Reply on RC1

Thanks for the feedback on this work. We have responded to each reviewer comment below. Our replies are in blue, and the revised manuscript text is written in bold.

This work estimates the global methane emission for the year 2019 at 2^{o}x2.5^{o} spatial resolution based on inverse modeling technique by utilizing the TROPOMI and GOSAT satellite observations. It validates TROPOMI and GOSAT observation against TCCON methane column measurements, using the GEOS-Chem CTM and also provides the sensitivities parameters such as averaging kernel and degrees of freedom for signal which quantify the number of independent pieces of information on the distribution of methane emissions. The paper provides the discussion on estimated methane emission at different major methane source regions around the world using GOSAT, TROPOMI, and joint data-set. I recommend its acceptance after the minor revision with following specific/minor comments:

specific comments:

1). There are techniques such a 4-dimentional variational data assimilation (4D-var) and local ensemble Kalman filter (LETKF) that also provides grid-based flux estimation of methane by assimilating satellite observations. How close the inversion technique used in this study is to those techniques? I suggest author to add a paragraph that discuss the limitations of the high-resolution Bayesian inversion technique using satellite observations.

All these three methods are based on the Bayes theorem to optimize emissions given the methane observations and bottom-up emissions, as described in the 3rd paragraph of Section 1. 4D-Var approximates the inverse Hessian of the model and does not provide error statistics. LETKF updates emissions sequentially, but approximates the evolving of the covariance matrix and needs to assume a localization distance. The analytical Bayesian inversion used here does not have these approximations, but its limitation is the expensive computational cost to construct the whole Jacobian matrix and the requirement that the forward model is linear. We made the following modification to clarify:

"Most inverse analyses use **4-dimensional variational data assimilation (4D-Var)** to **solve** the Bayesian problem **numerically**, which enables inference of emissions at any resolution but does not readily provide error statistics [Meirink et al., 2008; Monteil et al., 2013; Wecht et al., 2014; Stanevich et al., 2019]. Analytical solution **is possible if the CTM is linear, as is the case for methane, and** has the advantage of including posterior error statistics and hence information content as part of the solution [Brasseur and Jacob, 2017]. It requires explicit construction of the Jacobian matrix of the CTM, **which is computationally expensive**, but this is readily done with massively parallel computing. Once the Jacobian matrix has been constructed, it can be applied to conduct ensembles of inversions at no added cost exploring the dependence of the solution on inversion parameters or observational data selection. **The analytical method can be applied as a Kalman Filter by updating methane emissions sequentially [e.g., Chen and Prinn, 2006; Fraser et al., 2013; Henne et al., 2016] but optimizing all emissions together over the period of interest makes the best use of the information content from the observations [Maasakkers et al., 2019; Lu et al, 2021; Y. Zhang et al., 2021].**"

2). The methane emission has been estimated using annual mean methane concentration data of GOSAT and TROPOMI. How would the seasonal variability of methane concentration affect such emission estimate? Is it possible to extend such inverse modeling set-up to estimate the methane emission at monthly scale?

We use all observations in a year to optimize methane emissions, but this is different from using the annual mean of methane concentrations since each observation is weighted by its error and provides its unique constraint on the emissions. We estimate wetland methane emissions at a monthly scale given its strong seasonal variations, as described in the first paragraph of Section 3.2. We added the following sentence to that paragraph to explain our motivation to optimize annual mean non-wetland emissions:

"Trade-off is needed between spatial and temporal resolution in the state vector to avoid smoothing error in the inversion [Wecht et al, 2014] and for computational tractability. For non-wetland emissions we use high spatial resolution but only optimize the annual mean values because seasonality is relatively small and predictable. For wetland emissions, we cannot assume that the prior seasonality is correct [Maasakkers et al., 2019] and instead optimize monthly emissions at coarse spatial resolution."

Minor comments:

Line 367, We conducted ……. grid cell.

How significant it is to apply equal ratios to all sectors in the grid cell. How better this is in comparison to isotopic fractionation method.

We added the following sentence after the cited one:

"We conducted a global sectoral breakdown … **This assumption is due to the lack of additional information (e.g., isotopic fractionation [Ghosh et al., 2015; Zhang et al., 2016; Zazzeri et al., 2017]) to separate different sources."**

Line 371, Study claimed that 2ox2.5o grid makes sectoral attribution more accurate, but we don't know true sectorial contribution.

We removed this sentence.

Line 385, In China,……………..Plain. Please cite the figure number here.

We changed the sentence to:

"In China, both GOSAT and TROPOMI inversions adjust non-wetland methane emissions downward in the North China Plain **(Figure 5)**."

Line 399, the analysis is performed for 2019, why did the author cite 2014 report.

The last reported year for China to the UNFCCC is 2014. We changed the sentence to:

"At national scale, … very close to the value of 55 Tg a^{-1} **in the latest** report by China to the UNFCCC in 2014."

In Figure 3, large difference between GOSAT and TROPOMI can be seen during DJF at northward of 30oN. How does it affect inversion estimate?

We added the following sentence to the last paragraph of Section 2:

"The regional biases tend to be consistent across seasons, except for positive biases north of **40ºN** in DJF that could be associated with snow cover. **These biases may affect TROPOMI's constraints on the seasonal variations of methane sources.**"

We also made the following modifications in the 5th paragraph of Section 4.1:

"… the TROPOMI inversion would yield unrealistic wetland emissions and seasonalities (case 3 in Table S1). The problem may reflect systematic biases in the TROPOMI retrieval due to the low SWIR surface albedo over wetland surfaces (e.g., Brazil and central Africa, see Figure S4, and boreal wetlands in Canada and Russia), combined with seasonal imbalance in observations (cloudiness for tropical wetlands, sun angle and snow for boreal wetlands) **and seasonal biases at high northern latitudes (Figure 3).**"

Figure 7, Over India the estimate looks pretty close from all the methods, over Brazil, the joint inversion estimate is close to GOSAT, almost same story for Europe, but over CONUS the joint inversion is very high compared to both the inversion. How would you explain the joint inversion behavior over CONUS?

We made the following modifications in the last paragraph of Section 4.3.2:

"The joint inversion adjusts emissions upwards to **40** Tg a^{-1} due to the larger **averaging kernel** sensitivity over the south-central US, **where emissions have large upward adjustments**."