corresponding [$z_{ij}$] (e.g. the country and emission sector of interest).

### *2.3 Generation of Prior Emissions, Covariances, and Uncertainties*

In order to project fluxes from a top-down inversion back to emissions using the approach described in Section 2.2, sectoral emissions and their covariances, or $\mathbf{z_A}$ and $\mathbf{Z_A}$, at the desired spatial resolution are required. One challenge with the flux to emissions projection is that the *a priori* covariance matrix $\mathbf{Z_A}$ must be inverted (Equation 8), which can be computationally expensive because this matrix can be quite large as the number of sectors and spatial resolution of the emissions increases and because correlations within the matrix (next section) make it challenging to invert. In order to reduce computational expense for our chosen spatial resolution of 1 degree resolution (prior to calculating country wide emissions), we dis-aggregate global emissions into seven regions (Table 2) chosen by regions with peaks in the inversion sensitivity to the underlying fluxes as shown by the averaging kernel diagonals in Figure 2. The different

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categories are shown in Table 2 for each region and by sector along with the provenance (or manuscript reference) in the second column. Cross-terms in the averaging kernel (Equations 5, 9, and 10) matrix demonstrate that the change in emissions in one region affect the estimated emissions in another. Subdividing the fluxes into these 8 regions therefore introduces an extra error term in the total error covariance for each region; however this extra error is automatically included in the total error covariance for each region as demonstrated by Equation 10.

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Table 2: *A priori* emissions by source and region used with sectoral attribution

| Source Tg $CH_4$/yr | Ref | N. America (15%) | S. America (30%) | Africa (30%) | Europe W. Russia N. Africa Mid-East (15%) | E. Russia (30%) | India Eurasia (30%) | Asia (30%) | Indonesia Australia (20%) | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| Lon / Lat | | 175W-40W 25N-80N | 130W-30W 65S-25N | 24W-60E 40S-20N | 24W-60E 20N-80N | 60E-179E 50N-90N | 60E-90E 5N-50N | 90E-179E 5N-50N | 90E-179E 45S-5N | |
| Livestock | 1,2 | 7.7 +/-1.2 | 21.6 +/3.9 | 10.7 +/- 2.1 | 12.4 +/1.8 | 0.6 +/-0.1 | 19.1 +/- 5.0 | 11.7 +/2.4 | 3.9 +/- 0.8 | 87.6 +/- 7.4-17.2 |
| Rice | 2 | 0.4 +/-0.1 | 1.2 +/- 0.3 | 1.8 +/-0.6 | 0.6 +/-0.1 | 0.04 +/- 0.01 | 8.7 +/- 2.4 | 32.8 +/8.5 | 4.4 +/- 0.9 | 36.9 +/- 8.9-12.9 |
| Waste | 2 | 7.4 +/-1.1 | 4.1 +/-1.3 | 7.1 +/-2.0 | 23.9 +/3.6 | 0.9 +/-0.3 | 4.4 +/-1.3 | 6.8 +/-1.6 | 3.1 +/- 0.7 | 57.7 +/- 5.0 – 11.9 |
| Oil | 3 | 2.7 +/-0.4 | 4.5 +/-1.4 | 2.8 +/-0.8 | 17.7 +/- 2.9 | 10.6 +/3.3 | 0.6 +/-0.2 | 2.0 +/-0.6 | 0.7 +/- 0.1 | 41.6 +/- 4.7-9.7 |
| Coal | 3 | 3.2 +/-0.5 | 0.4 +/-0.1 | 0.78 +/- 0.22 | 2.3 +/-0.3 | 2.8 +/0.9 | 1.6 +/-0.5 | 19.2 +/5.9 | 1.2 +/- 0.3 | 31.4 +/- 6.1-9.8 |
| Gas | 3 | 7.5 +/-1.1 | 0.4 +/-0.1 | 0.7 +/-0.2 | 8.9 +/-1.3 | 0.4 +/0.1 | 3.7 +/-1.2 | 0.9 +/-0.3 | 1.1 +/- 0.2 | 24.5 +/- 2.1-4.7 |
| Fires | 4 | 1.4 +/-0.3 | 2.3 +/-0.4 | 4.9 +/-0.8 | 0.3 +/0.03 | 1.5 +/0.2 | 0.1 +/- 0.02 | 1.1 +/-0.2 | 3.6 +/- 0.6 | 15.1 +/- 1.1 – 2.5 |
| Wetlands Aquatic | 5,6 | 37.1 +/7.2 | 72.8 +/16.2 | 42.4 +/- 16.3 | 7.5 +/-1.5 | 8.6 +/2.0 | 3.7 +/-1.1 | 8.6 +/-1.9 | 19.0 +/- 6.5 | 199.8 +/- 25.2 - 52.8 |
| Seeps | 7 | 7.8 +/-1.1 | 2.0 +/-0.6 | 0.4 +/-0.1 | 14.1 +/2.5 | 2.8 +/0.8 | 0.8 +/-0.2 | 2.7 +/-0.7 | 1.3 +/- 0.2 | 32.0 +/- 3.0 – 6.2 |
| Total Tg $CH_4$/yr | | 75.2 +/- 7.6 – 12.9 | 109.3 +/- 16.8-24.4 | 71 +/- 16.6–23.1 | 87.8 +/- 5.9-14.1 | 28.9 +/- 4.0 – 7.8 | 42.7 +/- 5.9 – 11.9 | 85.8 +/- 11.0-22.1 | 38.3 +/- 6.7-10.4 | 526 +/- 29.5 – 127.7 |

Table 2: Prior emissions by source and regions. Single values for uncertainties are calculated by projecting the corresponding covariance to a single number for the indicated lon/lat region and taking the square root. Total values show a range of uncertainty with the lower bound being the sum (squared) of the individual region or sector (assumes errors are un-correlated) and the upper bound being the sum of the errors (assumes errors are completely correlated). The following references indicate the source for each emission type: 1) NASA CMS V1.0 (Wolf *et al*. 2017), 2) EDGAR 6.0 (Crippa *et al*. 2020), 3) NASA GFEI V1 (Scarpelli *et al*. 2020), 4) GFED 4.1 (van der Werf *et al*. 2017), 5) WETCHARTS 1.3.1 (Bloom *et al*. 2017), 6) GCP (Poulter *et al*. 2017), 7) Etiope *et al*. (2019). The target uncertainty for each region and sector is given in brackets underneath each region.

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The prior emissions used in our analysis represent, by necessity, a set of ad hoc choices that are informed by the scientific literature and experience of the co-authors of this paper with developing top-down flux estimates. For example, wastewater is not explicitly estimated as these emissions are spatially correlated with landfill emissions based on inspection of EDGAR inventories when projected to 1 degree resolution. The waste category should therefore be interpreted as a combination of landfill and wastewater. We also did not consider biofuels or termites for this estimate as they represent a small component of the budget. For these reasons, the biofuel and termite components of the methane budget will slightly bias our other sectoral estimates by 15-30 Tg $CH_4$/yr based on bottom up estimates reported in (Saunois *et al*. 2020). Our prior emissions for livestock are from a NASA Carbon Monitoring System product and is likely too low as this product ends in 2012. Prior wetland emissions are based on an ensemble of process models from the WETCHARTS system and the Global Carbon Project (Bloom *et al*. 2017; Poulter *et al*. 2017; Ma *et al*. 2021) and include the effects of lakes and rivers. A future version of this system will separately estimate these other sectors of the methane budget if further analysis using other satellite data (e.g. TROPOMI) shows that they can be distinguished from these other sectors.

**Covariance Generation**: Generating representative prior covariances is challenging as there are few global studies that allow for accurate representation of uncertainties for emissions across the globe and their correlations that are based on data and/or well calibrated models. This problem exists not just for methane emissions but with other inverse problems where there is little data representative of the quantities of interest (e.g. with remote sensing; Worden *et al*. 2004). For this reason we need to make another set of ad-hoc choices that is based on prior research in order to generate the covariances for each sector. We therefore use the following approach: first we assume that the total anthropogenic emissions (by sector) in "Annex 1" countries have an uncertainty of 15%. For example, we assume the total error for the N. American Coal sector is ~15%, and so on for each anthropogenic sector. Similarly, the total error for Annex 2 regions is 30%. These targeted uncertainties are listed underneath the label for each region in Table 2. These uncertainties are reported in Janssens *et al*. (2019) and are based on "expert opinion" as quantifying uncertainties over a country or region using bottom up-approaches can be challenging. Total regional uncertainty for a specific sector is calculated using Equation 11. In order for sectoral emissions at 1 degree resolution to project to a total regional

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uncertainty of 15%, there must be significant uncertainty of any given emission within that 1 degree grid cell. However, even assuming very large uncertainties for an emission within a 1 degree grid cell (e.g. 100%), the regional total uncertainty can be much smaller than 15% once projected over a large enough number of grid cells if the emission errors are assumed to be uncorrelated. To address this issue we also add correlations between nearby emissions; we start the diagonal values at 0.7 (squared) of the prior emissions, or 70% uncertainty, and with a correlation of 0.7 between neighboring emissions of the same type that are within 400 km (or four grid cells). The diagonal values and correlations are then adjusted until the projected uncertainty reaches 15% (for Annex 1) or 30% (Annex 2). Final values typically range from 0.6 (squared) to 1.0 for the diagonal and 0.7 to 0.9 for the off-diagonal values with variations in these numbers because of the different spatial distributions of the emissions. These numbers for the correlation and length scale are based on regional studies for N. America which also indicate that uncertainties for nearby emissions should be correlated (e.g. Maasakkers *et al*. 2016, 2019).

For wetlands, we use a slightly different approach for generating covariances. Here we calculate the root mean square (RMS) of an ensemble of different wetland process models (Bloom *et al*. 2017; Poulter *et al*. 2017; Ma *et al*. 2021) for a given region. We then follow a similar covariance generation approach as used for the anthropogenic emissions, iterating with different diagonal and off-diagonal values until the projected uncertainty for a region is approximately the same as the corresponding variance of the models.

While generating representative prior covariances is challenging, Equations 7 and 8 from the previous section allow us to swap in better priors and prior covariances as these become available. For example, if a researcher finds that the uncertainties expressed in $\mathbf{Z_A}$ over a given region for a given sector should be 10% instead of the value used (approximately 70%), then it is straightforward to update the covariance matrix to reflect this improved knowledge so that the attribution to each sector is improved. Of course this improved information could also be used to improve the $\mathbf{S_A}$ constraint matrix in Equation 1 to improve convergence of the top-down flux estimate. Furthermore the updated posterior covariances can be used for the next flux inversion based on other independent data and at some point these covariances, because they are based on observations, will best reflect our knowledge of the methane emission. Covariances and prior emissions are all publicly available, as well as python code that demonstrates how to use these files, so that a researcher can determine how other priors and changes to their uncertainty

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structure affects this top-down result or to use them for their own top-down inversions. Links to these data and codes are in the Data Repository section (Section 5).

**Uncertainty Calculation Approach:** The uncertainties shown in the Tables 1 and 2 are calculated in the following manner. First the prior uncertainties for each sector and for each region shown in Table 2 are calculated by projecting the regional (e.g. N. America, S. America) posterior error covariance to a single number corresponding to the mean emissions for that region using Equation 11. One approach is to then assume that these uncertainties are independent of each other in which case they are added in quadrature to get the total value; this is the smaller uncertainty shown in the **Total** column in Table 2. However, another method is to assume that the uncertainties are 100% correlated such that they should be added linearly; these are the values shown as the larger value in Table 2. We expect that the actual uncertainty is somewhere between these values. However, to be conservative we only report the larger value in Table 1 and for the remainder of the paper.

The prior uncertainties generated using the method described here are consistent with those reported in the literature even though the methodology differs. For example the values shown in the "prior" column of Table 1 are consistent (within reported ranges or uncertainties) of the equivalent sectors discussed in Saunois *et al*. (2020) and with the regional EDGAR v4.3.2 inventories as discussed in Janssens-Maaenhout *et al*. (2019). A caveat is that Janssens-Maaenhout *et al*. (2019) also reports global totals for each sector, from a range of inventories and models, that are 2-3 times larger for each sector than those shown here. Another caveat is that Saunois *et al*. (2020) includes a freshwater category with a 120 +/- 60 Tg $CH_4$/yr uncertainty whereas this category is subsumed into our Wetlands / Aquatic sector.

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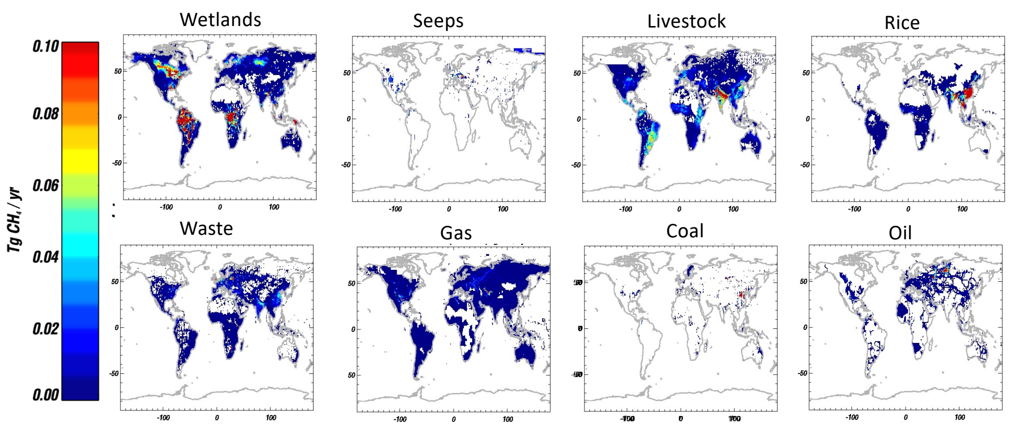


Figure 3: The square root of the diagonal of the *a priori* covariance for the eight largest sectors used in our analysis.

Figure 3 shows the (square root) diagonal of the covariance for each sector; as discussed previously, these are generally correlated with the magnitude of the emissions but also the chosen value for the regional total error (Table 2). Most of the sectors have enhancements and corresponding uncertainties that are spatially distinct. For example, the largest uncertainties for oil are located in Eastern Europe and Russia; the largest uncertainties for coal are in China, and the largest uncertainties for gas are in N. America and Central Asia. In turn, these fossil emissions are spatially distinct from wetlands and livestock. However, the largest uncertainties for rice and waste can spatially overlap those of livestock, especially in India and Asia, which indicates that remote sensing will be challenged to distinguish these emissions.

## 3.0 Results: Total Emissions and Emissions by Country

In this next section we first present global estimates, followed by a discussion of the sectoral emissions for the top-10 emitting countries, then emissions for all countries. Finally we test if different assumptions about bottom-up emissions as discussed in recent literature, i.e. larger wetland/aquatic emissions (Rosentreter *et al*. 2021), and larger fossil emissions (Schweitzke *et al*. 2017) affect our conclusions about the top-down results presented here.

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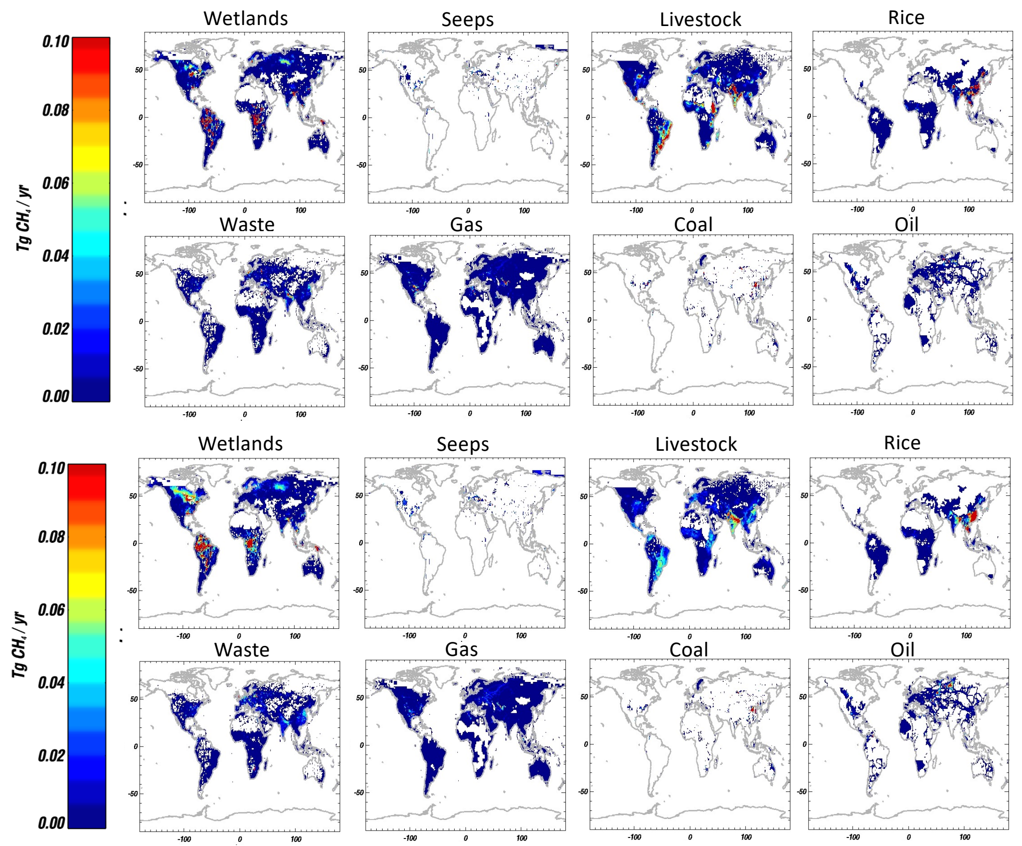


Figure 4: (top) Posterior methane emissions. (bottom) Poster emissions uncertainty as calculated by the square root of the diagonal of the posterior covariance matrix.

### *3.1 Global Methane Budget By Sector*

Emissions by sector and their uncertainty at 1 degree resolution are shown in Figure 4 with the top set of panels showing the posterior emissions and the bottom showing the uncertainties. As in Figure 3, the uncertainty at each longitude/latitude grid element is given by the square root of the diagonal of the total error covariance. Inspection of Figure 4 (bottom panel) and Figure 3 shows reduction of uncertainty in many parts of the world relate to the prior such as the larger wetlands and agricultural regions in India and Asia.

The right panel of Table 1 shows the global total posterior emissions by sector. The distribution of total emissions from the top-down is substantively different from the bottom-up. For example, posterior emissions for livestock and rice are larger than the prior by more than

1-sigma of the reported uncertainties. Top-down fossil emissions are also much lower than expected from the prior although consistent within their uncertainties. These differences reflect the top-down flux estimates (Figure 2) which show a lower posterior flux relative to the prior in fossil emitting regions such as Russia and N. America (with the exception of Southern USA) and increases in regions where livestock emissions are expected to be the largest source relative to other emissions such as India, Brazil, Argentina, and East Africa. Our results are consistent with previous top-down estimates based on the satellite GOSAT data. For example, the results here are based on the inversion framework from Zhang *et al*. (2021) and Qu *et al*. (2021), and are therefore generally consistent for the larger emissions such as wetlands, and livestock, or the emissions which are spatially distinct from other sources and therefore easier to resolve with remote sensing such as oil and coal. However, our estimates for rice, waste, seeps are very different and this is likely because our choice of priors for these sectors are different and because Qu *et al*. (2021) uses a uniform scaling approach to project fluxes to emissions whereas we account for the prior uncertainties. Similarly, our results for wetlands, livestock, and fossil emissions are consistent with previous GOSAT based inversions (e.g. Maasakkers *et al*. 2019; Zhang *et al*., 2021) with the caveat that these estimates are for earlier time periods and changes in emissions can affect interpretation of any differences. Ma *et al*. (2021) uses GOSAT based wetland estimates to show that wetland emissions for the years 2010-2018 are likely even lower than our results. As with results presented here they take into account the spatial resolution and prior of the top-down fluxes but use a different approach to quantify emissions; they select "high" performing wetland models based on comparison of an ensemble of models with mean wetland emissions and temporal variability. The total emissions for these highest performing models 117 – 189 Tg $CH_4$/yr is lower, but within the uncertainty of the results here. These difference in results, even when using similar models and data, highlight the importance of the choice of priors as well as the methodology by which fluxes are projected back to emissions as estimates for sectoral emissions can be very different from one estimate to the other depending on these choices.

Saunois *et al*. (2020) presents results from an ensemble of top-down estimates for emissions from wetlands (155-217 Tg $CH_4$/yr) , agriculture/waste (205-246 Tg $CH_4$/yr), biomass and biofuel burning (25-32 Tg $CH_4$/yr), and fossil emissions (91-121 Tg $CH_4$/yr). Our global total results shown in Table 1 are consistent with theirs (within uncertainties) although our result

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for agriculture and waste (263 +/- 24 Tg $CH_4$/yr ) is on the high side of theirs and our results for fossil emissions (82.1 +/- 12 Tg $CH_4$/yr) are on the low side of their estimates. These differences likely represent the differences in information content and sampling from satellite versus ground-based data as most of top-down ensembles reported in Saunois *et al*. (2020) are based on in situ measurements which do not sample areas of strong livestock emissions such as Brazil, India, and Ethiopia.

Onshore geological seeps represent a largely uncertain source of fossil emissions with values ranging from 2 to 30 Tg $CH_4$/yr. For example, the top-down flux estimate, used as a basis for the sectoral emissions attribution, assumes a prior of ~2 Tg $CH_4$/yr. However, our choice of prior (part of the $\mathbf{z_A}$ vector, Equation 7) is based on Etiope *et al*. (2019) with a value of 32.0 +/- 6.2, resulting in a posterior of 22.5 +/- 3.8 Tg $CH_4$/yr. This reduction in uncertainty is substantial suggesting that remote sensing is providing good information about this source, likely because seeps have a geographically distinct distribution relative to other sources. A caveat is it is possible that inventories are not specifying other emissions near seeps which would in turn mis-represent this attribution. We therefore suggest this category attention deserves measurements, especially from the up and coming high-resolution greenhouse gas measurements such as Carbon Mapper.

### *3.2 Top 10 Emitting Countries*

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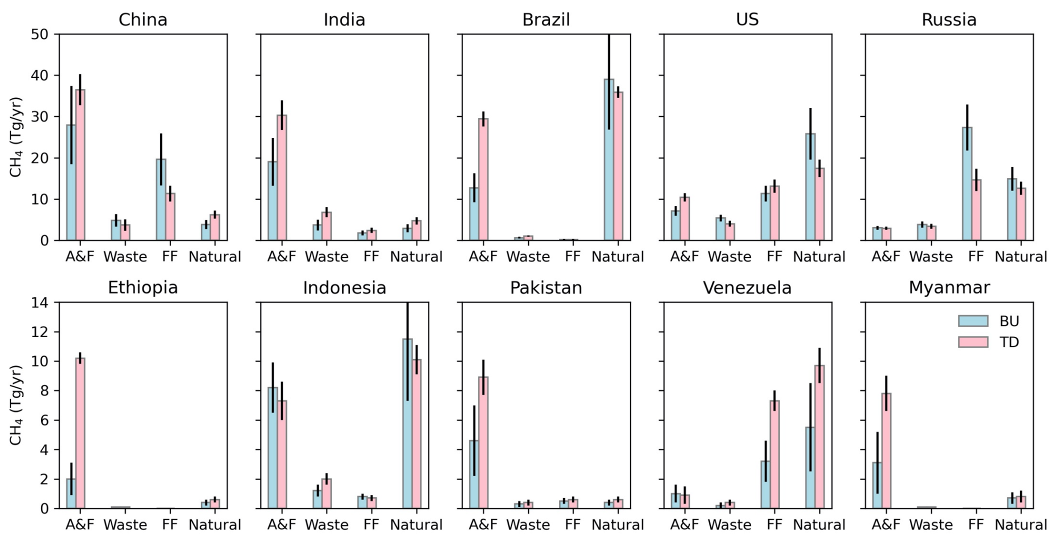


Figure 5: Emissions by sector for the top 10 emitters. AF represents agricultural and fires. FF represents fossil fuels or coal, oil, and gas. Natural represents wetlands, aquatic sources, and geological seeps. Bottom up (BU) inventory estimates are shown as blue bars and the remote sensing / top-down (TD) estimates are shown as the pink bars. The uncertainties in both quantities are shown as black lines. Uncertainty calculations for bottom up and top-down estimates are discussed in Section 2.

Figure 5 lists the top 10 emitting Countries ranked by total anthropogenic emissions as calculated using this remote sensing system. The different categories are AF, which includes the sectors for agriculture (livestock and rice) and fires. This category is similar to the Agriculture, Forestry, and Land Use category or "AFOLU" used in $CO_2$ based carbon inventories. W is the waste category, FF is the fossil category, which includes extraction, transport and use of coal, oil, and natural gas (Scarpelli *et al*. 2020; 2021). The Natural category, includes wetlands and geological seeps. The top five emitting countries are essentially the same from the bottom-up and top-down. However, top emitting countries with most emissions from the agriculture sector, likely due to livestock (see table in Section 4). While top-down and inventory emissions for China, USA, and Indonesia are consistent; there are major differences between our top-down results and inventories for the other countries. We next compare these results to those of previous studies; however, as stated earlier, these results should be treated cautiously and as a starting point for future research as differences can also be due to unquantified uncertainties in either the remote sensing data or the transport model used to relate concentrations to fluxes.

Our results are consistent with those from Maasakkers *et al*. (2019), Zhang *et al*. (2021) and Qu *et al*. (2021); however this is not too surprising as emissions that are reported here are based on the flux inversion system from these studies. A notable difference in methodology is that Qu *et al*. (2021) who also derives fluxes based on total column data from the Tropospheric Monitoring Instrument (TROPOMI). However, Qu *et al*. (2021) finds that country totals for the top-5 are essentially the same based on GOSAT and TROPOMI except for Brazil, but attributed large differences between TROPOMI and GOSAT to systematic errors in the TROPOMI total column data related to low surface albedo over Brazil; consequently, the TROPOMI based estimates in this region should be treated more cautiously.

Comparisons of these results to other estimates discussed in the literature can show substantial differences in either total emissions or attribution or both. For example Ganesan *et al*. (2017), using in situ and satellite atmospheric methane data, finds much lower total Indian emissions of 22 +/- 2.3 Tg $CH_4$/yr for the 2010-2015 time period as compared to 39.5 +/- 5.4 for our study (and the Qu *et al*. 2021, Zhang *et al*. 2021 studies) and 36.5 +/-5.3 from Janardanan *et al*. (2020). Miller *et al*. (2019) provides similar total emissions for China of 61.5 +/- 2.7 Tg $CH_4$/yr but different partitioning; for example they find that Coal is the largest source of emissions based on comparison of top-down fluxes to EDGAR emissions and using a relative weighting attribution flux to emissions attribution approach, whereas we find that agriculture (primarily Rice, Table 3 Section 4) is the largest sector. A major caveat is that attribution of emissions from total fluxes is challenging for China because many of the strongest emissions (e.g. coal, livestock, and rice as shown in Figures 3 and 4) overlap within the spatial resolution of the top-down estimate which is less than 2.5 degrees based on gridding used for the flux inversion and the variable sensitivity of the averaging kernel. While in principal these uncertainties due to limited spatial resolution are quantified based on our assumed prior covariance for each sector, it is quite possible that both our choice of the location of the emissions and corresponding prior covariance are incorrect due to less confidence in the emissions characterization in this region (Janssens-Maenhout *et al*. 2019).

We find that Myanmar has anonymously large agricultural emissions (primarily from livestock, Table 3 Section 4) relative to prior assumptions . However, it is possible that poorly

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characterized prior emissions drive this difference as Janardanan *et al*. (2020) reports similar top-down emissions of 6.1 +/- 0.8 Tg using a higher resolution satellite based flux inversion. Similarly Ethiopia has larger than expected agricultural (livestock emissions) as compared to the prior. However, the amount of cattle and livestock, between 80 and 90 million in 2015 and growing (Bachewe *et al*. 2018) is not that different in size than USA livestock, ~93 million in 2021 (statista.com), suggesting that they could also have comparable livestock emissions, which is supported by the results in Figure 5.

Russian posterior fossil emissions are substantially lower than those initially reported in Scarpelli *et al*. (2020), which are based on reports to the UNFCC in 2017. However, more recent reporting to the UNFCC also suggest a much smaller bottom-up fossil estimate of ~7 Tg $CH_4$/yr (Scarpelli *et al*. 2021). Table 3 (next section) indicates that remote sensing provides the best information about Russian oil and to some extent coal emissions as the reduction of uncertainty is largest for these sectors but has little change for gas emissions. Total emissions for oil and coal are 11.2 +/- 1.9 indicating that total fossil emissions are likely larger than expected for the latest reports to the UNFCC but smaller than previous. However, as discussed previously, these top-down estimates should be treated cautiously and only as a starting point for future studies due to the limited sensitivity and potential uncertainties.

### *3.3 Results for all Countries*

This section presents the complete table (Table 3, Appendix 1) of emissions by sector and country. The table is ordered by Degrees of Freedom for Signal (DOFS), which is a metric of sensitivity for inversion problems. As discussed in Section 2.1, the DOFS is a metric for the sensitivity of the flux estimate. For example, a DOFS of 1 means that this remote sensing system (GOSAT plus GEOS-Chem) can generally resolve the countries total emissions, assuming the sensitivity is evenly distributed across the country. More DOFS means that more emissions can be spatially resolved. The DOFS are calculated from the Averaging Kernel matrix provided by the GEOS-Chem based inversion (Section 2.1). To calculate the DOFS for a given country we project the diagonal of the Averaging Kernel (Figure 2) to 1-degree resolution and then add up these values based on the 1-degree country map used in this study. Note that the total DOFS between the reduced resolution flux inversion and the 1-degree map is preserved. Table 3 indicates that the GOSAT based top-down estimate can quantify total emissions (i.e. reduce uncertainty) for approximately 58 countries as the DOFS for the 58th country is more than 1 and less than 1 for the 59th country. As discussed previously, As DOFS approaches zero there is less reduction in uncertainty using the top-down system discussed here. Furthermore, inspection of Table 3 shows that even countries where DOFS are between 1 and 2 show little reduction of uncertainty; this happens because of cross-terms in the sensitivity project uncertainty from one sector or region into another as shown in Equation 10.

### *3.4 What Happens to (Top Down) Methane Budget if Priors for Wetland/Aquatic and Fossil Emissions are Substantially Increased?*

Equations 7 and 8 also allow us to test other prior emission inventories to determine if they are consistent with top-down fluxes. This approach is similar to the "prior swapping" approach described in Rodgers and Connor (2003) but can also include "prior covariance swapping" as discussed in Cusworth *et al*. (2021). This approach involves replacing the $\mathbf{z_A}$ and $\mathbf{Z_A}$ shown in Section 2.2 with different formulations. In this section we test what happens if we inflate the prior emissions for the wetland or fossil fuel categories such that they are consistent with other studies indicating much higher values than expected from top-down estimates, e.g. Rosentreter *et al*. (2021) for wetland/aquatic emissions and Schwietzke *et al*. (2017) for fossil emissions. Figure 6 shows the results of these two studies. The bars labeled "Ref" indicate the prior used for the results reported in this manuscript. The bars labeled "Wet" indicated the increased wetland study (which also includes increases to lake and river emissions as the wetland models include these categories, Bloom *et al*. 2017) and the bars labeled "FF" indicate the study where anthropogenic fossil fuels are increased by 50%. We find that even with a very large prior emissions for wetland/aquatic sources, the posterior gives an estimate of 208 +/- 12.8 Tg $CH_4$/yr as compared to 179.8 +/-10 for the reference values. This decrease from the inflated prior of ~340 Tg $CH_4$/ yr to 208 Tg $CH_4$/yr happens because the global total is constrained to ~560 Tg $CH_4$/yr through knowledge of the methane sink and because wetland emissions tend to be spatially distinct from other sources. For the same reasons, fossil emissions, especially coal, oil, and geological seeps show a substantial decrease in uncertainty. Consequently, the posterior emissions difference between the reference and inflated fossil studies are consistent within

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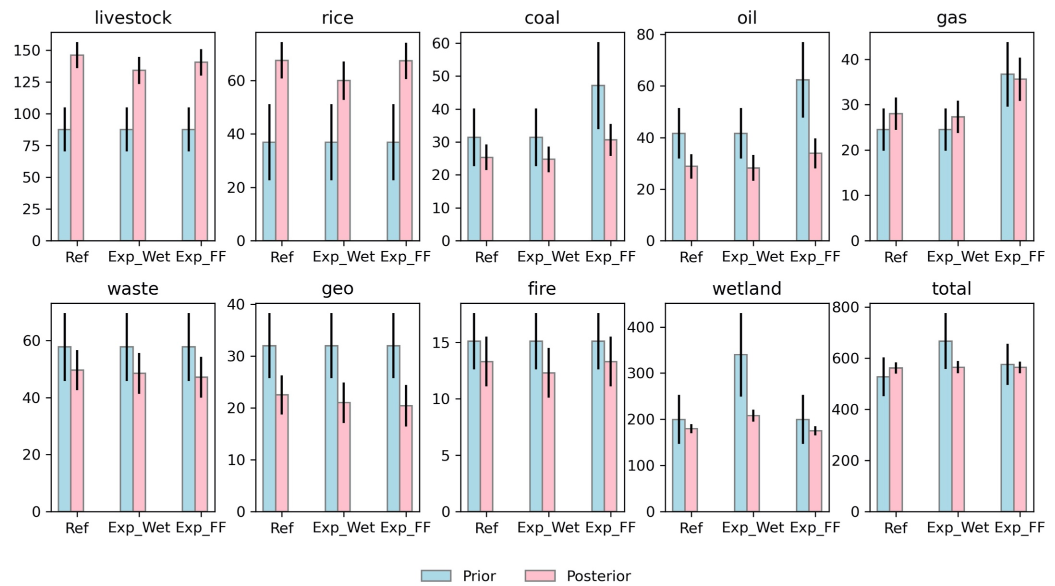


Figure 6: Comparison of total posterior emissions for reference case (ref, also Table1 posterior), if prior wetland emissions are inflated (Exp_Wet), and if prior anthropogenic fossil emissions are inflated (Exp_FF).

uncertainty and generally these emissions are much less than either the reference or inflated priors. For these reasons, it is challenging to reconcile these inflated aquatic emissions or inflated fossil emissions with top-down results. As noted previously, these comparisons should still be treated cautiously and as a starting point for further research because of poorly characterized systematic errors in the chemistry transport model used to related observed concentrations to fluxes and because sources that are not included in the prior state vector but co-located with other sectors cannot be distinguished. For example, if there are significant (unspecified) aquatic emissions that are co-located with livestock emissions then the corresponding livestock emissions estimate would be biased high.

## 4.0 Summary and Future Directions

In this paper we demonstrate, using a new Bayesian algorithm, estimates of emissions by sector at 1 degree resolution and by country, by using a combination of prior information of the emissions, satellite data, and a global chemistry transport model. Uncertainties are provided for representation (or smoothing) error and data precision but not for systematic errors in the transport model or data. Using a metric called the degrees-of-freedom for signal (DOFS), we show that the combination of GOSAT based satellite data with the GEOS-Chem model and prior uncertainties can estimate total emissions for about 58 of the 242 countries.

We find robust estimates for livestock, coal, natural gas, oil, seeps, fires, and wetlands as these can be distinguished from other sources using remote sensing given their distinct locations. We did not consider biofuels and termites in these initial estimates as they are thought to be small contributors to the methane; future estimates will add these other sources, especially in conjunction with more high resolution estimates that might be provided by regional TROPOMI inversions or future satellites such as CO2M, MethaneSAT or Carbon Mapper. We are also evaluating how to add systematic errors related to the atmospheric chemistry transport model and in the satellite data to our error analysis and we expect the next version of these estimates to contain these uncertainties. We also expect to add isotopic information through new flux estimates based on the surface network and the GEOS-Chem model; these independent data can be used to test the partitioning of biogenic, fossil, and pyrogenic emissions (e.g. Worden *et al*. 2017).

Our results can be used for comparison to country level, bottom-up inventories by sector that might be, for example, provided by the global stock take. However, any discrepancies between these top-down and inventory based estimates should be considered as a starting point for future investigations given the potential for systematic errors affecting the top-down results. The new Bayesian algorithm we demonstrate can be also used to test if different prior emissions result in similar (within the calculated uncertainties) posterior emissions estimates. Finally, the posterior emissions and covariances demonstrated in this manuscript can be used as priors in subsequent emissions estimates using data from other measurements such as from the upcoming CO2M, Methane-Sat, and Carbon Mapper instruments.

## 5.0 Data Repositories

The prior and posterior emissions and covariances are stored on https://cmsflux.jpl.nasa.gov/.

Please refer to Qu *et al*. (2021) for data related to the top-down flux inversion.

The provenance of individual inventories that are used to generate the emissions and inventories are shown in Table 2.

## 6.0 Author Contributions

JW led the integration of results and writing and developed the prior covariances. DC provided the emissions attribution with JW and AB and co-wrote Section 2.2. ZQ and YZ provided the flux estimates and co-wrote section 2.1. YY SM and AB supported the attribution derivation and analysis. BB and DC helped link results to the global stock take. TS and JM supported the inventory description and analysis. RD and DJ helped design the overall flux inversion and emissions attribution system described in the paper. All co-authors have read the paper and provided feedback.

## 7.0 Acknowledgements

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## 8.0 Appendix table of emissions for each country ordered by DOFS

Table 3: Table of Emissions for Each Country.

This table provides the top-down and bottom up estimates for each sector based on the methodology described in this paper. The table is ordered by DOFS which is the metric for sensitivity for the remote sensing system described in this paper. The first row for each country provides the top-down result and the second row is the bottom-up.

| Sector | Livestock Tg $CH_4$/yr | Rice Tg $CH_4$/yr | Waste Tg $CH_4$/yr | Fire Tg $CH_4$/yr | Oil Tg $CH_4$/yr | Coal Tg $CH_4$/yr | Gas Tg $CH_4$/yr | Seeps Tg $CH_4$/yr | Wetland/ Aquatic Tg $CH_4$/yr | DOFS | Total Anthro |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1) Brazil | 27.5+/-1.3 | 0.20+/-0.10 | 1.0+/-0.2 | 1.7+/-0.4 | 0.18+/-0.05 | 0.05+/-0.02 | 0.00+/-0.00 | 0.05+/-0.02 | 35.9+/-1.4 | 46 | 30.6+/-(1.4-2.0) |
| Inventory | 11.0+/-3.0 | 0.26+/-0.09 | 0.55+/-0.20 | 1.5+/-0.4 | 0.16+/-0.05 | 0.05+/-0.02 | 0.00+/-0.00 | 0.06+/-0.02 | 39.0+/-12.2 | | 13.5+/-(3.0-3.7) |
| 2) Russian Federation | 1.3+/-0.2 | 0.07+/-0.02 | 3.4+/-0.6 | 1.5+/-0.2 | 7.6+/-1.4 | 3.6+/-0.5 | 3.3+/-0.7 | 1.4+/-0.4 | 11.3+/-1.2 | 35.8 | 20.9+/-(1.8-3.7) |
| Inventory | 1.3+/-0.3 | 0.09+/-0.02 | 3.8+/-0.8 | 1.6+/-0.2 | 20.4+/-3.9 | 2.5+/-0.9 | 4.4+/-0.8 | 2.6+/-0.6 | 12.3+/-2.3 | | 34.1+/-(4.2-6.8) |
| 3) United States of America | 9.9+/-0.9 | 0.27+/-0.07 | 4.0+/-0.7 | 0.22+/-0.04 | 2.4+/-0.3 | 2.8+/-0.4 | 7.9+/-0.9 | 2.7+/-0.8 | 14.6+/-1.3 | 32.2 | 27.6+/-(1.5-3.3) |
| Inventory | 6.4+/-1.1 | 0.38+/-0.06 | 5.4+/-0.8 | 0.26+/-0.06 | 1.7+/-0.3 | 3.0+/-0.5 | 6.5+/-1.1 | 6.7+/-1.1 | 19.0+/-5.3 | | 23.8+/-(1.9-3.9) |
| 4) Canada | 0.90+/-0.15 | 0.00+/-0.00 | 0.43+/-0.37 | 0.76+/-0.20 | 0.74+/-0.26 | 0.05+/-0.01 | 0.82+/-0.17 | 1.1+/-0.2 | 9.2+/-0.7 | 31.5 | 3.7+/-(0.5-1.2) |
| Inventory | 0.91+/-0.15 | 0.00+/-0.00 | 1.2+/-0.4 | 1.1+/-0.3 | 0.88+/-0.27 | 0.05+/-0.01 | 0.80+/-0.18 | 1.1+/-0.2 | 18.0+/-4.6 | | 5.0+/-(0.6-1.3) |
| 5) China | 6.6+/-1.7 | 29.6+/-2.1 | 3.7+/-1.4 | 0.23+/-0.03 | 1.1+/-0.3 | 10.1+/-1.6 | 0.11+/-0.03 | 1.2+/-0.3 | 5.0+/-0.8 | 26.5 | 51.5+/-(3.4-7.1) |
| Inventory | 8.6+/-2.1 | 19.1+/-7.4 | 4.8+/-1.5 | 0.23+/-0.03 | 0.99+/-0.28 | 18.5+/-5.9 | 0.12+/-0.03 | 1.0+/-0.3 | 2.8+/-0.8 | | 52.3+/-(9.8-17.3) |
| 6) India | 23.9+/-2.0 | 6.3+/-1.6 | 6.8+/-1.2 | 0.09+/-0.02 | 0.03+/-0.01 | 0.91+/-0.37 | 1.5+/-0.2 | 0.12+/-0.06 | 4.6+/-0.8 | 20.8 | 39.5+/-(2.8-5.4) |
| Inventory | 13.0+/-4.1 | 5.9+/-1.7 | 3.7+/-1.3 | 0.09+/-0.02 | 0.03+/-0.01 | 0.84+/-0.38 | 0.90+/-0.24 | 0.13+/-0.06 | 2.8+/-0.9 | | 24.5+/-(4.6-7.7) |
| 7) Democratic Republic of the Congo | 0.05+/-0.02 | 0.06+/-0.03 | 0.22+/-0.05 | 1.5+/-0.3 | -0.07+/-0.04 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 17.6+/-1.0 | 16.9 | 1.8+/-(0.4-0.5) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.06+/- 0.02 | 0.07+/- 0.03 | 0.24+/- 0.05 | 1.1+/- 0.4 | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.04+/- 0.01 | 21.2+/- 11.1 | | 1.6+/- (0.4- 0.5) |
| 8) Indonesia | 0.95+/- 0.23 | 4.2+/- 0.6 | 2.0+/- 0.4 | 2.1+/- 0.5 | 0.48+/- 0.14 | 0.13+/- 0.05 | 0.08+/- 0.01 | 0.65+/- 0.17 | 9.4+/- 0.8 | 16.1 | 10.0+/- (0.9- 1.9) |
| Inventory | 0.83+/- 0.23 | 4.3+/- 0.9 | 1.2+/- 0.4 | 3.0+/- 0.6 | 0.54+/- 0.14 | 0.14+/- 0.05 | 0.09+/- 0.01 | 0.62+/- 0.17 | 10.9+/- 4.0 | | 10.1+/- (1.2- 2.4) |
| 9) Peru | -0.52+/- 0.20 | - 0.11+/- 0.10 | 0.04+/- 0.07 | 0.02+/- 0.01 | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.05+/- 0.02 | 7.8+/- 0.5 | 6.9 | - 0.48+/- (0.24- 0.43) |
| Inventory | 0.48+/- 0.26 | 0.15+/- 0.09 | 0.14+/- 0.08 | 0.02+/- 0.01 | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.06+/- 0.02 | 10.9+/- 8.1 | | 0.88+/- (0.29- 0.49) |
| 10) Australia | 1.3+/-0.3 | 0.02+/- 0.00 | 3.0+/- 0.3 | 0.48+/- 0.05 | 0.02+/- 0.00 | 1.7+/- 0.2 | 0.38+/- 0.06 | 0.22+/- 0.07 | 1.0+/- 0.2 | 6.9 | 6.9+/- (0.5- 0.9) |
| Inventory | 2.2+/-0.5 | 0.03+/- 0.00 | 1.4+/- 0.5 | 0.48+/- 0.05 | 0.02+/- 0.00 | 1.0+/- 0.3 | 0.37+/- 0.06 | 0.27+/- 0.08 | 1.1+/- 0.2 | | 5.5+/- (0.8- 1.4) |
| 11) Venezuela (Bolivarian Republic of) | 0.77+/- 0.52 | 0.02+/- 0.03 | 0.41+/- 0.17 | 0.08+/- 0.03 | 7.3+/- 0.7 | 0.00+/- 0.00 | 0.01+/- 0.00 | 1.3+/- 0.4 | 8.4+/- 0.9 | 5 | 8.6+/- (0.9- 1.5) |
| Inventory | 0.85+/- 0.55 | 0.03+/- 0.02 | 0.25+/- 0.18 | 0.08+/- 0.03 | 3.2+/- 1.4 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.66+/- 0.37 | 4.8+/- 2.6 | | 4.4+/- (1.5- 2.1) |
| 12) Colombia | -1.97+/- 0.64 | 0.05+/- 0.14 | 0.18+/- 0.31 | 0.03+/- 0.01 | 0.33+/- 0.10 | 0.32+/- 0.14 | 0.01+/- 0.00 | 0.37+/- 0.23 | -0.79+/- 0.73 | 5 | - 1.05+/- (0.74- 1.34) |
| Inventory | 1.3+/-0.8 | 0.16+/- 0.12 | 0.46+/- 0.33 | 0.03+/- 0.01 | 0.26+/- 0.11 | 0.37+/- 0.14 | 0.01+/- 0.00 | 0.40+/- 0.24 | 3.7+/- 2.0 | | 2.6+/- (0.9- 1.5) |
| 13) Argentina | 6.6+/-0.6 | 0.03+/- 0.04 | 0.22+/- 0.07 | 0.09+/- 0.03 | 0.29+/- 0.10 | 0.00+/- 0.00 | 0.06+/- 0.02 | 0.26+/- 0.08 | 5.2+/- 0.6 | 4.6 | 7.3+/- (0.6- 0.9) |
| Inventory | 2.6+/-1.2 | 0.04+/- 0.03 | 0.15+/- 0.07 | 0.08+/- 0.03 | 0.31+/- 0.10 | 0.00+/- 0.00 | 0.06+/- 0.02 | 0.18+/- 0.09 | 2.4+/- 1.3 | | 3.2+/- (1.2- 1.4) |
| 14) Papua New Guinea | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.02+/- 0.00 | 0.08+/- 0.02 | 0.03+/- 0.02 | 0.01+/- 0.00 | 0.01+/- 0.00 | 0.13+/- 0.05 | 2.8+/- 0.4 | 4.4 | 0.19+/- (0.03- 0.06) |
| Inventory | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.02+/- 0.00 | 0.08+/- 0.02 | 0.04+/- 0.02 | 0.01+/- 0.00 | 0.01+/- 0.00 | 0.15+/- 0.05 | 6.0+/- 4.4 | | 0.19+/- (0.03- 0.06) |
| 15) Iran (Islamic Republic of) | 2.2+/-0.2 | 0.18+/- 0.06 | 0.69+/- 0.12 | 0.00+/- 0.00 | 3.0+/- 0.4 | 0.02+/- 0.00 | 0.73+/- 0.16 | 0.26+/- 0.07 | 0.46+/- 0.13 | 4.3 | 6.8+/- (0.5- 1.0) |
| Inventory | 0.74+/- 0.36 | 0.15+/- 0.05 | 0.41+/- 0.12 | 0.00+/- 0.00 | 3.4+/- 1.6 | 0.02+/- 0.00 | 0.47+/- 0.17 | 0.26+/- 0.07 | 0.19+/- 0.14 | | 5.2+/- (1.7- 2.3) |
| 16) Bolivia (Plurinational State of) | 0.60+/- 0.28 | 0.02+/- 0.02 | 0.03+/- 0.02 | 0.31+/- 0.16 | 0.05+/- 0.02 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.18+/- 0.08 | 2.2+/- 0.5 | 4.3 | 1.0+/- (0.3- 0.5) |
| Inventory | 0.61+/- 0.32 | 0.03+/- 0.02 | 0.03+/- 0.02 | 0.34+/- 0.16 | 0.05+/- 0.02 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.19+/- 0.08 | 3.4+/- 2.4 | | 1.1+/- (0.4- 0.5) |
| 17) Mexico | 4.1+/-0.5 | 0.00+/- 0.00 | 1.2+/- 0.5 | 0.12+/- 0.04 | 0.07+/- 0.03 | 0.12+/- 0.04 | 0.55+/- 0.12 | 0.19+/- 0.07 | 1.1+/- 0.3 | 3.7 | 6.1+/- (0.7- 1.2) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 2.0+/-0.9 | 0.01+/-0.00 | 2.4+/-1.3 | 0.12+/-0.04 | 0.07+/-0.03 | 0.09+/-0.04 | 0.34+/-0.12 | 0.19+/-0.07 | 0.81+/-0.32 | | 5.0+/-(1.5-2.3) |
| 18) Pakistan | 6.7+/-0.6 | 2.2+/-0.5 | 0.39+/-0.16 | 0.01+/-0.00 | 0.26+/-0.09 | 0.06+/-0.04 | 0.29+/-0.11 | 0.53+/-0.16 | 0.08+/-0.03 | 3.6 | 9.9+/-(0.9-1.6) |
| Inventory | 3.4+/-1.9 | 1.2+/-0.5 | 0.28+/-0.16 | 0.01+/-0.00 | 0.19+/-0.09 | 0.06+/-0.04 | 0.25+/-0.11 | 0.35+/-0.18 | 0.08+/-0.03 | | 5.4+/-(2.0-2.8) |
| 19) Congo | 0.01+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.06+/-0.04 | -0.26+/-0.11 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 7.5+/-0.9 | 3.4 | -0.18+/-(0.12-0.16) |
| Inventory | 0.01+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.07+/-0.04 | 0.21+/-0.14 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 8.0+/-6.4 | | 0.30+/-(0.15-0.19) |
| 20) United Republic of Tanzania | 2.8+/-0.4 | 0.18+/-0.13 | 0.13+/-0.04 | 0.34+/-0.10 | 0.00+/-0.00 | 0.00+/-0.00 | 0.05+/-0.03 | 0.06+/-0.02 | 1.9+/-0.4 | 3 | 3.5+/-(0.4-0.7) |
| Inventory | 0.96+/-0.59 | 0.20+/-0.14 | 0.12+/-0.04 | 0.23+/-0.10 | 0.00+/-0.00 | 0.00+/-0.00 | 0.05+/-0.03 | 0.06+/-0.02 | 1.5+/-0.8 | | 1.6+/-(0.6-0.9) |
| 21) South Africa | 1.9+/-0.2 | 0.00+/-0.00 | 0.72+/-0.15 | 0.05+/-0.01 | 0.00+/-0.00 | 0.71+/-0.13 | 0.00+/-0.00 | 0.04+/-0.01 | 0.21+/-0.07 | 3 | 3.4+/-(0.3-0.5) |
| Inventory | 0.52+/-0.30 | 0.00+/-0.00 | 0.65+/-0.25 | 0.05+/-0.01 | 0.00+/-0.00 | 0.43+/-0.19 | 0.00+/-0.00 | 0.04+/-0.01 | 0.16+/-0.07 | | 1.6+/-(0.4-0.7) |
| 22) Ethiopia | 10.1+/-0.4 | 0.01+/-0.00 | 0.12+/-0.04 | 0.09+/-0.05 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.14+/-0.04 | 0.43+/-0.11 | 2.9 | 10.3+/-(0.4-0.5) |
| Inventory | 1.9+/-1.1 | 0.01+/-0.00 | 0.10+/-0.04 | 0.08+/-0.05 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.12+/-0.05 | 0.27+/-0.12 | | 2.1+/-(1.1-1.2) |
| 23) Angola | 0.13+/-0.03 | 0.00+/-0.00 | 0.08+/-0.05 | 0.75+/-0.22 | -1.38+/-0.21 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 1.4+/-0.1 | 2.8 | -0.41+/-(0.31-0.51) |
| Inventory | 0.15+/-0.03 | 0.01+/-0.00 | 0.14+/-0.05 | 0.74+/-0.31 | 0.63+/-0.36 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.41+/-0.16 | | 1.7+/-(0.5-0.8) |
| 24) Myanmar | 0.67+/-0.47 | 6.9+/-0.6 | 0.05+/-0.01 | 0.23+/-0.06 | 0.00+/-0.00 | 0.01+/-0.00 | 0.01+/-0.00 | 0.08+/-0.04 | 0.72+/-0.31 | 2.7 | 7.8+/-(0.8-1.2) |
| Inventory | 0.83+/-0.56 | 2.0+/-1.4 | 0.05+/-0.01 | 0.24+/-0.06 | 0.00+/-0.00 | 0.01+/-0.00 | 0.01+/-0.00 | 0.09+/-0.04 | 0.64+/-0.33 | | 3.2+/-(1.5-2.1) |
| 25) Thailand | 0.21+/-0.18 | 2.7+/-0.8 | 0.27+/-0.16 | 0.10+/-0.03 | 0.10+/-0.16 | 0.02+/-0.01 | 0.07+/-0.06 | 0.06+/-0.02 | 0.18+/-0.35 | 2.4 | 3.5+/-(0.8-1.4) |
| Inventory | 0.31+/-0.18 | 2.9+/-2.2 | 0.26+/-0.16 | 0.10+/-0.03 | 0.21+/-0.16 | 0.02+/-0.01 | 0.09+/-0.06 | 0.06+/-0.02 | 0.62+/-0.39 | | 3.8+/-(2.2-2.8) |
| 26) Nigeria | 1.4+/-0.4 | 1.2+/-0.3 | 0.53+/-0.15 | 0.12+/-0.05 | 0.13+/-0.08 | 0.38+/-0.12 | 0.25+/-0.13 | 0.04+/-0.01 | 1.6+/-0.3 | 2.3 | 4.0+/-(0.6-1.2) |
| Inventory | 0.87+/-0.52 | 0.49+/-0.40 | 0.47+/-0.15 | 0.12+/-0.05 | 0.15+/-0.08 | 0.25+/-0.12 | 0.20+/-0.13 | 0.04+/-0.01 | 0.84+/-0.49 | | 2.5+/-(0.7-1.5) |
| 27) Malaysia | 0.04+/-0.02 | 0.10+/-0.07 | 0.26+/-0.20 | 0.04+/-0.01 | 0.11+/-0.03 | 0.00+/-0.00 | 0.11+/-0.08 | 0.27+/-0.13 | 0.68+/-0.27 | 2.2 | 0.66+/-(0.23-0.41) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.05+/-0.02 | 0.19+/-0.06 | 0.47+/-0.22 | 0.04+/-0.01 | 0.11+/-0.03 | 0.00+/-0.00 | 0.30+/-0.08 | 0.27+/-0.13 | 1.1+/-0.5 | | 1.2+/-(0.2-0.4) |
| 28) Sudan | 0.32+/-0.03 | 0.00+/-0.00 | 0.08+/-0.02 | 0.02+/-0.02 | 0.14+/-0.03 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.17+/-0.03 | 2.1 | 0.57+/-(0.05-0.10) |
| Inventory | 0.04+/-0.04 | 0.00+/-0.00 | 0.07+/-0.02 | 0.03+/-0.02 | 0.06+/-0.03 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.11+/-0.03 | | 0.21+/-(0.06-0.11) |
| 29) Zambia | 0.13+/-0.05 | 0.00+/-0.00 | 0.07+/-0.03 | 0.81+/-0.16 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.91+/-0.24 | 2.1 | 1.0+/-(0.2-0.2) |
| Inventory | 0.13+/-0.05 | 0.00+/-0.00 | 0.08+/-0.04 | 0.42+/-0.19 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.87+/-0.43 | | 0.64+/-(0.20-0.27) |
| 30) South Sudan | 0.05+/-0.03 | 0.00+/-0.00 | 0.02+/-0.00 | -0.07+/-0.16 | 0.26+/-0.06 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 3.1+/-0.4 | 2.1 | 0.25+/-(0.17-0.25) |
| Inventory | 0.03+/-0.03 | 0.00+/-0.00 | 0.02+/-0.00 | 0.34+/-0.16 | 0.11+/-0.06 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 1.8+/-1.3 | | 0.50+/-(0.18-0.26) |
| 31) Turkey | 0.89+/-0.28 | 0.04+/-0.02 | 1.8+/-0.5 | 0.01+/-0.00 | 0.02+/-0.01 | 0.23+/-0.04 | 0.10+/-0.03 | 0.33+/-0.15 | 0.10+/-0.05 | 2 | 3.1+/-(0.6-0.9) |
| Inventory | 0.70+/-0.33 | 0.05+/-0.02 | 2.0+/-0.8 | 0.01+/-0.00 | 0.02+/-0.01 | 0.22+/-0.04 | 0.10+/-0.03 | 0.47+/-0.17 | 0.10+/-0.05 | | 3.1+/-(0.9-1.2) |
| 32) Saudi Arabia | 0.16+/-0.05 | 0.00+/-0.00 | 0.29+/-0.07 | 0.00+/-0.00 | 0.12+/-0.09 | 0.00+/-0.00 | 0.65+/-0.21 | 0.09+/-0.03 | 0.00+/-0.00 | 1.9 | 1.2+/-(0.2-0.4) |
| Inventory | 0.10+/-0.06 | 0.00+/-0.00 | 0.23+/-0.07 | 0.00+/-0.00 | 0.29+/-0.11 | 0.00+/-0.00 | 0.53+/-0.26 | 0.10+/-0.03 | 0.00+/-0.00 | | 1.2+/-(0.3-0.5) |
| 33) Kazakhstan | 0.58+/-0.08 | 0.02+/-0.01 | 0.15+/-0.03 | 0.05+/-0.01 | 0.12+/-0.06 | 1.2+/-0.3 | 0.15+/-0.05 | 0.25+/-0.07 | 0.39+/-0.09 | 1.9 | 2.3+/-(0.4-0.6) |
| Inventory | 0.54+/-0.08 | 0.03+/-0.01 | 0.13+/-0.04 | 0.05+/-0.01 | 0.20+/-0.07 | 0.90+/-0.38 | 0.17+/-0.06 | 0.21+/-0.07 | 0.36+/-0.10 | | 2.0+/-(0.4-0.6) |
| 34) Central African Republic | 0.04+/-0.07 | 0.00+/-0.00 | 0.02+/-0.00 | -0.79+/-0.17 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.04+/-0.01 | -1.00+/-0.19 | 1.8 | -0.73+/-(0.18-0.25) |
| Inventory | 0.13+/-0.07 | 0.00+/-0.00 | 0.02+/-0.00 | 0.40+/-0.19 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.04+/-0.01 | 0.52+/-0.32 | | 0.55+/-(0.20-0.27) |
| 35) Viet Nam | 0.58+/-0.21 | 3.6+/-0.9 | 0.20+/-0.10 | 0.08+/-0.02 | 0.02+/-0.04 | 0.09+/-0.03 | 0.04+/-0.03 | 0.08+/-0.02 | 0.61+/-0.50 | 1.7 | 4.6+/-(0.9-1.3) |
| Inventory | 0.35+/-0.22 | 2.7+/-1.6 | 0.19+/-0.10 | 0.07+/-0.02 | 0.12+/-0.10 | 0.09+/-0.03 | 0.04+/-0.03 | 0.08+/-0.02 | 1.0+/-0.6 | | 3.6+/-(1.7-2.1) |
| 36) France | 2.2+/-0.4 | 0.00+/-0.00 | 0.86+/-0.28 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.05+/-0.01 | 0.20+/-0.06 | 0.09+/-0.05 | 1.7 | 3.1+/-(0.5-0.7) |
| Inventory | 1.2+/-0.6 | 0.00+/-0.00 | 0.70+/-0.33 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.05+/-0.01 | 0.19+/-0.06 | 0.08+/-0.05 | | 2.0+/-(0.7-1.0) |
| 37) Uzbekistan | 0.79+/-0.23 | 0.02+/-0.01 | 0.10+/-0.04 | 0.00+/-0.00 | 0.04+/-0.02 | 0.01+/-0.00 | 2.9+/-0.4 | 0.04+/-0.01 | 0.04+/-0.02 | 1.6 | 3.9+/-(0.5-0.8) |
| Inventory | 0.56+/-0.26 | 0.03+/-0.01 | 0.08+/-0.04 | 0.00+/-0.00 | 0.03+/-0.02 | 0.01+/-0.00 | 2.3+/-1.0 | 0.04+/-0.01 | 0.04+/-0.02 | | 3.0+/-(1.1-1.4) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| 38) Turkmenistan | 0.35+/-0.11 | 0.04+/-0.01 | 0.02+/-0.01 | 0.00+/-0.00 | 1.5+/-0.3 | 0.00+/-0.00 | 1.1+/-0.2 | 1.2+/-0.2 | 0.01+/-0.00 | 1.6 | 3.0+/-(0.4-0.6) |
| Inventory | 0.22+/-0.11 | 0.05+/-0.01 | 0.02+/-0.01 | 0.00+/-0.00 | 0.85+/-0.33 | 0.00+/-0.00 | 0.58+/-0.26 | 0.58+/-0.30 | 0.01+/-0.00 | | 1.7+/-(0.4-0.7) |
| 39) Philippines | 0.25+/-0.14 | -0.20+/-0.52 | 0.84+/-0.31 | 0.01+/-0.00 | 0.01+/-0.01 | 0.04+/-0.01 | 0.01+/-0.00 | 0.29+/-0.15 | 0.45+/-0.15 | 1.5 | 0.96+/-(0.62-0.99) |
| Inventory | 0.26+/-0.14 | 1.6+/-0.9 | 0.52+/-0.33 | 0.01+/-0.00 | 0.01+/-0.01 | 0.04+/-0.01 | 0.01+/-0.00 | 0.32+/-0.15 | 0.25+/-0.16 | | 2.4+/-(1.0-1.4) |
| 40) Paraguay | 0.64+/-0.40 | 0.01+/-0.02 | 0.03+/-0.03 | 0.05+/-0.03 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 1.4+/-0.6 | 1.5 | 0.74+/-(0.40-0.47) |
| Inventory | 0.59+/-0.48 | 0.02+/-0.02 | 0.03+/-0.03 | 0.05+/-0.03 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 1.5+/-1.1 | | 0.69+/-(0.49-0.56) |
| 41) Guyana | 0.01+/-0.01 | 0.07+/-0.07 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 1.5+/-0.3 | 1.5 | 0.09+/-(0.08-0.09) |
| Inventory | 0.01+/-0.01 | 0.08+/-0.07 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 1.4+/-1.3 | | 0.10+/-(0.07-0.08) |
| 42) Mozambique | 0.09+/-0.02 | 0.04+/-0.03 | 0.08+/-0.02 | 0.64+/-0.14 | 0.00+/-0.00 | 0.02+/-0.01 | 0.01+/-0.01 | 0.04+/-0.01 | 1.2+/-0.2 | 1.4 | 0.87+/-(0.15-0.22) |
| Inventory | 0.10+/-0.03 | 0.04+/-0.03 | 0.08+/-0.02 | 0.35+/-0.15 | 0.00+/-0.00 | 0.02+/-0.01 | 0.01+/-0.01 | 0.04+/-0.01 | 0.62+/-0.25 | | 0.60+/-(0.16-0.24) |
| 43) Egypt | 1.1+/-0.3 | 0.23+/-0.13 | 2.0+/-0.3 | 0.00+/-0.00 | 0.43+/-0.11 | 0.00+/-0.00 | 0.09+/-0.04 | 0.04+/-0.01 | 0.06+/-0.02 | 1.4 | 3.9+/-(0.4-0.8) |
| Inventory | 0.44+/-0.29 | 0.22+/-0.12 | 0.66+/-0.41 | 0.00+/-0.00 | 0.33+/-0.12 | 0.00+/-0.00 | 0.07+/-0.04 | 0.04+/-0.01 | 0.04+/-0.02 | | 1.7+/-(0.5-1.0) |
| 44) Cameroon | 0.42+/-0.15 | 0.05+/-0.04 | 0.13+/-0.10 | 0.08+/-0.05 | 0.01+/-0.02 | 0.00+/-0.00 | 0.04+/-0.03 | 0.04+/-0.01 | -0.69+/-0.30 | 1.3 | 0.71+/-(0.20-0.39) |
| Inventory | 0.23+/-0.18 | 0.04+/-0.04 | 0.24+/-0.10 | 0.09+/-0.05 | 0.03+/-0.02 | 0.00+/-0.00 | 0.03+/-0.03 | 0.04+/-0.01 | 0.72+/-0.47 | | 0.67+/-(0.22-0.42) |
| 45) Algeria | 0.25+/-0.11 | 0.00+/-0.00 | 0.16+/-0.08 | 0.00+/-0.00 | 0.05+/-0.01 | 0.00+/-0.00 | 3.2+/-0.3 | 0.12+/-0.02 | 0.04+/-0.03 | 1.3 | 3.7+/-(0.3-0.5) |
| Inventory | 0.22+/-0.12 | 0.00+/-0.00 | 0.19+/-0.09 | 0.00+/-0.00 | 0.05+/-0.01 | 0.00+/-0.00 | 1.2+/-0.6 | 0.11+/-0.02 | 0.05+/-0.03 | | 1.6+/-(0.6-0.8) |
| 46) Bangladesh | 1.0+/-0.5 | 1.2+/-1.3 | 0.15+/-0.08 | 0.01+/-0.00 | 0.00+/-0.00 | 0.01+/-0.01 | 0.04+/-0.03 | 0.04+/-0.01 | 1.4+/-0.6 | 1.3 | 2.4+/-(1.4-2.0) |
| Inventory | 0.92+/-0.60 | 2.6+/-1.5 | 0.12+/-0.08 | 0.01+/-0.00 | 0.00+/-0.00 | 0.01+/-0.01 | 0.04+/-0.03 | 0.04+/-0.01 | 0.98+/-0.60 | | 3.7+/-(1.6-2.2) |
| 47) Ukraine | 0.44+/-0.16 | 0.00+/-0.00 | 0.48+/-0.16 | 0.05+/-0.01 | 0.07+/-0.02 | 0.57+/-0.19 | 0.99+/-0.39 | -0.05+/-0.24 | 0.33+/-0.17 | 1.3 | 2.6+/-(0.5-0.9) |
| Inventory | 0.36+/-0.16 | 0.01+/-0.00 | 0.50+/-0.17 | 0.05+/-0.01 | 0.07+/-0.02 | 0.66+/-0.20 | 1.0+/-0.5 | 0.67+/-0.31 | 0.31+/-0.18 | | 2.7+/-(0.6-1.0) |
| 48) Germany | 1.7+/-0.5 | 0.00+/-0.00 | 2.0+/-0.6 | 0.00+/-0.00 | 0.01+/-0.00 | 0.10+/-0.03 | 0.18+/-0.10 | 0.22+/-0.09 | 0.09+/-0.06 | 1.3 | 4.0+/-(0.8-1.2) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 1.0+/-0.6 | 0.00+/- 0.00 | 1.6+/- 0.8 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.10+/- 0.03 | 0.18+/- 0.10 | 0.21+/- 0.09 | 0.08+/- 0.06 | | 2.9+/- (1.0- 1.5) |
| 49) Madagascar | 1.3+/-0.2 | 0.56+/- 0.13 | 0.02+/- 0.00 | 0.12+/- 0.04 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.02 | 0.04+/- 0.01 | 1.1+/- 0.2 | 1.3 | 2.1+/- (0.2- 0.4) |
| Inventory | 0.32+/- 0.21 | 0.18+/- 0.15 | 0.02+/- 0.00 | 0.09+/- 0.04 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.04+/- 0.01 | 0.34+/- 0.20 | | 0.66+/- (0.26- 0.42) |
| 50) Spain | 1.1+/-0.2 | 0.02+/- 0.01 | 0.94+/- 0.27 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.03+/- 0.01 | 0.09+/- 0.02 | 0.09+/- 0.05 | 1.2 | 2.1+/- (0.4- 0.5) |
| Inventory | 0.57+/- 0.31 | 0.03+/- 0.01 | 0.81+/- 0.37 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.03+/- 0.01 | 0.09+/- 0.02 | 0.08+/- 0.05 | | 1.4+/- (0.5- 0.7) |
| 51) Gabon | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.55+/- 0.21 | 1.2 | 0.02+/- (0.01- 0.01) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.01+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.69+/- 0.60 | | 0.03+/- (0.01- 0.01) |
| 52) Kenya | 1.5+/-0.4 | 0.01+/- 0.01 | 0.08+/- 0.03 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.10+/- 0.04 | 0.48+/- 0.15 | 1.2 | 1.6+/- (0.4- 0.4) |
| Inventory | 0.92+/- 0.67 | 0.01+/- 0.01 | 0.07+/- 0.03 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.10+/- 0.04 | 0.34+/- 0.17 | | 1.0+/- (0.7- 0.7) |
| 53) Suriname | 0.01+/- 0.00 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 2.3+/- 0.3 | 1.1 | 0.04+/- (0.02- 0.03) |
| Inventory | 0.01+/- 0.00 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 1.7+/- 1.5 | | 0.04+/- (0.02- 0.03) |
| 54) Chad | 1.9+/-0.2 | 0.00+/- 0.03 | 0.03+/- 0.01 | - 0.02+/- 0.05 | 0.02+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 1.7+/- 0.3 | 1.1 | 2.0+/- (0.2- 0.3) |
| Inventory | 0.32+/- 0.22 | 0.03+/- 0.03 | 0.03+/- 0.01 | 0.09+/- 0.05 | 0.07+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.67+/- 0.40 | | 0.55+/- (0.23- 0.36) |
| 55) Ecuador | -0.31+/- 0.21 | 0.01+/- 0.12 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.02 | -0.32+/- 0.34 | 1 | - 0.26+/- (0.24- 0.36) |
| Inventory | 0.30+/- 0.24 | 0.13+/- 0.11 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.06+/- 0.02 | 0.72+/- 0.79 | | 0.48+/- (0.27- 0.38) |
| 56) Uganda | 0.17+/- 0.34 | 0.01+/- 0.01 | 0.01+/- 0.00 | 0.05+/- 0.04 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.05 | 0.04+/- 0.01 | 0.23+/- 0.37 | 1 | 0.31+/- (0.35- 0.45) |
| Inventory | 0.47+/- 0.41 | 0.01+/- 0.01 | 0.01+/- 0.00 | 0.07+/- 0.04 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.06+/- 0.05 | 0.04+/- 0.01 | 0.82+/- 0.68 | | 0.63+/- (0.41- 0.51) |
| 57) Japan | 0.42+/- 0.10 | 3.0+/- 0.4 | 0.51+/- 0.17 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.00 | 0.01+/- 0.01 | 5.7+/- 0.4 | 1.2+/- 0.2 | 1 | 4.0+/- (0.4- 0.7) |
| Inventory | 0.22+/- 0.10 | 0.89+/- 0.46 | 0.28+/- 0.18 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.00 | 0.01+/- 0.01 | 0.96+/- 0.58 | 0.44+/- 0.21 | | 1.4+/- (0.5- 0.8) |
| 58) Cambodia | 0.13+/- 0.11 | 1.4+/- 0.4 | 0.02+/- 0.01 | 0.21+/- 0.08 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.05+/- 0.02 | 0.86+/- 0.57 | 0.95 | 1.8+/- (0.4- 0.7) |
| Inventory | 0.12+/- 0.11 | 0.66+/- 0.66 | 0.02+/- 0.01 | 0.21+/- 0.08 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.05+/- 0.02 | 0.87+/- 0.72 | | 1.0+/- (0.7- 0.9) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| 59) Poland | 0.31+/-0.23 | 0.00+/-0.00 | 0.19+/-0.40 | 0.00+/-0.00 | 0.05+/-0.01 | 0.42+/-0.16 | 0.07+/-0.04 | 0.22+/-0.12 | 0.08+/-0.06 | 0.95 | 1.0+/-(0.5-0.8) |
| Inventory | 0.42+/-0.24 | 0.00+/-0.00 | 0.95+/-0.48 | 0.00+/-0.00 | 0.05+/-0.01 | 0.52+/-0.17 | 0.08+/-0.04 | 0.28+/-0.12 | 0.10+/-0.06 | | 2.0+/-(0.6-0.9) |
| 60) Italy | 0.30+/-0.22 | 0.06+/-0.04 | 0.66+/-0.41 | 0.01+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.16+/-0.09 | -0.61+/-0.55 | 0.13+/-0.08 | 0.93 | 1.2+/-(0.5-0.8) |
| Inventory | 0.55+/-0.24 | 0.07+/-0.03 | 0.88+/-0.45 | 0.01+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.17+/-0.09 | 2.9+/-1.1 | 0.13+/-0.08 | | 1.7+/-(0.5-0.8) |
| 61) Uruguay | 1.8+/-0.3 | 0.05+/-0.07 | 0.04+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.18+/-0.09 | 0.89 | 1.9+/-(0.3-0.4) |
| Inventory | 0.62+/-0.55 | 0.08+/-0.07 | 0.03+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.17+/-0.09 | | 0.73+/-(0.56-0.64) |
| 62) Iraq | 0.27+/-0.08 | 0.01+/-0.00 | 0.23+/-0.08 | 0.00+/-0.00 | 0.13+/-0.05 | 0.00+/-0.00 | 0.01+/-0.00 | 0.16+/-0.06 | 0.02+/-0.01 | 0.88 | 0.65+/-(0.12-0.22) |
| Inventory | 0.13+/-0.09 | 0.01+/-0.00 | 0.15+/-0.09 | 0.00+/-0.00 | 0.13+/-0.06 | 0.00+/-0.00 | 0.01+/-0.00 | 0.13+/-0.07 | 0.02+/-0.01 | | 0.43+/-(0.14-0.24) |
| 63) Mali | 1.2+/-0.2 | 0.19+/-0.10 | 0.04+/-0.01 | 0.05+/-0.03 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.22+/-0.07 | 0.86 | 1.5+/-(0.2-0.3) |
| Inventory | 0.52+/-0.33 | 0.13+/-0.12 | 0.04+/-0.01 | 0.05+/-0.03 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.18+/-0.07 | | 0.75+/-(0.35-0.49) |
| 64) Chile | 0.43+/-0.12 | 0.00+/-0.00 | 0.49+/-0.11 | 0.01+/-0.01 | 0.01+/-0.01 | 0.01+/-0.00 | 0.02+/-0.01 | 0.15+/-0.05 | 0.28+/-0.07 | 0.85 | 0.97+/-(0.16-0.26) |
| Inventory | 0.24+/-0.14 | 0.00+/-0.00 | 0.18+/-0.12 | 0.01+/-0.01 | 0.01+/-0.01 | 0.01+/-0.00 | 0.02+/-0.01 | 0.13+/-0.05 | 0.27+/-0.08 | | 0.48+/-(0.18-0.29) |
| 65) United Kingdom of Great Britain and Northern Ireland | 0.61+/-0.41 | 0.00+/-0.00 | 0.55+/-0.74 | 0.00+/-0.00 | 0.01+/-0.00 | 0.02+/-0.01 | 0.16+/-0.10 | 0.55+/-0.21 | 0.12+/-0.08 | 0.78 | 1.3+/-(0.8-1.3) |
| Inventory | 0.75+/-0.44 | 0.00+/-0.00 | 3.8+/-2.3 | 0.00+/-0.00 | 0.01+/-0.00 | 0.02+/-0.01 | 0.16+/-0.10 | 0.55+/-0.22 | 0.12+/-0.08 | | 4.8+/-(2.3-2.8) |
| 66) Republic of Korea | 0.30+/-0.12 | 1.5+/-0.2 | 0.08+/-0.05 | 0.00+/-0.00 | 0.14+/-0.09 | 0.02+/-0.01 | 0.12+/-0.08 | 0.04+/-0.01 | 0.06+/-0.04 | 0.78 | 2.2+/-(0.3-0.6) |
| Inventory | 0.15+/-0.13 | 0.35+/-0.29 | 0.06+/-0.05 | 0.00+/-0.00 | 0.10+/-0.09 | 0.02+/-0.01 | 0.08+/-0.08 | 0.04+/-0.01 | 0.05+/-0.04 | | 0.77+/-(0.34-0.64) |
| 67) New Zealand | 1.5+/-0.2 | 0.00+/-0.00 | 0.26+/-0.11 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.01+/-0.00 | 0.18+/-0.07 | 0.43+/-0.12 | 0.77 | 1.8+/-(0.3-0.4) |
| Inventory | 0.70+/-0.41 | 0.00+/-0.00 | 0.21+/-0.12 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.01+/-0.00 | 0.17+/-0.07 | 0.27+/-0.12 | | 0.93+/-(0.43-0.53) |
| 68) Afghanistan | 0.70+/-0.19 | 0.04+/-0.01 | 0.03+/-0.01 | 0.00+/-0.00 | 0.01+/-0.01 | 0.13+/-0.05 | 0.01+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | 0.74 | 0.92+/-(0.20-0.28) |
| Inventory | 0.40+/-0.27 | 0.05+/-0.01 | 0.03+/-0.01 | 0.00+/-0.00 | 0.01+/-0.01 | 0.11+/-0.05 | 0.01+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | | 0.60+/-(0.28-0.35) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| 69) Niger | 1.5+/-0.2 | 0.01+/- 0.01 | 0.13+/- 0.05 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.08+/- 0.02 | 0.72 | 1.6+/- (0.2- 0.3) |
| Inventory | 0.50+/- 0.34 | 0.01+/- 0.01 | 0.12+/- 0.05 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.04+/- 0.02 | | 0.65+/- (0.35- 0.41) |
| 70) Cote d'Ivoire | 0.04+/- 0.05 | 0.02+/- 0.04 | 0.03+/- 0.02 | 0.05+/- 0.03 | 0.78+/- 0.31 | 0.00+/- 0.00 | 0.11+/- 0.09 | 0.04+/- 0.01 | -0.03+/- 0.29 | 0.72 | 1.0+/- (0.3- 0.5) |
| Inventory | 0.06+/- 0.05 | 0.04+/- 0.04 | 0.04+/- 0.02 | 0.05+/- 0.03 | 0.65+/- 0.41 | 0.00+/- 0.00 | 0.11+/- 0.09 | 0.04+/- 0.01 | 0.46+/- 0.35 | | 0.94+/- (0.43- 0.64) |
| 71) Sweden | 0.12+/- 0.04 | 0.00+/- 0.00 | 0.12+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 1.8+/- 0.4 | 0.71 | 0.25+/- (0.07- 0.09) |
| Inventory | 0.11+/- 0.04 | 0.00+/- 0.00 | 0.11+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.86+/- 0.56 | | 0.22+/- (0.07- 0.10) |
| 72) Zimbabwe | 0.01+/- 0.11 | 0.00+/- 0.00 | 0.01+/- 0.05 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.03+/- 0.03 | 0.71 | 0.05+/- (0.12- 0.18) |
| Inventory | 0.16+/- 0.13 | 0.00+/- 0.00 | 0.14+/- 0.07 | 0.03+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.06+/- 0.04 | | 0.33+/- (0.15- 0.22) |
| 73) United Arab Emirates | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.37+/- 0.18 | 0.00+/- 0.00 | 0.72+/- 0.21 | 0.00+/- 0.00 | 0.05+/- 0.05 | 0.04+/- 0.01 | 0.01+/- 0.01 | 0.71 | 1.2+/- (0.3- 0.5) |
| Inventory | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.27+/- 0.20 | 0.00+/- 0.00 | 1.3+/- 0.7 | 0.00+/- 0.00 | 0.07+/- 0.05 | 0.04+/- 0.01 | 0.01+/- 0.01 | | 1.6+/- (0.7- 1.0) |
| 74) Romania | 0.14+/- 0.15 | 0.00+/- 0.00 | 0.09+/- 0.18 | 0.01+/- 0.00 | 0.14+/- 0.04 | 0.19+/- 0.10 | 0.18+/- 0.15 | 0.79+/- 0.45 | 0.02+/- 0.05 | 0.7 | 0.75+/- (0.29- 0.62) |
| Inventory | 0.22+/- 0.16 | 0.00+/- 0.00 | 0.30+/- 0.19 | 0.01+/- 0.00 | 0.13+/- 0.05 | 0.24+/- 0.10 | 0.22+/- 0.15 | 2.1+/- 1.0 | 0.06+/- 0.05 | | 1.1+/- (0.3- 0.6) |
| 75) Nepal | -1.08+/- 0.29 | - 0.04+/- 0.24 | 0.09+/- 0.05 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.06+/- 0.03 | 0.19+/- 0.08 | 0.69 | - 0.98+/- (0.38- 0.60) |
| Inventory | 0.54+/- 0.45 | 0.40+/- 0.25 | 0.06+/- 0.05 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.07+/- 0.03 | 0.10+/- 0.09 | | 1.0+/- (0.5- 0.8) |
| 76) Botswana | 0.08+/- 0.04 | 0.00+/- 0.00 | 0.40+/- 0.24 | 0.03+/- 0.01 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.16+/- 0.11 | 0.66 | 0.52+/- (0.24- 0.29) |
| Inventory | 0.09+/- 0.04 | 0.00+/- 0.00 | 3.9+/- 1.8 | 0.03+/- 0.01 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.20+/- 0.13 | | 4.0+/- (1.8- 1.9) |
| 77) Finland | 0.07+/- 0.03 | 0.00+/- 0.00 | 0.11+/- 0.29 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.17+/- 0.32 | 0.63 | 0.18+/- (0.29- 0.32) |
| Inventory | 0.07+/- 0.03 | 0.00+/- 0.00 | 0.60+/- 0.36 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.68+/- 0.49 | | 0.67+/- (0.36- 0.38) |
| 78) Ghana | 0.02+/- 0.08 | 0.01+/- 0.04 | 0.08+/- 0.04 | 0.06+/- 0.05 | 0.04+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | -0.10+/- 0.29 | 0.63 | 0.21+/- (0.12- 0.25) |
| Inventory | 0.10+/- 0.09 | 0.05+/- 0.05 | 0.09+/- 0.04 | 0.09+/- 0.05 | 0.05+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.49+/- 0.39 | | 0.37+/- (0.12- 0.26) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| 79) Lao People's Democratic Republic | 0.09+/- 0.10 | - 0.27+/- 0.18 | 0.01+/- 0.01 | 0.10+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.05+/- 0.01 | 0.07+/- 0.14 | 0.59 | - 0.06+/- (0.21- 0.32) |
| Inventory | 0.12+/- 0.10 | 0.25+/- 0.21 | 0.01+/- 0.01 | 0.10+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.05+/- 0.01 | 0.21+/- 0.15 | | 0.49+/- (0.23- 0.35) |
| 80) Democratic People's Republic of Korea | 0.06+/- 0.03 | 0.34+/- 0.09 | 0.15+/- 0.08 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.63+/- 0.22 | 0.00+/- 0.00 | 0.05+/- 0.01 | 0.10+/- 0.04 | 0.55 | 1.2+/- (0.3- 0.4) |
| Inventory | 0.05+/- 0.03 | 0.15+/- 0.08 | 0.10+/- 0.08 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.48+/- 0.27 | 0.00+/- 0.00 | 0.05+/- 0.01 | 0.07+/- 0.05 | | 0.78+/- (0.29- 0.47) |
| 81) French Guiana | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.37+/- 0.17 | 0.48 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.30+/- 0.36 | | 0.00+/- (0.00- 0.00) |
| 82) Tajikistan | 0.27+/- 0.13 | 0.00+/- 0.00 | 0.06+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.16+/- 0.08 | 0.05+/- 0.01 | 0.01+/- 0.01 | 0.47 | 0.50+/- (0.16- 0.26) |
| Inventory | 0.18+/- 0.16 | 0.01+/- 0.00 | 0.04+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.13+/- 0.10 | 0.05+/- 0.01 | 0.01+/- 0.01 | | 0.37+/- (0.19- 0.30) |
| 83) Honduras | 0.54+/- 0.11 | 0.00+/- 0.00 | 0.08+/- 0.04 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.08+/- 0.03 | 0.80+/- 0.24 | 0.46 | 0.65+/- (0.12- 0.17) |
| Inventory | 0.15+/- 0.14 | 0.00+/- 0.00 | 0.05+/- 0.04 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.07+/- 0.03 | 0.55+/- 0.48 | | 0.22+/- (0.15- 0.20) |
| 84) Burkina Faso | 0.36+/- 0.17 | 0.02+/- 0.02 | 0.02+/- 0.01 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.04+/- 0.01 | 0.02+/- 0.01 | 0.45 | 0.44+/- (0.17- 0.23) |
| Inventory | 0.32+/- 0.26 | 0.02+/- 0.02 | 0.02+/- 0.01 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.04+/- 0.01 | 0.02+/- 0.01 | | 0.41+/- (0.26- 0.32) |
| 85) Syrian Arab Republic | 0.15+/- 0.08 | 0.00+/- 0.00 | 0.15+/- 0.06 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.09+/- 0.02 | 0.00+/- 0.00 | 0.41 | 0.33+/- (0.10- 0.15) |
| Inventory | 0.12+/- 0.09 | 0.00+/- 0.00 | 0.13+/- 0.08 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.09+/- 0.02 | 0.00+/- 0.00 | | 0.28+/- (0.12- 0.18) |
| 86) Azerbaijan | 0.46+/- 0.14 | 0.00+/- 0.00 | 0.06+/- 0.03 | 0.00+/- 0.00 | 0.36+/- 0.25 | 0.00+/- 0.00 | 0.03+/- 0.02 | - 0.35+/- 0.51 | 0.03+/- 0.02 | 0.41 | 0.92+/- (0.29- 0.44) |
| Inventory | 0.20+/- 0.16 | 0.00+/- 0.00 | 0.05+/- 0.03 | 0.00+/- 0.00 | 0.48+/- 0.25 | 0.00+/- 0.00 | 0.03+/- 0.02 | 2.8+/- 1.7 | 0.02+/- 0.02 | | 0.76+/- (0.30- 0.46) |
| 87) Morocco | 0.31+/- 0.12 | 0.00+/- 0.00 | 0.11+/- 0.09 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.08+/- 0.02 | 0.00+/- 0.00 | 0.4 | 0.48+/- (0.16- 0.24) |
| Inventory | 0.25+/- 0.15 | 0.00+/- 0.00 | 0.21+/- 0.10 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.02 | 0.09+/- 0.02 | 0.00+/- 0.00 | | 0.51+/- (0.18- 0.28) |
| 88) Somalia | 1.4+/-0.2 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.04+/- 0.01 | 0.21+/- 0.06 | 0.39 | 1.4+/- (0.2- 0.3) |
| Inventory | 0.52+/- 0.41 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.04+/- 0.01 | 0.13+/- 0.06 | | 0.58+/- (0.41- 0.43) |

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|---|---|---|---|---|---|---|---|---|---|---|
| 89) Kyrgyzstan | 0.15+/- 0.03 | 0.00+/- 0.00 | 0.12+/- 0.05 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.15+/- 0.06 | 0.05+/- 0.01 | 0.07+/- 0.06 | 0.39 | 0.44+/- (0.08- 0.15) |
| Inventory | 0.14+/- 0.04 | 0.00+/- 0.00 | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.09+/- 0.06 | 0.04+/- 0.01 | 0.08+/- 0.06 | | 0.32+/- (0.09- 0.16) |
| 90) Libya | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.43+/- 0.10 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.17+/- 0.05 | 0.01+/- 0.01 | 0.38 | 0.53+/- (0.11- 0.15) |
| Inventory | 0.05+/- 0.02 | 0.00+/- 0.00 | 0.05+/- 0.02 | 0.00+/- 0.00 | 0.32+/- 0.12 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.15+/- 0.05 | 0.02+/- 0.01 | | 0.44+/- (0.12- 0.17) |
| 91) Oman | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.00+/- 0.00 | 0.12+/- 0.03 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.04+/- 0.01 | 0.03+/- 0.02 | 0.38 | 0.19+/- (0.04- 0.07) |
| Inventory | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.12+/- 0.04 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.04+/- 0.01 | 0.03+/- 0.02 | | 0.18+/- (0.04- 0.07) |
| 92) Bulgaria | 0.01+/- 0.05 | 0.00+/- 0.00 | - 0.21+/- 0.16 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.01+/- 0.00 | - 0.04+/- 0.16 | 0.02+/- 0.05 | 0.38 | - 0.14+/- (0.17- 0.23) |
| Inventory | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.31+/- 0.20 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.01+/- 0.00 | 0.31+/- 0.17 | 0.06+/- 0.05 | | 0.43+/- (0.21- 0.27) |
| 93) Nicaragua | 0.56+/- 0.17 | 0.01+/- 0.01 | 0.03+/- 0.03 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.16+/- 0.08 | 0.52+/- 0.16 | 0.37 | 0.61+/- (0.17- 0.21) |
| Inventory | 0.23+/- 0.21 | 0.01+/- 0.01 | 0.03+/- 0.03 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.14+/- 0.09 | 0.23+/- 0.22 | | 0.28+/- (0.21- 0.25) |
| 94) Namibia | 0.04+/- 0.04 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | -0.01+/- 0.03 | 0.34 | 0.07+/- (0.04- 0.06) |
| Inventory | 0.08+/- 0.04 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.05+/- 0.04 | | 0.11+/- (0.04- 0.06) |
| 95) Austria | 0.06+/- 0.11 | 0.00+/- 0.00 | 0.02+/- 0.08 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.19+/- 0.10 | 0.03+/- 0.02 | 0.33 | 0.10+/- (0.14- 0.21) |
| Inventory | 0.18+/- 0.14 | 0.00+/- 0.00 | 0.13+/- 0.09 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.25+/- 0.11 | 0.03+/- 0.02 | | 0.33+/- (0.17- 0.25) |
| 96) Guinea | 0.06+/- 0.11 | 0.37+/- 0.14 | 0.02+/- 0.01 | 0.09+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.04+/- 0.01 | 0.03+/- 0.01 | 0.32 | 0.56+/- (0.18- 0.32) |
| Inventory | 0.15+/- 0.13 | 0.19+/- 0.18 | 0.02+/- 0.01 | 0.08+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.04+/- 0.01 | 0.03+/- 0.01 | | 0.46+/- (0.22- 0.37) |
| 97) Sri Lanka | 0.07+/- 0.04 | 0.41+/- 0.23 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.72+/- 0.18 | 0.3 | 0.49+/- (0.23- 0.27) |
| Inventory | 0.06+/- 0.04 | 0.37+/- 0.25 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.25+/- 0.23 | | 0.44+/- (0.25- 0.30) |
| 98) Greece | 0.04+/- 0.06 | 0.00+/- 0.00 | - 0.04+/- 0.15 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.00+/- 0.00 | 0.17+/- 0.06 | 0.03+/- 0.06 | 0.3 | 0.04+/- (0.16- 0.23) |
| Inventory | 0.10+/- 0.07 | 0.01+/- 0.00 | 0.24+/- 0.17 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.00+/- 0.00 | 0.18+/- 0.06 | 0.06+/- 0.06 | | 0.39+/- (0.19- 0.25) |
| 99) Malawi | 0.15+/- 0.05 | 0.01+/- 0.01 | 0.02+/- 0.01 | 0.07+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.58+/- 0.12 | 0.29 | 0.25+/- (0.05- 0.08) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.06+/-0.05 | 0.01+/-0.01 | 0.02+/-0.01 | 0.03+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.21+/-0.15 | | 0.12+/-(0.05-0.09) |
| 100) Guatemala | 0.60+/-0.17 | 0.00+/-0.00 | 0.11+/-0.06 | 0.02+/-0.01 | 0.01+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.08+/-0.04 | 0.13+/-0.05 | 0.29 | 0.73+/-(0.18-0.25) |
| Inventory | 0.23+/-0.21 | 0.00+/-0.00 | 0.07+/-0.06 | 0.02+/-0.01 | 0.01+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.08+/-0.04 | 0.10+/-0.06 | | 0.33+/-(0.22-0.30) |
| 101) Mongolia | 0.55+/-0.08 | 0.00+/-0.00 | 0.01+/-0.01 | 0.04+/-0.01 | 0.02+/-0.01 | 0.01+/-0.00 | 0.00+/-0.00 | 0.11+/-0.04 | 0.14+/-0.03 | 0.28 | 0.64+/-(0.09-0.12) |
| Inventory | 0.37+/-0.09 | 0.00+/-0.00 | 0.01+/-0.01 | 0.04+/-0.01 | 0.02+/-0.01 | 0.01+/-0.00 | 0.00+/-0.00 | 0.09+/-0.04 | 0.13+/-0.03 | | 0.45+/-(0.09-0.12) |
| 102) Czech Republic | 0.01+/-0.07 | 0.00+/-0.00 | 0.00+/-0.13 | 0.00+/-0.00 | 0.00+/-0.00 | 0.23+/-0.11 | 0.02+/-0.02 | 0.09+/-0.05 | 0.01+/-0.01 | 0.27 | 0.26+/-(0.19-0.33) |
| Inventory | 0.09+/-0.08 | 0.00+/-0.00 | 0.23+/-0.16 | 0.00+/-0.00 | 0.00+/-0.00 | 0.29+/-0.12 | 0.02+/-0.02 | 0.11+/-0.05 | 0.01+/-0.01 | | 0.63+/-(0.21-0.37) |
| 103) Eritrea | 0.67+/-0.06 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.10+/-0.03 | 0.02+/-0.01 | 0.27 | 0.68+/-(0.06-0.07) |
| Inventory | 0.08+/-0.08 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.08+/-0.03 | 0.02+/-0.01 | | 0.10+/-(0.08-0.08) |
| 104) Norway | 0.07+/-0.01 | 0.00+/-0.00 | 0.02+/-0.01 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.01+/-0.01 | 0.04+/-0.01 | 0.41+/-0.15 | 0.26 | 0.11+/-(0.02-0.04) |
| Inventory | 0.06+/-0.01 | 0.00+/-0.00 | 0.02+/-0.01 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.01+/-0.01 | 0.04+/-0.01 | 0.26+/-0.17 | | 0.11+/-(0.02-0.04) |
| 105) Belarus | 0.28+/-0.17 | 0.00+/-0.00 | 1.2+/-0.5 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.03+/-0.01 | 0.04+/-0.01 | 0.07+/-0.10 | 0.26 | 1.6+/-(0.5-0.7) |
| Inventory | 0.24+/-0.17 | 0.00+/-0.00 | 2.3+/-1.5 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.03+/-0.01 | 0.04+/-0.01 | 0.11+/-0.10 | | 2.6+/-(1.5-1.7) |
| 106) Switzerland | 0.25+/-0.13 | 0.00+/-0.00 | 0.04+/-0.05 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.01 | 0.16+/-0.06 | 0.06+/-0.05 | 0.24 | 0.30+/-(0.13-0.18) |
| Inventory | 0.17+/-0.15 | 0.00+/-0.00 | 0.05+/-0.05 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.01 | 0.15+/-0.07 | 0.05+/-0.05 | | 0.23+/-(0.16-0.21) |
| 107) Hungary | 0.03+/-0.05 | 0.00+/-0.00 | 0.17+/-0.16 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.02+/-0.02 | 0.05+/-0.02 | 0.03+/-0.02 | 0.24 | 0.23+/-(0.16-0.23) |
| Inventory | 0.05+/-0.05 | 0.00+/-0.00 | 0.28+/-0.20 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.02+/-0.02 | 0.06+/-0.02 | 0.03+/-0.02 | | 0.36+/-(0.20-0.27) |
| 108) Senegal | 0.03+/-0.12 | 0.05+/-0.05 | 0.04+/-0.02 | 0.02+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.02+/-0.02 | 0.23 | 0.15+/-(0.14-0.21) |
| Inventory | 0.18+/-0.15 | 0.05+/-0.06 | 0.04+/-0.02 | 0.03+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.03+/-0.02 | | 0.30+/-(0.17-0.25) |
| 109) Netherlands | 1.2+/-0.3 | 0.00+/-0.00 | 0.36+/-0.13 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.03+/-0.02 | 0.05+/-0.01 | 0.03+/-0.03 | 0.23 | 1.6+/-(0.3-0.4) |
| Inventory | 0.37+/-0.30 | 0.00+/-0.00 | 0.20+/-0.15 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.02+/-0.02 | 0.05+/-0.01 | 0.03+/-0.03 | | 0.60+/-(0.33-0.47) |

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Atmospheric Chemistry and Physics Discussions

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|---|---|---|---|---|---|---|---|---|---|---|
| 110) Serbia | -0.02+/- 0.05 | 0.00+/- 0.00 | 0.01+/- 0.07 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.03+/- 0.01 | 0.01+/- 0.01 | 0.04+/- 0.02 | 0.01+/- 0.02 | 0.23 | 0.05+/- (0.09-0.15) |
| Inventory | 0.06+/- 0.06 | 0.00+/- 0.00 | 0.11+/- 0.08 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.03+/- 0.01 | 0.01+/- 0.01 | 0.05+/- 0.02 | 0.01+/- 0.02 | | 0.23+/- (0.10-0.16) |
| 111) Panama | 0.09+/- 0.07 | 0.01+/- 0.01 | 0.03+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.02 | 0.85+/- 0.18 | 0.23 | 0.13+/- (0.08-0.11) |
| Inventory | 0.09+/- 0.07 | 0.01+/- 0.01 | 0.04+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.02 | 0.30+/- 0.25 | | 0.15+/- (0.08-0.11) |
| 112) Georgia | 0.10+/- 0.06 | 0.00+/- 0.00 | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.07+/- 0.05 | 0.47+/- 0.17 | 0.01+/- 0.01 | 0.23 | 0.25+/- (0.10-0.17) |
| Inventory | 0.07+/- 0.07 | 0.00+/- 0.00 | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.07+/- 0.06 | 0.41+/- 0.19 | 0.01+/- 0.01 | | 0.22+/- (0.10-0.18) |
| 113) Tunisia | -0.01+/- 0.06 | 0.00+/- 0.00 | 0.03+/- 0.03 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.05+/- 0.02 | 0.01+/- 0.02 | 0.23 | 0.06+/- (0.07-0.12) |
| Inventory | 0.09+/- 0.06 | 0.00+/- 0.00 | 0.07+/- 0.04 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.07+/- 0.02 | 0.02+/- 0.02 | | 0.20+/- (0.08-0.12) |
| 114) Mauritania | 0.49+/- 0.10 | 0.01+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.01+/- 0.00 | 0.22 | 0.51+/- (0.10-0.12) |
| Inventory | 0.19+/- 0.15 | 0.01+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.01+/- 0.00 | | 0.22+/- (0.15-0.17) |
| 115) Yemen | 0.16+/- 0.10 | 0.00+/- 0.00 | 0.07+/- 0.03 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.09+/- 0.02 | 0.02+/- 0.01 | 0.22 | 0.24+/- (0.11-0.14) |
| Inventory | 0.14+/- 0.11 | 0.00+/- 0.00 | 0.06+/- 0.03 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.08+/- 0.02 | 0.01+/- 0.01 | | 0.22+/- (0.12-0.15) |
| 116) Cuba | 0.12+/- 0.15 | 0.03+/- 0.04 | 0.13+/- 0.15 | 0.02+/- 0.01 | 0.10+/- 0.06 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.08+/- 0.04 | 0.07+/- 0.17 | 0.22 | 0.40+/- (0.23-0.42) |
| Inventory | 0.24+/- 0.16 | 0.05+/- 0.04 | 0.24+/- 0.16 | 0.02+/- 0.01 | 0.11+/- 0.06 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.08+/- 0.04 | 0.26+/- 0.19 | | 0.66+/- (0.24-0.44) |
| 117) Portugal | 0.12+/- 0.08 | 0.01+/- 0.01 | -0.29+/- 0.22 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.01+/- 0.01 | 0.2 | -0.16+/- (0.24-0.31) |
| Inventory | 0.11+/- 0.09 | 0.01+/- 0.00 | 0.42+/- 0.28 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.01+/- 0.01 | | 0.55+/- (0.30-0.38) |
| 118) Jordan | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.14+/- 0.08 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.2 | 0.22+/- (0.09-0.13) |
| Inventory | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.14+/- 0.12 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.20+/- (0.12-0.16) |
| 119) Bahamas | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.2 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 120) Benin | -0.08+/- 0.08 | 0.00+/- 0.01 | 0.03+/- 0.01 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.04+/- 0.01 | 0.02+/- 0.03 | 0.19 | -0.01+/- |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | (0.09-0.14) |
| Inventory | 0.09+/- 0.10 | 0.01+/- 0.01 | 0.03+/- 0.01 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.03+/- 0.03 | | 0.17+/- (0.10-0.16) |
| 121) Rwanda | -0.02+/- 0.05 | 0.00+/- 0.01 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.04+/- 0.01 | 0.19+/- 0.09 | 0.17 | 0.03+/- (0.06-0.10) |
| Inventory | 0.05+/- 0.06 | 0.01+/- 0.01 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.04+/- 0.01 | 0.10+/- 0.12 | | 0.10+/- (0.06-0.10) |
| 122) Slovakia | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.05+/- 0.06 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.04+/- 0.04 | 0.07+/- 0.02 | 0.00+/- 0.00 | 0.17 | 0.12+/- (0.07-0.12) |
| Inventory | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.09+/- 0.07 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.05+/- 0.04 | 0.08+/- 0.02 | 0.00+/- 0.00 | | 0.17+/- (0.08-0.13) |
| 123) Croatia | 0.00+/- 0.04 | 0.00+/- 0.00 | 0.02+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.01+/- 0.00 | 0.06+/- 0.05 | 0.01+/- 0.01 | 0.16 | 0.06+/- (0.06-0.10) |
| Inventory | 0.05+/- 0.04 | 0.00+/- 0.00 | 0.06+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.01+/- 0.00 | 0.11+/- 0.05 | 0.01+/- 0.01 | | 0.15+/- (0.06-0.10) |
| 124) Israel | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.33+/- 0.11 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.02 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.16 | 0.40+/- (0.12-0.16) |
| Inventory | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.23+/- 0.18 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.29+/- (0.18-0.23) |
| 125) Belize | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.22+/- 0.09 | 0.16 | 0.02+/- (0.01-0.01) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.14+/- 0.14 | | 0.02+/- (0.01-0.01) |
| 126) Bhutan | 0.01+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.14 | 0.02+/- (0.02-0.02) |
| Inventory | 0.01+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.02+/- (0.02-0.02) |
| 127) Dominican Republic | -0.09+/- 0.15 | 0.02+/- 0.07 | 0.02+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.01 | -0.02+/- 0.06 | 0.14 | -0.05+/- (0.17-0.26) |
| Inventory | 0.19+/- 0.17 | 0.07+/- 0.06 | 0.05+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.01 | 0.09+/- 0.07 | | 0.31+/- (0.19-0.28) |
| 128) Burundi | 0.01+/- 0.03 | 0.00+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.13+/- 0.04 | 0.14 | 0.04+/- (0.04-0.06) |
| Inventory | 0.03+/- 0.04 | 0.00+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.03+/- 0.05 | | 0.05+/- (0.04-0.06) |
| 129) Sierra Leone | 0.02+/- 0.03 | 0.16+/- 0.07 | 0.02+/- 0.01 | 0.04+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.10+/- 0.09 | 0.14 | 0.25+/- (0.08-0.14) |
| Inventory | 0.03+/- 0.03 | 0.07+/- 0.09 | 0.02+/- 0.01 | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.11+/- 0.09 | | 0.16+/- (0.10-0.16) |
| 130) Costa Rica | 0.17+/- 0.08 | 0.01+/- 0.01 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.11+/- 0.05 | 0.64+/- 0.12 | 0.13 | 0.18+/- (0.08-0.10) |

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| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.09+/- 0.09 | 0.01+/- 0.01 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.10+/- 0.06 | 0.16+/- 0.16 | | 0.11+/- (0.09- 0.11) |
| 131) Liberia | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.05+/- 0.06 | 0.12 | 0.04+/- (0.01- 0.03) |
| Inventory | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.08+/- 0.06 | | 0.04+/- (0.01- 0.03) |
| 132) Belgium | 0.29+/- 0.10 | 0.00+/- 0.00 | 0.15+/- 0.07 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.12 | 0.45+/- (0.12- 0.18) |
| Inventory | 0.12+/- 0.11 | 0.00+/- 0.00 | 0.10+/- 0.09 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.24+/- (0.14- 0.21) |
| 133) Togo | -0.02+/- 0.04 | 0.00+/- 0.01 | 0.02+/- 0.01 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.03+/- 0.04 | 0.12 | 0.03+/- (0.05- 0.09) |
| Inventory | 0.03+/- 0.04 | 0.01+/- 0.01 | 0.02+/- 0.01 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.05+/- 0.04 | | 0.09+/- (0.05- 0.09) |
| 134) Taiwan | 0.00+/- 0.00 | 0.01+/- 0.08 | - 0.11+/- 0.12 | 0.00+/- 0.00 | 0.01+/- 0.02 | 0.00+/- 0.00 | 0.02+/- 0.02 | - 0.21+/- 0.15 | 0.02+/- 0.03 | 0.11 | - 0.07+/- (0.15- 0.25) |
| Inventory | 0.00+/- 0.00 | 0.08+/- 0.08 | 0.14+/- 0.13 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.20+/- 0.16 | 0.03+/- 0.03 | | 0.27+/- (0.15- 0.25) |
| 135) Equatorial Guinea | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | - 0.12+/- 0.09 | 0.01+/- 0.00 | 0.01+/- 0.01 | 0.05+/- 0.02 | -0.15+/- 0.06 | 0.11 | - 0.11+/- (0.09- 0.10) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.15+/- 0.09 | 0.01+/- 0.00 | 0.01+/- 0.01 | 0.05+/- 0.02 | 0.05+/- 0.07 | | 0.16+/- (0.09- 0.10) |
| 136) Cyprus | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.1 | 0.03+/- (0.02- 0.03) |
| Inventory | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.03+/- (0.02- 0.03) |
| 137) Kuwait | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.35+/- 0.30 | 0.00+/- 0.00 | 0.05+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.09+/- 0.04 | 0.00+/- 0.00 | 0.1 | 0.40+/- (0.30- 0.33) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.53+/- 0.41 | 0.00+/- 0.00 | 0.06+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.09+/- 0.04 | 0.00+/- 0.00 | | 0.59+/- (0.41- 0.45) |
| 138) Trinidad and Tobago | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.11+/- 0.04 | 0.00+/- 0.00 | 0.07+/- 0.04 | 0.22+/- 0.06 | 0.00+/- 0.00 | 0.1 | 0.19+/- (0.05- 0.09) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.06+/- 0.04 | 0.00+/- 0.00 | 0.05+/- 0.04 | 0.10+/- 0.07 | 0.00+/- 0.00 | | 0.12+/- (0.06- 0.09) |
| 139) Ireland | 0.19+/- 0.28 | 0.00+/- 0.00 | 0.06+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.05+/- 0.06 | 0.09 | 0.26+/- (0.28- 0.33) |
| Inventory | 0.39+/- 0.30 | 0.00+/- 0.00 | 0.07+/- 0.05 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.06+/- 0.06 | | 0.47+/- (0.31- 0.36) |
| 140) Haiti | -0.03+/- 0.07 | 0.00+/- 0.01 | 0.03+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.09 | 0.02+/- (0.08- 0.13) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.09+/- 0.08 | 0.01+/- 0.01 | 0.04+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.15+/- (0.09- 0.14) |
| 141) Denmark | 0.57+/- 0.14 | 0.00+/- 0.00 | 0.25+/- 0.09 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.03+/- 0.02 | 0.09 | 0.82+/- (0.16- 0.23) |
| Inventory | 0.18+/- 0.14 | 0.00+/- 0.00 | 0.13+/- 0.10 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.02+/- 0.02 | | 0.32+/- (0.17- 0.24) |
| 142) Lesotho | 0.14+/- 0.02 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.09 | 0.15+/- (0.02- 0.03) |
| Inventory | 0.02+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.03+/- (0.03- 0.03) |
| 143) Estonia | 0.01+/- 0.01 | 0.00+/- 0.00 | - 0.01+/- 0.07 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | -0.06+/- 0.07 | 0.08 | 0.01+/- (0.07- 0.08) |
| Inventory | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.11+/- 0.08 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.07+/- 0.08 | | 0.13+/- (0.08- 0.09) |
| 144) Qatar | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.01 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.08 | 0.03+/- (0.02- 0.03) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.03+/- (0.02- 0.03) |
| 145) Latvia | 0.03+/- 0.03 | 0.00+/- 0.00 | 0.01+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.05 | 0.08 | 0.05+/- (0.04- 0.06) |
| Inventory | 0.03+/- 0.03 | 0.00+/- 0.00 | 0.05+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.04+/- 0.01 | 0.05+/- 0.05 | | 0.09+/- (0.04- 0.07) |
| 146) Guinea-Bissau | 0.00+/- 0.03 | 0.05+/- 0.04 | 0.01+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.02+/- 0.06 | 0.08 | 0.07+/- (0.05- 0.09) |
| Inventory | 0.03+/- 0.03 | 0.04+/- 0.05 | 0.01+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.08+/- 0.07 | | 0.09+/- (0.06- 0.10) |
| 147) Bosnia and Herzegovina | -0.02+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.07 | - 0.02+/- (0.05- 0.07) |
| Inventory | 0.04+/- 0.04 | 0.00+/- 0.00 | 0.04+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.02 | 0.00+/- 0.00 | | 0.08+/- (0.05- 0.08) |
| 148) Albania | -0.03+/- 0.05 | 0.00+/- 0.00 | - 0.01+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.07+/- 0.04 | 0.00+/- 0.01 | 0.06 | - 0.04+/- (0.06- 0.08) |
| Inventory | 0.05+/- 0.05 | 0.00+/- 0.00 | 0.04+/- 0.04 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.10+/- 0.04 | 0.01+/- 0.01 | | 0.10+/- (0.06- 0.09) |
| 149) Lithuania | 0.05+/- 0.04 | 0.00+/- 0.00 | - 0.02+/- 0.06 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.01+/- 0.03 | 0.06 | 0.04+/- (0.08- 0.12) |
| Inventory | 0.06+/- 0.04 | 0.00+/- 0.00 | 0.09+/- 0.08 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.04+/- 0.01 | 0.02+/- 0.03 | | 0.17+/- (0.09- 0.13) |
| 150) Armenia | 0.06+/- 0.03 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.08+/- 0.03 | 0.01+/- 0.02 | 0.06 | 0.10+/- (0.04- 0.07) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.03+/-0.03 | 0.00+/-0.00 | 0.02+/-0.01 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.03+/-0.03 | 0.08+/-0.04 | 0.01+/-0.02 | | 0.07+/-(0.04-0.07) |
| 151) Lebanon | 0.01+/-0.01 | 0.00+/-0.00 | 0.07+/-0.06 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | 0.06 | 0.09+/-(0.06-0.08) |
| Inventory | 0.01+/-0.01 | 0.00+/-0.00 | 0.10+/-0.09 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | | 0.11+/-(0.09-0.10) |
| 152) El Salvador | 0.16+/-0.05 | 0.00+/-0.00 | 0.02+/-0.01 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.16+/-0.07 | 0.05 | 0.18+/-(0.05-0.06) |
| Inventory | 0.04+/-0.05 | 0.00+/-0.00 | 0.01+/-0.01 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.06+/-0.08 | | 0.05+/-(0.05-0.07) |
| 153) Kosovo | -0.01+/-0.03 | 0.00+/-0.00 | -0.02+/-0.04 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | 0.05 | -0.03+/-(0.05-0.07) |
| Inventory | 0.03+/-0.03 | 0.00+/-0.00 | 0.04+/-0.04 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | | 0.08+/-(0.05-0.07) |
| 154) Swaziland | 0.04+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | 0.05 | 0.05+/-(0.02-0.02) |
| Inventory | 0.01+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | | 0.02+/-(0.02-0.02) |
| 155) The former Yugoslav Republic of Macedonia | 0.00+/-0.02 | 0.00+/-0.00 | -0.01+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | 0.05 | 0.00+/-(0.03-0.04) |
| Inventory | 0.02+/-0.02 | 0.00+/-0.00 | 0.02+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | | 0.05+/-(0.03-0.04) |
| 156) Brunei Darussalam | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.02+/-0.03 | 0.00+/-0.00 | -0.01+/-0.04 | 0.04+/-0.01 | 0.00+/-0.00 | 0.04 | 0.01+/-(0.05-0.07) |
| Inventory | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.03+/-0.03 | 0.00+/-0.00 | 0.04+/-0.04 | 0.04+/-0.01 | 0.00+/-0.00 | | 0.07+/-(0.05-0.07) |
| 157) Grenada | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | 0.04 | 0.00+/-(0.00-0.00) |
| Inventory | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | | 0.00+/-(0.00-0.00) |
| 158) Slovenia | 0.01+/-0.02 | 0.00+/-0.00 | 0.00+/-0.01 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.02+/-0.02 | 0.03 | 0.02+/-(0.03-0.04) |
| Inventory | 0.02+/-0.02 | 0.00+/-0.00 | 0.01+/-0.02 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.02+/-0.02 | | 0.04+/-(0.03-0.04) |
| 159) Montenegro | -0.01+/-0.02 | 0.00+/-0.00 | 0.00+/-0.01 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.01+/-0.01 | 0.03 | -0.01+/-(0.02-0.03) |
| Inventory | 0.02+/-0.02 | 0.00+/-0.00 | 0.01+/-0.01 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.01+/-0.01 | | 0.03+/-(0.02-0.03) |
| 160) Svalbard and Jan | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.00+/-0.00 | 0.01+/-0.00 | 0.00+/-0.00 | 0.04+/-0.01 | 0.00+/-0.00 | 0.03 | 0.02+/-(0.00-0.01) |

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| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mayen Islands | | | | | | | | | | | |
| Inventory | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.02+/- (0.00- 0.01) |
| 161) Western Sahara | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.03 | 0.01+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.01+/- (0.00- 0.00) |
| 162) Puerto Rico | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.06 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.02 | 0.06+/- (0.06- 0.06) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.06+/- 0.06 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.06+/- (0.06- 0.06) |
| 163) Djibouti | 0.02+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.01 | 0.01+/- 0.01 | 0.02 | 0.04+/- (0.02- 0.03) |
| Inventory | 0.01+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.01+/- 0.01 | | 0.02+/- (0.02- 0.03) |
| 164) Republic of Moldova | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.05+/- 0.06 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.13+/- 0.09 | 0.00+/- 0.00 | 0.02 | 0.07+/- (0.06- 0.08) |
| Inventory | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.07+/- 0.06 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.17+/- 0.10 | 0.00+/- 0.00 | | 0.09+/- (0.06- 0.08) |
| 165) Jamaica | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.07+/- 0.06 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.07+/- 0.03 | 0.00+/- 0.00 | 0.02 | 0.08+/- (0.06- 0.07) |
| Inventory | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.07+/- 0.06 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.06+/- 0.03 | 0.00+/- 0.00 | | 0.08+/- (0.07- 0.08) |
| 166) Sao Tome and Principe | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.02 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 167) Turks and Caicos Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.02 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 168) Jersey | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.01 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 169) Timor-Leste | 0.02+/- 0.01 | 0.01+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.09+/- 0.04 | 0.00+/- 0.00 | 0.01 | 0.08+/- (0.02- 0.04) |
| Inventory | 0.01+/- 0.01 | 0.01+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.03+/- 0.01 | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.08+/- 0.04 | 0.00+/- 0.00 | | 0.08+/- (0.02- 0.04) |
| 170) Bonaire Saint Eustatius and Saba | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.01 | 0.01+/- (0.00- 0.01) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.01+/- (0.00-0.01) |
| 171) Cayman Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.01 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 172) Fiji | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.01 | 0.01+/- (0.02-0.02) |
| Inventory | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.03+/- (0.02-0.02) |
| 173) Saint Vincent and the Grenadines | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.01 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 174) Saint Pierre and Miquelon | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.01 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 175) United States Minor Outlying Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0.01 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 176) Iceland | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.02+/- 0.02 | 0.01 | 0.02+/- (0.01-0.01) |
| Inventory | 0.01+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.02+/- 0.02 | | 0.02+/- (0.01-0.01) |
| 177) Aland Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 178) Mayotte | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 179) Solomon Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.01+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.01+/- (0.00-0.00) |
| 180) French Southern Territories | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 181) Comoros | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.01+/- (0.01- 0.01) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.01+/- (0.01- 0.01) |
| 182) New Caledonia | -0.01+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.02- 0.03) |
| Inventory | 0.04+/- 0.03 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.04+/- (0.03- 0.03) |
| 183) Vanuatu | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.01+/- (0.01- 0.01) |
| Inventory | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.01+/- (0.01- 0.01) |
| 184) United States Virgin Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 185) British Virgin Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 186) Anguilla | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 187) Montserrat | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 188) Seychelles | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 189) Saint Lucia | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 190) Cape Verde | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |

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|---|---|---|---|---|---|---|---|---|---|---|
| 191) Martinique | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.01+/- (0.01- 0.01) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.01+/- (0.01- 0.01) |
| 192) Barbados | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 193) Guadeloupe | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.02+/- (0.01- 0.02) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.02+/- (0.01- 0.02) |
| 194) Malta | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.01) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.01+/- (0.00- 0.01) |
| 195) Maldives | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 196) Reunion | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.03+/- (0.02- 0.02) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.03+/- 0.02 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.03+/- (0.02- 0.02) |
| 197) Mauritius | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.02+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.02+/- (0.01- 0.01) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.01+/- 0.01 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.02+/- (0.01- 0.01) |
| 198) Dominica | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.01+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 199) Antigua and Barbuda | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.01+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 200) Saint Kitts and Nevis | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 201) French Polynesia | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 202) Falkland Islands (Malvinas) | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 203) Tonga | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 204) Western Samoa | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 205) Greenland | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.05+/- 0.01 | 0.03+/- 0.01 | | 0.00+/- (0.00- 0.00) |
| 206) Spratly Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 207) American Samoa | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 208) Marshall Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 209) Kiribati | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 210) Micronesia (Federated States of) | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00- 0.00) |
| 211) Northern Mariana Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00- 0.00) |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 212) Faeroe Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 213) Wallis and Futuna Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 214) Guam | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 215) Cook Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 216) Palau | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 217) Bermuda | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 218) Nauru | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 219) Saint Helena | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 220) Pitcairn | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 221) Tuvalu | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| 222) Bouvet Island | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 223) Tokelau | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 224) South Georgia and the South Sandwich Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 225) Niue | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 226) Norfolk Island | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 227) British Indian Ocean Territory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |
| 228) Heard Island and McDonald Islands | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | 0 | 0.00+/- (0.00-0.00) |
| Inventory | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.00+/- 0.00 | 0.04+/- 0.01 | 0.00+/- 0.00 | | 0.00+/- (0.00-0.00) |

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## 9.0References

Alvarez, R. A., Zavala-Araiza, D., Lyon, D. R. and Allen et al, D. T.: Assessment of methane emissions from the US oil and gas supply chain, Science, 361, 186–188, doi:10.1126/science.aar7204, 2018.

Bachewe, F. N., Minten, B., Tadesse, F. and Taffesse, A. S.: The evolving livestock sector in Ethiopia: Growth by heads, not by productivity. 2018.

Bergamaschi, P., Houweling, S., Segers, A., Krol, M., Frankenberg, C., Scheepmaker, R. A., Dlugokencky, E., Wofsy, S. C., Kort, E. A., Sweeney, C., Schuck, T., Brenninkmeijer, C., Chen, H., Beck, V. and Gerbig, C.: Atmospheric CH 4in the first decade of the 21st century: Inverse modeling analysis using SCIAMACHY satellite retrievals and NOAA surface measurements, Journal of Geophysical Research-Atmospheres, 118(13), 7350–7369, doi:10.1002/jgrd.50480, 2013.

Bloom, A. A., Bowman, K. W., Lee, M., Turner, A. J., Schroeder, R., Worden, J. R., Weidner, R., Mcdonald, K. C. and Jacob, D. J.: A global wetland methane emissions and uncertainty dataset for, Geosci. Model Dev., 1–16, doi:10.5194/gmd-10-2141-2017, 2017.

Bloom, A. A., Palmer, P. I., Fraser, A., Reay, D. S. and Frankenberg, C.: Large-Scale Controls of Methanogenesis Inferred from Methane and Gravity Spaceborne Data, Science, 327(5963), 322–325, doi:10.1126/science.1175176, 2010.

Bowman, K. W., Rodgers, C. D., Kulawik, S. S., Worden, J., Sarkissian, E., Osterman, G., Steck, T., Lou, M., Eldering, A. and Shephard, M.: Tropospheric emission spectrometer: Retrieval method and error analysis, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 44(5), 1297–1307, 2006.

Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, V., Canadell, J., Chhabra, A., DeFries, R., Galloway, J., Heimann. M, Jones, C., Le Quéré, C., Myneni, R. B., Piao, S., and Thornton, P.: Carbon and Other Biogeochemical Sycles, in: Climate Change 2013: The Physical Science Basis, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Cli- mate Change, edited by: Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M., Cambridge University Press, Cambridge, UK, New York, NY, USA, 2013.

Connor, B. J., Boesch, H., Toon, G., Sen, B., Miller, C. and Crisp, D.: Orbiting Carbon Observatory: Inverse method and prospective error analysis, J. Geophys. Res, 113(D5), D05305, doi:10.1029/2006JD008336, 2008.

Crippa, M., Solazzo, E., Huang, G., Guizzardi, D., Koffi, E., Muntean, M., Schieberle, C., Friedrich, R. and Janssens-Maenhout, G.: High resolution temporal profiles in the Emissions Database for Global Atmospheric Research, Scientific Data, 1–17, doi:10.1038/s41597-020-0462-2, 2020.

https://doi.org/10.5194/acp-2021-955
Preprint. Discussion started: 7 December 2021




Cusworth, D. H., Bloom, A. A., Ma, S., Miller, C. E., Bowman, K., Yin, Y., Maasakkers, J. D., Zhang, Y., Scarpelli, T. R., Qu, Z., Jacob, D. J. and Worden, J. R.: A Bayesian framework for deriving sector-based methane emissions from top-down fluxes, Nature Communications Earth and Environment, 1–8, doi:10.1038/s43247-021-00312-6, 2021.

Dlugokencky, E. J., Nisbet, E. G., Fisher, R. and Lowry, D.: Global atmospheric methane: budget, changes and dangers, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 369(1943), 2058–2072, doi:10.1098/rsta.2010.0341, 2011.

Duren, R. M., Thorpe, A. K., Foster, K. T., Rafiq, T., Hopkins, F. M., Yadav, V., Bue, B. D., Thompson, D. R., Conley, S., Colombi, N. K., Frankenberg, C., McCubbin, I. B., Eastwood, M. L., Falk, M., Herner, J. D., Croes, B. E., Green, R. O. and Miller, C. E.: California's methane super-emitters, Nature, 575(7781), 180–184, doi:10.1038/s41586-019-1720-3, 2019.

Etiope, G., Ciotoli, G., Schwietzke, S. and Schoell, M.: Gridded maps of geological methane emissions and their isotopic signature, Earth System Science Data, 11, 1–22, doi:10.5194/essd-11-1-2019, 2019.

Frankenberg, C., Meirink, J., Van Weele, M., Platt, U. and Wagner, T.: Assessing methane emissions from global space-borne observations, Science, 308(5724), 1010–1014, doi:10.1126/science.1106644, 2005.

Fung, I., Prather, M., John, J., Lerner, J. and Matthews, E.: Three-dimensional model synthesis of the global methane cycle, Journal of Geophysical Research - Atmospheres, 96(D7), 13.033–13.065, 1991.

Ganesan, A. L., Rigby, M., Lunt, M. F., Parker, R. J., Boesch, H., Goulding, N., Umezawa, T., Zahn, A., Chatterjee, A., Prinn, R. G., Tiwari, Y. K., Schoot, M. and Krummel, P. B.: Atmospheric observations show accurate reporting and little growth in India's methane emissions, Nat Commun, 1–7, doi:10.1038/s41467-017-00994-7, 2017.

Ganesan, A. L., Schwietzke, S., Poulter, B., Arnold, T., Lan, X., Rigby, M., Vogel, F. R., Werf, G. R., Janssens-Maenhout, G., Boesch, H., Pandey, S., Manning, A. J., Jackson, R. B., Nisbet, E. G. and Manning, M. R.: Advancing Scientific Understanding of the Global Methane Budget in Support of the Paris Agreement, Global Biogeochemical Cycles, 9(1), 53–38, doi:10.1029/2018GB006065, 2019.

Ganesan, A. L., Stell, A. C., Gedney, N., Comyn-Platt, E., Hayman, G., Rigby, M., Poulter, B. and Hornibrook, E. R. C.: Spatially Resolved Isotopic Source Signatures of Wetland Methane Emissions, Geophys. Res. Lett, 45(8), 3737–3745, doi:10.1029/2008GB003299, 2018.

Hmiel, B., Petrenko, V. V., Dyonisius, M. N., Buizert, C., Smith, A. M., Place, P. F., Harth, C., Beaudette, R., Hua, Q., Yang, B., Vimont, I., Michel, S. E., Severinghaus, J. P., Etheridge, D., Bromley, T., Schmitt, J., Faïn, X., Weiss, R. F. and Dlugokencky, E.: Preindustrial 14CH4 indicates greater anthropogenic fossil CH4 emissions, Nature, 1–5, doi:10.1038/s41586-020-1991-8, 2020.

Janardanan, R., Maksyutov, S., Tsuruta, A., Wang, F., Tiwari, Y. K., Valsala, V., Ito, A., Yoshida, Y., Kaiser, J. W., Janssens-Maenhout, G., Arshinov, M., Sasakawa, M., Tohjima, Y., Worthy, D. E. J., Dlugokencky, E. J., Ramonet, M., Arduini, J., Lavric, J. V., Piacentino, S., Krummel, P. B., Langenfelds, R. L., Mammarella, I. and Matsunaga, T.: Country-scale analysis of methane emissions with a high-resolution inverse model using GOSAT and surface observations, Remote Sensing, 12(3), 375, doi:10.3390/rs12030375, 2020.

Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., Bergamaschi, P., Pagliari, V., Olivier, J. G. J., Peters, J. A. H. W., van Aardenne, J. A., Monni, S., Doering, U., Petrescu, A. M. R., Solazzo, E. and Oreggioni, G. D.: EDGAR v4.3.2 Global Atlas of the three major greenhouse gas emissions for the period 1970–2012, Earth Syst. Sci. Data, 11(3), 959–1002, doi:10.5194/essd-11-959-2019, 2019.

Jiang, Z., Jones, D. B. A., Worden, H. M., Deeter, M. N., Henze, D. K., Worden, J., Bowman, K. W., Brenninkmeijer, C. A. M. and Schuck, T. J.: Impact of model errors in convective transport on CO source estimates inferred from MOPITT CO retrievals, Journal of Geophysical Research-Atmospheres, 118(4), 2073–2083, doi:10.1002/jgrd.50216, 2013.

Kirschke, S., Bousquet, P., Ciais, P., Saunois, M., Canadell, J. G., Dlugokencky, E. J., Bergamaschi, P., Bergmann, D., Blake, D. R., Bruhwiler, L., Cameron-Smith, P., Castaldi, S., Chevallier, F., Feng, L., Fraser, A., Heimann, M., Hodson, E. L., Houweling, S., Josse, B., Fraser, P. J., Krummel, P. B., Lamarque, J.-F., Langenfelds, R. L., Le Quéré, C., Naik, V., O'Doherty, S., Palmer, P. I., Pison, I., Plummer, D., Poulter, B., Prinn, R. G., Rigby, M., Ringeval, B., Santini, M., Schmidt, M., Shindell, D. T., Simpson, I. J., Spahni, R., Steele, L. P., Strode, S. A., Sudo, K., Szopa, S., van der Werf, G. R., Voulgarakis, A., van Weele, M., Weiss, R. F., Williams, J. E. and Zeng, G.: Three decades of global methane sources and sinks, Nature Geoscience, 1–11, doi:10.1038/ngeo1955, 2013.

Lu, X., Jacob, D. J., Zhang, Y., Maasakkers, J. D., Sulprizio, M. P., Shen, L., et al.: Global methane budget and trend, 2010–2017: complementarity of inverse analyses using in situ (GLOBALVIEWplus $CH_4$ ObsPack) and satellite (GOSAT) observations, Atmos. Chem. Phys., 21, 4637–4657, https://doi.org/10.5194/acp-21-4637-2021, 2021.

Maasakkers, J. D., Jacob, D. J., Sulprizio, M. P., Scarpelli, T. R., Nesser, H., Sheng, J., Zhang, Y., Lu, X., Bloom, A. A., Bowman, K. W., Worden, J. R. and Parker, R. J.: 2010–2015 North American methane emissions, sectoral contributions, and trends: a high-resolution inversion of GOSAT observations of atmospheric methane, Atmospheric Chemistry and Physics, 21(6), 4339–4356, doi:10.5194/acp-21-4339-2021, 2021.

Maasakkers, J. D., Jacob, D. J., Sulprizio, M. P., Scarpelli, T. R., Nesser, H., Sheng, J.-X., Zhang, Y., Hersher, M., Bloom, A. A., Bowman, K. W., Worden, J. R., Janssens-Maenhout, G. and Parker, R. J.: Global distribution of methane emissions, emission trends, and OH concentrations and trends inferred from an inversion of GOSAT satellite data for 2010–2015, Atmospheric Chemistry and Physics, 19(11), 7859–7881, doi:10.5194/acp-19-7859-2019, 2019.

Maasakkers, J. D., Jacob, D. J., Sulprizio, M. P., Turner, A. J., Weitz, M., Wirth, T., Hight, C., DeFigueiredo, M., Desai, M., Schmeltz, R., Hockstad, L., Bloom, A. A., Bowman, K. W., Jeong,

https://doi.org/10.5194/acp-2021-955
Preprint. Discussion started: 7 December 2021




S. and Fischer, M. L.: Gridded National Inventory of U.S. Methane Emissions, Environ. Sci. Technol., 50(23), 13123–13133, doi:10.1021/acs.est.6b02878, 2016.

McNorton, J. R., Bousserez, N., Agustí-Panareda, A., Balsamo, G., Choulga, M., Dawson, A., Engelen, R., Kipling, Z. and Lang, S.: Representing model uncertainty for global atmospheric CO<sub>2</sub> flux inversions using ECMWF-IFS-46R1, Geosci. Model Dev., 13(5), 2297–2313, doi:10.5194/gmd-13-2297-2020, 2020.

Melton, J. R., Wania, R., Hodson, E. L., Poulter, B., Ringeval, B., Spahni, R., Bohn, T., Avis, C. A., Beerling, D. J., Chen, G., Eliseev, A. V., Denisov, S. N., Hopcroft, P. O., Lettenmaier, D. P., Riley, W. J., Singarayer, J. S., Subin, Z. M., Tian, H., Zürcher, S., Brovkin, V., van Bodegom, P. M., Kleinen, T., Yu, Z. C. and Kaplan, J. O.: Present state of global wetland extent and wetland methane modelling: conclusions from a model inter-comparison project (WETCHIMP), Biogeosciences, 10(2), 753–788, doi:10.5194/bg-10-753-2013, 2013.

Miller, S. M., Michalak, A. M., Detmers, R. G., Hasekamp, O. P., Bruhwiler, L. M. P. and Schwietzke, S.: China's coal mine methane regulations have not curbed growing emissions, Nat Commun, 10(1), 1–8, doi:10.1038/s41467-018-07891-7, 2019.

Pandey, S., Gautam, R., Houweling, S., van der Gon, H. D., Sadavarte, P., Borsdorff, T., Hasekamp, O., Landgraf, J., Tol, P., van Kempen, T., Hoogeveen, R., van Hees, R., Hamburg, S. P., Maasakkers, J. D. and Aben, I.: Satellite observations reveal extreme methane leakage from a natural gas well blowout, Proceedings of the National Academy of Sciences of the United States of America, 116(52), 26376–26381, doi:10.1073/pnas.1908712116, 2019.

Parker, R., Boesch, H., Cogan, A., Fraser, A., Feng, L., Palmer, P. I., Messerschmidt, J., Deutscher, N., Griffith, D. W. T., Notholt, J., Wennberg, P. O. and Wunch, D.: Methane observations from the Greenhouse Gases Observing SATellite: Comparison to ground-based TCCON data and model calculations, Geophys. Res. Lett, 38(15), L15807, doi:10.1029/2011GL047871, 2011.

Poulter, B., Bousquet, P., Canadell, J. G., Ciais, P., Peregon, A., Saunois, M., Arora, V. K., Beerling, D. J., Brovkin, V., Jones, C. D., Joos, F., Gedney, N., Ito, A., Kleinen, T., Koven, C. D., McDonald, K., Melton, J. R., Peng, C., Peng, S., Prigent, C., Schroeder, R., Riley, W. J., Saito, M., Spahni, R., Tian, H., Taylor, L., Viovy, N., Wilton, D., Wiltshire, A., Xu, X., Zhang, B., Zhang, Z. and Zhu, Q.: Global wetland contribution to 2000–2012 atmospheric methane growth rate dynamics, Environ. Res. Lett., 12(9), 094013, doi:10.1088/1748-9326/aa8391, 2017.

Prather, M. J., Holmes, C. D. and Hsu, J.: Reactive greenhouse gas scenarios: Systematic exploration of uncertainties and the role of atmospheric chemistry, Geophysical Research Letters, 39(9), doi:10.1029/2012GL051440, 2012.

Qu, Z., Jacob, D. J., Shen, L., Lu, X., Zhang, Y., Scarpelli, T. R., Nesser, H., Sulprizio, M. P., Maasakkers, J. D., Bloom, A. A., Worden, J., Parker, R. J. and Delgado, A. L.: Global distribution of methane emissions: a comparative inverse analysis of observations from the TROPOMI and GOSAT satellite instruments, Atmospheric Chemistry and Physics, doi:10.5194/acp-21-14159-2021, 2021.

https://doi.org/10.5194/acp-2021-955
Preprint. Discussion started: 7 December 2021


Atmospheric Chemistry and Physics Discussions

Rodgers, C. D. and Connor, B. J.: Intercomparison of remote sounding instruments, Journal of Geophysical Research-Atmospheres, 108, 4116, doi:10.1029/2002JD002299, 2003.

Rosentreter, J. A., Borges, A. V., Deemer, B. R., Holgerson, M. A., Liu, S., Song, C., Melack, J., Raymond, P. A., Duarte, C. M., Allen, G. H., Olefeldt, D., Poulter, B., Battin, T. I. and Eyre, B. D.: Half of global methane emissions come from highly variable aquatic ecosystem sources, Nature Geoscience, 14(4), 225–230, doi:10.1038/s41561-021-00715-2, 2021.

Saunois, M., Stavert, A. R., Poulter, B., Bousquet, P., Canadell, J. G., Jackson, R. B., Raymond, P. A., Dlugokencky, E. J., Houweling, S., Patra, P. K., Ciais, P., Arora, V. K., Bastviken, D., Bergamaschi, P., Blake, D. R., Brailsford, G., Bruhwiler, L., Carlson, K. M., Carrol, M., Castaldi, S., Chandra, N., Crevoisier, C., Crill, P. M., Covey, K., Curry, C. L., Etiope, G., Frankenberg, C., Gedney, N., Hegglin, M. I., Höglund-Isaksson, L., Hugelius, G., Ishizawa, M., Ito, A., Janssens-Maenhout, G., Jensen, K. M., Joos, F., Kleinen, T., Krummel, P. B., Langenfelds, R. L., Laruelle, G. G., Liu, L., Machida, T., Maksyutov, S., McDonald, K. C., McNorton, J., Miller, P. A., Melton, J. R., Morino, I., Müller, J., Murguia-Flores, F., Naik, V., Niwa, Y., Noce, S., O'Doherty, S., Parker, R. J., Peng, C., Peng, S., Peters, G. P., Prigent, C., Prinn, R., Ramonet, M., Regnier, P., Riley, W. J., Rosentreter, J. A., Segers, A., Simpson, I. J., Shi, H., Smith, S. J., Steele, L. P., Thornton, B. F., Tian, H., Tohjima, Y., Tubiello, F. N., Tsuruta, A., Viovy, N., Voulgarakis, A., Weber, T. S., van Weele, M., van der Werf, G. R., Weiss, R. F., Worthy, D., Wunch, D., Yin, Y., Yoshida, Y., Zhang, W., Zhang, Z., Zhao, Y., Zheng, B., Zhu, Q., Zhu, Q. and Zhuang, Q.: The Global Methane Budget 2000–2017, Earth Syst. Sci. Data, 12(3), 1561–1623, doi:10.5194/essd-12-1561-2020, 2020.

Scarpelli, T. R., Jacob, D. J., Maasakkers, J. D., Sulprizio, M. P., J-X, S., Rose, K., Romeo, L., Worden, J. R. and Janssens-Maenhout, G.: A global gridded (0.1 degrees x 0: 1 degrees) inventory of methane emissions from oil, gas, and coal exploitation based on national reports to the United …. 2020.

Schaefer, H., Fletcher, S. E. M., Veidt, C., Lassey, K. R., Brailsford, G. W., Bromley, T. M., Dlugokencky, E. J., Michel, S. E., Miller, J. B., Levin, I., Lowe, D. C., Martin, R. J., Vaughn, B. H. and White, J. W. C.: A 21st century shift from fossil-fuel to biogenic methane emissions indicated by 13CH4, Science, doi:10.1126/science.aad2705, 2016.

Schwietzke, S., Sherwood, O. A., Bruhwiler, L. M. P., Miller, J. B., Etiope, G., Dlugokencky, E. J., Michel, S. E., Arling, V. A., Vaughn, B. H., White, J. W. C. and Tans, P. P.: Upward revision of global fossil fuel methane emissions based on isotope database, Nature, 538(7623), 88–91, doi:10.1038/nature19797, 2016.

Shen, L., D. Zavala-Araiza, R. Gautam, M. Omara, T. Scarpelli, J. Sheng, M.P. Sulprizio, J. Zhuang, Y. Zhang, Z. Qu, X. Lu, S. Hamburg, and D.J. Jacob, *Unravelling a large methane emission discrepancy in Mexico using satellite observations* , Remote Sensing Environ., 260, 112461, 2021.

Shindell, D. T., Faluvegi, G., Koch, D. M., Schmidt, G. A., Unger, N. and Bauer, S. E.: Improved Attribution of Climate Forcing to Emissions, Science, 326(5953), 716–718, doi:10.1126/science.1174760, 2009.

https://doi.org/10.5194/acp-2021-955
Preprint. Discussion started: 7 December 2021

Atmospheric Chemistry and Physics Discussions

Turner, A. J., Frankenberg, C. and Kort, E. A.: Interpreting contemporary trends in atmospheric methane, Proceedings of the National Academy of Sciences of the United States of America, 8(8), 201814297–9, doi:10.1073/pnas.1814297116, 2019.

Turner, A. J., Frankenberg, C., Wennberg, P. and Jacob, D.: Ambiguity in the causes for decadal trends in atmospheric methane and hydroxyl. 2017.

Turner, A. J., Fung, I., Naik, V., Horowitz, L. W. and Cohen, R. C.: Modulation of hydroxyl variability by ENSO in the absence of external forcing, Proceedings of the National Academy of Sciences of the United States of America, 115(36), 8931–8936, doi:10.1073/pnas.1807532115, 2018.

van der Werf, G. R., Randerson, J. T., Giglio, L., van Leeuwen, T. T., Chen, Y., Rogers, B. M., Mu, M., van Marle, M. J. E., Morton, D. C., Collatz, G. J., Yokelson, R. J. and Kasibhatla, P. S.: Global fire emissions estimates during 1997–2016, Earth Syst. Sci. Data, 9(2), 697–720, doi:10.5194/acp-9-5785-2009, 2017.

Varon, D. J., McKeever, J., Jervis, D., Maasakkers, J. D., Pandey, S., Houweling, S., Aben, I., Scarpelli, T. and Jacob, D. J.: Satellite Discovery of Anomalously Large Methane Point Sources From Oil/Gas Production, Geophys. Res. Lett, 361(23), 186–10, doi:10.1029/2019GL083798, 2019.

Worden, J. R., Bloom, A. A., Pandey, S., Jiang, Z., Worden, H. M., Walker, T. W., Houweling, S. and Röckmann, T.: Reduced biomass burning emissions reconcile conflicting estimates of the post-2006 atmospheric methane budget, Nat Commun, 1–11, doi:10.1038/s41467-017-02246-0, 2017.

Worden, J., Kulawik, S., Shepard, M., Clough, S., Worden, H., Bowman, K. and Goldman, A.: Predicted errors of tropospheric emission spectrometer nadir retrievals from spectral window selection, Journal of Geophysical Research-Atmospheres, 109(D9), D09308, doi:10.1029/2004JD004522, 2004.

Yu, X., Millet, D. B., Wells, K. C., Henze, D. K., Cao, H., Griffis, T. J., Kort, E. A., Plant, G., Deventer, M. J., Kolka, R. K., Roman, D. T., Davis, K. J., Desai, A. R., Baier, B. C., McKain, K., Czarnetzki, A. C. and Bloom, A. A.: Aircraft-based inversions quantify the importance of wetlands and livestock for Upper Midwest methane emissions, Atmospheric Chemistry and Physics, 21(2), 951–971, doi:10.5194/acp-21-951-2021, 2021.

Zavala-Araiza, D., Lyon, D. R., Alvarez, R. A., Davis, K. J., Harriss, R., Herndon, S. C., Karion, A., Kort, E. A., Lamb, B. K., Lan, X., Marchese, A. J., Pacala, S. W., Robinson, A. L., Shepson, P. B., Sweeney, C., Talbot, R., Townsend-Small, A., Yacovitch, T. I., Zimmerle, D. J. and Hamburg, S. P.: Reconciling divergent estimates of oil and gas methane emissions, Proceedings of the National academy of Sciences, 201522126, doi:10.1073/pnas.1522126112, 2015.

Zhang, Y., Jacob, D. J., Lu, X., Maasakkers, J. D., Scarpelli, T. R., Sheng, J.-X., Shen, L., Qu, Z., Sulprizio, M. P., Chang, J., Bloom, A. A., Ma, S., Worden, J., Parker, R. J. and Boesch, H.: Attribution of the accelerating increase in atmospheric methane during 2010–2018 by inverse

https://doi.org/10.5194/acp-2021-955
Preprint. Discussion started: 7 December 2021


analysis of GOSAT observations, Atmospheric Chemistry and Physics, 21(5), 3643–3666, doi:10.5194/acp-21-3643-2021, 2021.