

1 **Reply to comments on “Toward a versatile spaceborne architecture**
2 **for immediate monitoring of the global methane pledge” by Yuchen**
3 **Wang et al.**
4

5 **Reply to Reviewer #1:**
6

7 This paper proposes an interesting method to address the important issue of quantifying current methane emissions. The
8 authors justifiably argue that no current satellite instrument provides both the coverage and the spatial resolution to accurately
9 measure global methane concentrations; to address this lack they propose a two-step method that uses data from two very
10 different instruments: the wide swath, coarse spatial resolution TROPOMI and narrow swath but very high spatial resolution
11 PRISMA. The TROPOMI data are used to locate high methane emission regions and the methane hotspots within these regions,
12 then the co-located PRISMA data are examined for the presence of plumes. Emissions over the hotspots and plumes are
13 estimated by combining wind speed information with an integrated mass enhancement model.

14 The approach is demonstrated for short periods over five small regions and the results are compared with surveys over
15 two other regions. The median and range of the plume emissions are qualitatively consistent with those obtained using data
16 from another (non-specified) satellite instrument over the Permian basin, and much higher than those from an aircraft campaign
17 over California. The hotspot and plume emissions are also compared with emissions from the EDGAR_v6.0 inventory; the
18 hotspot emissions were somewhat consistent with the inventory, while the plume emissions were much higher.

19 Summarizing the above, this is an interesting method with very interesting results. The authors evidently put a great deal
20 of effort and enthusiasm into this work. However, the paper presents several problems, principally lack of detail on how some
21 of the results were obtained. I have listed the main technical issues below, which need to be addressed before the paper can be
22 published. An overarching issue is English language usage. Verb tenses are frequently used incorrectly (e.g, past or conditional
23 future for present), and nouns and adjectives are interchanged. Before resubmitting the authors should have either a native
24 English speaker or someone with excellent English revise the paper. I will be happy to provide more specific wording changes
25 once this been done, if they are still necessary.

26 **Response:** We truly appreciate these positive responses and thorough summarizations. We are also very grateful for the
27 valuable comments and suggestions and have addressed all of them in our revised manuscript. Particularly, we have
28 supplemented more technical details to clarify the procedure of our framework. In addition, our co-authors (involving native
29 English speakers) have carefully gone through the entire manuscript to improve the English level.

30 The followings are our point-to-point responses to the reviewer’s comments. The responses are shown in brown font,
31 while the added/rewritten parts are presented in blue font. All revised figures and tables are also included in the manuscripts.
32

33 1. The method for identifying high emission areas and plumes appears to be visual identification. The authors do mention
34 a Boolean mask for identifying the former, but no details are provided and the reader is left wondering what this means. This
35 needs to be clarified. Such an intensive method is feasible for a small analysis, such as presented in figures 1-3, but obviously
36 not for long term, global emission estimates. Here the authors suggest a machine learning approach for further applications of
37 their method, which is a reasonable suggestion. However, this issue makes the year long results presented in S3 and S4
38 questionable. Were the TROPOMI maps obtained by applying the Sun oversampling method for an entire year over the original
39 methane concentrations? If so which wind fields were used to obtain the emissions, both for the regional and plume estimates?
40 How were the PRISMA data averaged over the year? Given the variability in wind direction, I don't think it makes sense to
41 look for plumes in averaged data. These plots need to either explained in much greater detail, or omitted entirely from the
42 paper. If they are to be included, then the authors need to be clear which results (short term or annual) are used in all other
43 plots.

44 **Response:** Thank you for these valuable comments and suggestions. First, we have supplemented more technical details
45 to clarify the role of the Boolean mask method. As you pointed out, in the first tier of our framework, we apply visual inspection
46 to identify methane hotspots using the TROPOMI-based methane retrievals. The transformation from visual inspection to
47 automatic recognition would significantly advance long-term, global methane monitoring. However, no satisfactory set of
48 criteria is found that could be suitable for this study. This was mainly because, in localized regions, methane budgets respond
49 to the changes in not only super-emitters but also complex external factors (e.g., meteorology, topography, and background
50 concentrations). Similar compromises are also adopted in previous studies. Therefore, automatic recognition enabled by
51 artificial intelligence would play an essential role in the versatile spaceborne architecture for long-term, global methane
52 monitoring (Ouerghi et al., 2021; Paoletti et al., 2018; Yang et al., 2018; Yu et al., 2017; Zhang et al., 2018).

53 Regarding the identified methane hotspots, we utilize a Boolean mask to select plume-influenced pixels downwind of the
54 source. The background distribution (mean \pm standard deviation) is defined by an upwind sample of the measured columns, in
55 which the hourly wind field data came from the ERA5 reanalysis dataset produced by the European Centre for Medium-Range
56 Weather Forecasts (ECMWF) (Hoffmann et al., 2019). We then sample the surrounding (5×5) pixels centred on each pixel
57 and compare the corresponding distributions to the background distribution based on a Student's t-test. Pixels with a
58 distribution substantially higher than the background at a confidence level of 95% are assigned to the plume. More details in
59 the Boolean plume mask can be found in previous studies (Pandey et al., 2019; Varon et al., 2018).

60 Second, we agree that it might make no sense to look for plumes in averaged data due to the variable wind direction and
61 have thus omitted the oversampled methane maps in the first tier of our framework (Fig. S3). In turn, using year-round
62 snapshots in the second tier of our framework, we inspect the identified super-emitters (Figs. 1b ~ 1g) repeatedly and find
63 more methane plumes as expected (Fig. S4). This reinforces the above hypothesis for the widespread occurrence of methane
64 super-emitters.

65 **Added/rewritten part in Sect. 2.3:** In the first tier of our framework, we apply visual inspection to identify methane
66 hotspots using the TROPOMI-based methane retrievals. The transformation from visual inspection to automatic recognition

67 would significantly advance long-term, global methane monitoring. However, no satisfactory set of criteria is found that could
68 be suitable for this study. This was mainly because, in localized regions, methane budgets respond to the changes in not only
69 super-emitters but also complex external factors (e.g., meteorology, topography, and background concentrations). Similar
70 compromises are also adopted in previous studies. Therefore, automatic recognition enabled by artificial intelligence would
71 play an essential role in the versatile spaceborne architecture for long-term, global methane monitoring (Ouerghi et al., 2021;
72 Paoletti et al., 2018; Yang et al., 2018; Yu et al., 2017; Zhang et al., 2018).

73 Regarding the identified methane hotspots, we utilize a Boolean mask to select plume-influenced pixels downwind of the
74 source. The background distribution (mean \pm standard deviation) is defined by an upwind sample of the measured columns, in
75 which the hourly wind field data came from the ERA5 reanalysis dataset produced by the European Centre for Medium-Range
76 Weather Forecasts (ECMWF) (Hoffmann et al., 2019). We then sample the surrounding (5×5) pixels centred on each pixel
77 and compare the corresponding distributions to the background distribution based on a Student's t-test. Pixels with a
78 distribution substantially higher than the background at a confidence level of 95% are assigned to the plume. More details in
79 the Boolean plume mask can be found in previous studies (Pandey et al., 2019; Varon et al., 2018).

80 **Added/rewritten part in Sect. 3.2:** To further explore such a hypothesis, we extend the temporal sample window of our
81 multi-tiered framework. Using year-round snapshots in the second tier of our framework, we inspect the identified super-
82 emitters (Figs. 1b ~ 1g) repeatedly and find more methane plumes as expected (Fig. S3). This reinforces the above hypothesis
83 for the widespread occurrence of methane super-emitters.

84

85 2. The plume maps would be more interesting if the plume source were clearly marked.

86 **Response:** Thanks. We have marked all the plume sources in Fig. 1 and Fig. S3.

87

88 3. How was the background vector used in equation 1 derived?

89 **Response:** Thanks. We have supplemented brief descriptions for this issue. The $\vec{\mu}$ and Σ represent the mean background
90 radiance and corresponding covariance, respectively, calculated with their common formulas after subtracting the current
91 signal estimates from the data. Specifically, the $\vec{\mu}$ is calculated from the data with the removal of the most recent enhancement
92 estimates, while the Σ is then calculated with updated $\vec{\mu}$ and the most recent enhancement estimates. More technical details are
93 reported in previous studies (Foote et al., 2020). Note that, owing to the non-uniform response of individual detectors in
94 PRISMA, they are calculated based on per-column spectrums in order to consider different responses of across-track detectors
95 to radiance.

96 **Added/rewritten part in Sect. 2.2:** The $\vec{\mu}$ and Σ represent the mean background radiance and corresponding covariance,
97 respectively, calculated with their common formulas after subtracting the current signal estimates from the data. Specifically,
98 the $\vec{\mu}$ is calculated from the data with the removal of the most recent enhancement estimates, while the Σ is then calculated
99 with updated $\vec{\mu}$ and the most recent enhancement estimates. More technical details are reported in previous studies (Foote et

100 al., 2020). Note that, owing to the non-uniform response of individual detectors in PRISMA, they are calculated based on per-
101 column spectrums in order to consider different responses of across-track sensors to radiance.

102

103 4. What does this sentence mean: methane enhancements detected in spectrometers generally exhibit sparsity, especially
104 over low albedo surfaces.

105 **Response:** Sorry for the confusion we caused. We have revised this sentence to clarify this issue. In principle, it would
106 be more difficult to detect methane enhancements in pixels over low-albedo surfaces. Although methane absorption is
107 independent of albedo, the resulting signal in absolute radiance is weakened with surface albedo decreasing.

108 **Added/rewritten part in Sect. 2.2:** In principle, it would be more difficult to detect methane enhancements in pixels
109 over low-albedo surfaces. Although methane absorption is independent of albedo, the resulting signal in absolute radiance is
110 weakened with surface albedo decreasing.

111

112 5. Please define the co-location criteria between the TROPOMI and PRISMA datasets.

113 **Response:** Thanks. We have supplemented the definition the co-location criteria between the TROPOMI and PRISMA
114 datasets. Regarding the identified regional hotspots, we also apply visual inspection to search for plumes within their
115 surrounding 30 km scales (i.e., corresponding to the swath width of PRISMA) in the second tier of our framework.

116 **Added/rewritten part in Sect. 2.3:** Regarding the identified regional hotspots, we also apply visual inspection to search
117 for plumes within their surrounding 30 km scales (i.e., corresponding to the swath width of PRISMA) in the second tier of our
118 framework (Irakulis-Loitxate et al., 2021; Lauvaux et al., 2022; Martin et al., 2018; Varon et al., 2020).

119

120 6. The section on comparing the TROPOMI/PRISMA results with the California and Permian surveys needs to provide
121 more detail on those surveys (instrument, time of year, temporal and spatial extent). It also needs to emphasize that these
122 comparisons are basically tests of reasonableness, not true quantitative comparisons.

123 **Response:** Thanks. We have supplemented more technical details on these surveys. The California survey aims to provide
124 the first view of methane super-emitters across the state. This survey is conducted with the Next Generation Airborne
125 Visible/Infrared Imaging Spectrometer (AVIRIS-NG), with 5 nm SWIR spectral sampling, 1.8 km view field, 3 m horizontal
126 resolution, and 3 km cruise altitude, and contains five campaigns over several months from 2016 to 2018. Moreover, this
127 instrument is unique due to its high signal-to-noise ratio and is capable of characterizing methane super-emitters with emissions
128 as small as 2 ~ 10 kg/h for typical surface winds of 5 m/s.

129 The Permian survey takes advantage of imaging spectroscopy technologies to provide the first spaceborne region-scale
130 and high-resolution survey of methane super-emitters in the Permian basin. This survey is acquired by 30 hyperspectral images
131 from three satellite missions, including Gaofen-5, ZY1, and PRISMA, and focuses on an area of roughly 200 × 150 km² in the
132 Delaware sub-basin of the Permian basin within several days (mostly on four different dates: 15 May 2019, 1 November 2019,

133 29 December 2019, and 8 February 2020). More technical details on these two surveys can be found in previous studies (Duren
134 et al., 2019; Irakulis-Loitxate et al., 2021).

135 Moreover, we agree that such comparisons are basically reasonableness test rather than stringently quantitative validations
136 due to measurement divergencies between these datasets (e.g., spatial resolution and detection limit). Collectively, although
137 such comparisons are not quantitative comparisons due to measurement divergencies between these datasets (e.g., spatial
138 resolution and detection limit), they offer further context for the emission magnitude of the identified methane super-emitters
139 and indicate the outstanding strength of our results that could be analogous to abundant outcomes from field campaigns. More
140 importantly, this highlights the urgent need for global monitoring of ‘nameless’ O&G facilities that possibly emit methane as
141 much as the California field and Permian basin.

142 **Added/rewritten part in Sect. 3.2:** The California survey aims to provide the first view of methane super-emitters across
143 the state. This survey is conducted with the Next Generation Airborne Visible/Infrared Imaging Spectrometer (AVIRIS-NG),
144 with 5 nm SWIR spectral sampling, 1.8 km view field, 3 m horizontal resolution, and 3 km cruise altitude, and contains five
145 campaigns over several months from 2016 to 2018. Moreover, this instrument is unique due to its high signal-to-noise ratio
146 and is capable of characterizing methane super-emitters with emissions as small as 2 ~ 10 kg/h for typical surface winds of 5
147 m/s.

148 The Permian survey takes advantage of imaging spectroscopy technologies to provide the first spaceborne region-scale
149 and high-resolution survey of methane super-emitters in the Permian basin. This survey is acquired by 30 hyperspectral images
150 from three satellite missions, including Gaofen-5, ZY1, and PRISMA, and focuses on an area of roughly 200 × 150 km² in the
151 Delaware sub-basin of the Permian basin within several days (mostly on four different dates: 15 May 2019, 1 November 2019,
152 29 December 2019, and 8 February 2020). More technical details on these two surveys can be found in previous studies (Duren
153 et al., 2019; Irakulis-Loitxate et al., 2021).

154 Collectively, although such comparisons are not quantitative comparisons due to measurement divergencies between
155 these datasets (e.g., spatial resolution and detection limit), they offer further context for the emission magnitude of the
156 identified methane super-emitters and indicate the outstanding strength of our results that could be analogous to abundant
157 outcomes from field campaigns. More importantly, this highlights the urgent need for global monitoring of ‘nameless’ O&G
158 facilities that possibly emit methane as much as the California field and Permian basin.

159
160 7. The phrase “on a per column basis” is frequently used: what does this mean?

161 **Response:** Sorry for the confusion we caused. We have supplemented some sentences to explain this phrase at its first
162 appearance. The matched-filter algorithm focuses on the individual columns rather than the whole scene to resolve methane
163 enhancements. This means that the methane enhancement per column is calculated separately (i.e., methane enhancements
164 were calculated on a per-column basis). More explanations can be found in Guanter et al. (2021).

165 **Added/rewritten part in Sect. 2.2:** The matched-filter algorithm focuses on the individual columns rather than the whole
166 scene to resolve methane enhancements. This means that the methane enhancement per column is calculated separately (i.e.,
167 methane enhancements were calculated on a per-column basis). More explanations can be found in Guanter et al. (2021).
168

169 8. The detailed uncertainty analysis is confusing, disorganized and hard to follow. Please put some more thought in how
170 to present this information.

171 **Response:** Thank you very much for this constructive suggestion. We have reorganized and revised the detailed
172 uncertainty analysis in Supplementary Information to clarify this issue, which has been explicitly divided into three sub-issues:
173 (1) uncertainties in the PRISMA-based methane retrievals; (2) uncertainties in the TROPOMI-based methane emission
174 estimates; and (3) uncertainties in PRISMA-based methane emission estimates. Note that operational TROPOMI-based
175 methane retrieval products have been evaluated strictly and proved to be reliable globally (except in low- and high-albedo and
176 snow-covered areas) (Lorente et al., 2021; Sha et al., 2021) and the related uncertainty analysis is thus omitted here. As a result,
177 we could confirm the reliable performance of our framework. Comprehensive uncertainty analysis is illustrated in
178 Supplementary Information.
179

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1 **Reply to comments on “Toward a versatile spaceborne architecture**
2 **for immediate monitoring of the global methane pledge” by Yuchen**
3 **Wang et al.**
4
5

6 **Reply to Reviewer #2:**
7

8 This paper aims at proposing a framework to utilize current space-borne methane observations to monitor regional
9 emission hotspots and qualify super emitters. The framework combines two methods: one based on global mapping using
10 TROPOMI and the other based on PRISMA (or other high-resolution mappings for small target areas). However, it is not clear
11 what makes this framework different from previous studies (many are cited here), and it is suggested that the authors should
12 clearly state the novel aspects of their method.

13 **Response:** We truly appreciate this valuable suggestion. We have revised related sentences and supplemented clear
14 statements for the novel aspects of their method. Collectively, existing studies still struggle to surveillance global methane
15 super-emitters due to the fact that individual satellite missions, either TROPOMI or PRISMA, cannot coordinate large-scale
16 swath and high-resolution sampling. To address this issue, we present a two-tiered, space-based framework that coordinates
17 TROPOMI and PRISMA for both planet-scale and plant-level methane retrievals.

18 **Added/rewritten part in Sect. 1:** Collectively, existing studies still struggle to surveillance global methane super-
19 emitters due to the fact that individual satellite missions, either TROPOMI or PRISMA, cannot coordinate large-scale swath
20 and high-resolution sampling. To address this issue, we present a two-tiered, space-based framework that coordinates
21 TROPOMI and PRISMA for both planet-scale and plant-level methane retrievals.
22

23 Additionally, the approach is only demonstrated over short periods for five small areas, and the results are well compared
24 with previous studies. The method for identifying high emission areas and plumes appears to be “visual inspection”, which
25 raises questions about how this "framework" could scale to "immediate monitoring of the global methane." This is a key point
26 that needs to be addressed for “a versatile spaceborne architecture.” Besides, the detection limit of this method and how it
27 deals with hotspots from natural sources or other anthropogenic sectors other than oil and gas (landfill, agriculture) should be
28 better illustrated before the paper is considered for publication.

29 **Response:** Thanks for these insightful comments. Yes, we applied visual inspection to identify methane hotspots and
30 plumes using the TROPOMI-based and PRISMA-based methane retrievals. We agree that “visual inspection” is one of the
31 key obstacles to realizing long-term, global methane monitoring. First, we have revised the title to clarify the existing gap to a
32 versatile spaceborne architecture. Second, we have further explained the key role of automatic recognition in long-term, global

33 methane monitoring. The transformation from visual inspection to automatic recognition would significantly advance long-
34 term, global methane monitoring. However, no satisfactory set of automatic criteria is found that could be suitable for this
35 study. This is mainly because, in localized regions, methane budgets respond to the changes in not only super-emitters but also
36 complex external factors (e.g., meteorology, topography, and background concentrations). Similar compromises are also
37 adopted in previous studies. Therefore, automatic recognition enabled by artificial intelligence would play an essential role in
38 the versatile spaceborne architecture for long-term, global methane monitoring (Ouerghi et al., 2021; Paoletti et al., 2018;
39 Yang et al., 2018; Yu et al., 2017; Zhang et al., 2018).

40 Besides, the detection limit of this framework depends mainly on the TROPOMI-based and PRISMA-based methane
41 retrievals, which have been well discussed in previous studies (Guanter et al., 2021; Hu et al., 2018). Here we have thus
42 supplemented associated discussions on this detection limit briefly. As the robust relationship between the “minimum source”
43 and the related methane enhancement interpreted by Jacob et al. (2016) and Guanter et al. (2021), the detection threshold for
44 the TROPOMI instrument is 4000 kg/h with a wind speed of 5 km/h. Following the same relationship in the PRISMA
45 instrument, we estimate that a retrieval precision of 114 ppb (6.1% with the assumed background concentration of 1850 ppb),
46 such as in the case of the Hassi Messaoud site (Fig. S10e1), would lead to a detection limit of 800 kg/h for the same wind
47 speed (analogous to the reported range of 500 ~ 900 kg/h) (Guanter et al., 2021; Irakulis-Loitxate et al., 2022).

48 Similar instruments and detection limits are generally comparable to emissions from anthropogenic sectors, like O&G
49 and coal mines in this study or landfills, agriculture, and waste management in previous studies (Maasakkers et al., 2023;
50 Sadavarte et al., 2021; T. et al., 2022). However, no conclusive evidence shows by far that short-term (e.g., daily) satellite-
51 based measurements with such detection limits can capture methane hotspots driven by natural sources (e.g., wetlands). In
52 contrast, long-term (e.g., year-round) satellite-based measurements with much higher detection limits have shown the potential
53 (Pandey et al., 2021).

54 **Added/rewritten part in Title:** Toward a versatile spaceborne architecture for immediate monitoring of the global
55 methane pledge.

56 **Added/rewritten part in Sect. 2.3:** The transformation from visual inspection to automatic recognition would
57 significantly advance long-term, global methane monitoring. However, no satisfactory set of criteria is found that could be
58 suitable for this study. This is mainly because, in localized regions, methane budgets respond to the changes in not only super-
59 emitters but also complex external factors (e.g., meteorology, topography, and background concentrations). Similar
60 compromises are also adopted in previous studies. Therefore, automatic recognition enabled by artificial intelligence would
61 play an essential role in the versatile spaceborne architecture for long-term, global methane monitoring (Ouerghi et al., 2021;
62 Paoletti et al., 2018; Yang et al., 2018; Yu et al., 2017; Zhang et al., 2018).

63 **Added/rewritten part in Sect. 2.5:** The detection limit of this framework depends mainly on the TROPOMI-based and
64 PRISMA-based methane retrievals, which have been well discussed in previous studies (Guanter et al., 2021; Hu et al., 2018).
65 Here we have thus supplemented associated discussions on this detection limit briefly. As the robust relationship between the
66 “minimum source” and the related methane enhancement interpreted by Jacob et al. (2016) and Guanter et al. (2021), the

67 detection threshold for the TROPOMI instrument is 4000 kg/h with a wind speed of 5 km/h. Following the same relationship
68 in the PRISMA instrument, we estimate that a retrieval precision of 114 ppb (6.1% with the assumed background concentration
69 of 1850 ppb), such as in the case of the Hassi Messaoud site (Fig. S10e1), would lead to a detection limit of 800 kg/h for the
70 same wind speed (analogous to the reported range of 500 ~ 900 kg/h) (Guanter et al., 2021; Irakulis-Loitxate et al., 2022).
71 Similar instruments and detection limits are generally comparable to emissions from anthropogenic sectors, like O&G and
72 coal mines in this study or landfills, agriculture, and waste management in previous studies (Maasackers et al., 2023; Sadavarte
73 et al., 2021; T. et al., 2022). However, no conclusive evidence shows by far that short-term (e.g., daily) satellite-based
74 measurements with such detection limits can capture methane hotspots driven by natural sources (e.g., wetlands). In contrast,
75 long-term (e.g., year-round) satellite-based measurements with much higher detection limits have shown the potential (Pandey
76 et al., 2021).

77

78 **Technical Points:**

79 The title and the abstract are a bit perplexing. The multi-tiered reads mostly two-tiered. I think clarifying these basic
80 points would be helpful for the reader. In the abstract, it would be nice if the authors could briefly describe what this “versatile
81 spaceborne architecture” is, and what data it is based on using what methods. At the moment, one needs to read the paper to a
82 large extent to get some idea of “this framework”. The paper could also benefit from adjusting the scope of the text to the
83 results presented here.

84 **Response:** Thanks for this constructive suggestion. Accordingly, we have revised the title and abstract to clarify these
85 key points, particularly distinguishing the two-tiered and versatile spaceborne architectures, and have also adjusted the scope
86 of the text to the results presented here.

87 **Added/rewritten part in Title:** Toward a versatile spaceborne architecture for immediate monitoring of the global
88 methane pledge

89 **Added/rewritten part in Abstract:** The global methane pledge paves a fresh, critical way toward Carbon Neutrality.
90 However, it remains largely invisible and highly controversial due to the fact that planet-scale and plant-level methane
91 retrievals have rarely been coordinated. This has never been more essential within a narrow window to reach the Paris target.
92 Here we present a two-tiered spaceborne architecture to address this issue. Using this framework, we patrol the world, like the
93 United States, China, the Middle East, and North Africa, and simultaneously uncover methane-abundant regions and plumes.
94 These include new super-emitters, potential leakages, and unprecedented multiple plumes in a single source. More importantly,
95 this framework is shown to challenge official emission reports that possibly mislead estimates from global, regional, to site
96 scales, particularly by missing super-emitters. Our results show that, in principle, we can extend the above framework to be
97 multi-tiered by adding upcoming stereoscopic measurements and suitable artificial intelligence, thus versatile for immediate
98 and future monitoring of the global methane pledge.

99

100 Line 51: Ocko et al., 2021 only refers to the anthropogenic methane sources. It is important to state this precisely, not to
101 confuse it with the large portion of methane emissions from natural sources. The current text might be misleading.

102 **Response:** Sorry for the misleading we caused. We have revised this sentence to make rigorous statements. Fortunately,
103 methane is short-lived (~ ten years), and, particularly, that from human activities can be reduced in half using existing
104 technologies by 2030 (Ocko et al., 2021).

105 **Added/rewritten part in Sect. 1:** Fortunately, methane is short-lived (~ ten years) (J et al., 2013), and, particularly, that
106 from human activities can be reduced in half using existing technologies by 2030 (Ocko et al., 2021).

107

108 Line 55, line 59, and many other places: please check references.

109 **Response:** Thanks. We have carefully gone through the paper to check the references.

110

111 Fig. 1 How is “colocation” defined? Using what kind of criteria?

112 **Response:** Thanks. We have supplemented the definition the co-location criteria between the TROPOMI and PRISMA
113 datasets. Regarding the identified regional hotspots, we also apply visual inspection to search for plumes within their
114 surrounding 30 km scales (i.e., corresponding to the swath width of PRISMA) in the second tier of our framework (Irakulis-
115 Loitxate et al., 2021; Martin et al., 2018; T. et al., 2022; Varon et al., 2020).

116 **Added/rewritten part in Sect. 2.3:** Regarding the identified regional hotspots, we also apply visual inspection to search
117 for plumes within their surrounding 30 km scales (i.e., corresponding to the swath width of PRISMA) in the second tier of our
118 framework (Irakulis-Loitxate et al., 2021; Martin et al., 2018; T. et al., 2022; Varon et al., 2020).

119

120 Fig. 2 What temporal periods are considered here to calculate the percentage?

121 **Response:** Thanks. We have supplemented the description of the temporal periods that are considered to calculate the
122 percentages. The overpass moments are explicitly shown Fig. 1, most of which are inconsistent between for the first- and
123 second-tier monitoring.

124 **Added/rewritten part in Sect. 3.2:** The overpass moments are explicitly shown Fig. 1, most of which are inconsistent
125 between for the first- and second-tier monitoring.

126

127 Fig. 4 How to reconcile PRISMA and TROPOMI results? It seems there are still differences in the order of magnitude.

128 **Response:** Thanks. Yes, there are differences in the order of magnitude between the TROPOMI-based and PRISMA-
129 based results, and we have supplemented additional discussions to clarify this issue. The main cause is that the TROPOMI-
130 based and PRISMA-based results represent the methane emissions from different special scales. The former results represent
131 region-scale methane budgets, while the latter ones resolve the emission magnitude from the individual methane super-emitter
132 therein (Fig. 1). Although the latter results can explain a large fraction of the former ones (Fig. 2), the gaps remain mainly due
133 to inconsistent overpass moments between the two-tiered results or sources still missed by the PRISMA-based results. In other

134 words, closing the temporal gaps between the two tiers or improving the detection ability of the second tier would help to
135 reconcile the first- and second-tiered results.

136 **Added/rewritten part in Sect. 3.2:** Note that there are differences in the order of magnitude between the TROPOMI-
137 based and PRISMA-based results. The main cause is that the TROPOMI-based and PRISMA-based results represent the
138 methane emissions from different spatial scales. The former results represent region-scale methane budgets, while the latter
139 ones resolve the emission magnitude from the individual methane super-emitter therein (Fig. 1). Although the latter results can
140 explain a large fraction of the former ones (Fig. 2), the gaps remain mainly due to inconsistent overlap moments between the
141 two-tiered results or sources still missed by the PRISMA-based results. In other words, closing the temporal gaps between the
142 two tiers or improving the detection ability of the second tier would help to reconcile the first- and second-tiered results.

1 **Reply to comments on “Toward a versatile spaceborne architecture**
2 **for immediate monitoring of the global methane pledge” by Yuchen**
3 **Wang et al.**
4

5 **Reply to CC #1:**
6

7 The article shows a very interesting approach to investigate the different methane emissions using available satellites
8 (TROPOMI and PRIMA) and suggesting that a multitiered constellation could be implemented. Some comments on the article
9 of possible improvements.

10 **Response:** We truly appreciate your positive responses and valuable comments. We have addressed all of them in our
11 revised manuscript.

12 The followings are our point-to-point responses to the reviewer’s comments. The responses are shown in brown font,
13 while the added/rewritten parts are presented in blue font. All revised figures and tables are also included in the manuscripts.
14

15 Line 60 you introduce the term “super-emitters” for first time, the term should be defined better (how big/small, released
16 methane, how spread, etc.) in contrast with hot spots and area sources. This should be tailored for the satellite swath and
17 resolution.

18 **Response:** Thanks for this valuable comment. We have supplemented the descriptions to clarify the definition of “super-
19 emitters”. In this study, super-emitters can generally be defined to be emission sources that comprise highly concentrated
20 methane plumes and dominate localized methane budgets ($\sim 5 \times 5 \text{ km}^2$). In contrast to region-scale hotspots (or area sources),
21 they can be attributed to individual facilities (e.g., factories, chimneys, and pipelines), typically with side lengths varying from
22 several meters to tens of meters depending on monitoring instruments.

23 **Added/rewritten part in Sect. 1:** Super-emitters can generally be defined to be emission sources that comprise highly
24 concentrated methane plumes and dominate localized methane budgets ($\sim 5 \times 5 \text{ km}^2$). In contrast to region-scale hotspots (or
25 area sources), they can be attributed to individual facilities (e.g., factories, chimneys, and pipelines), typically with side lengths
26 varying from several meters to tens of meters depending on monitoring instruments.
27

28 Between lines 80 to 92 a review of existing and capable of detecting methane satellites is shown. However, the swath,
29 passes, resolution, etc. is not given for all satellites. I would suggest to add a table with such information. This would help to
30 better understand/propose a future multi-tiered constellation which could act globally.

31 **Response:** Thanks. This is a very valuable suggestion. We have supplemented a table (Table 1) to collect the potential
32 satellites and their necessary information (e.g., swath and resolution).

33

34 A conclusions section with a better explanation of what number of satellites (which ones in the pipeline / resolution), and
35 aircrafts needed to have a proper coverage would be needed. Also, would it be night monitoring important, which method or
36 missions could be used? Atmospheric Lidars? Would the retrieval of structured atmospheric column help the analysis?

37 **Response:** Very illuminating suggestions. We have supplemented brief discussions to clarify these three issues. Overall,
38 this multi-tiered framework based on multifarious satellites, aircrafts, and UAVs keeps pursuing wider coverages and faster
39 revisits. We would thus derive the next objective in this manner, i.e., how to achieve effective, efficient, and economic
40 monitoring of global methane pledges, in which how to make better coverage-resolution balance between instruments is crucial.
41 This will be the topic of a next separate study.

42 Second, yes, nighttime methane monitoring is important because abnormal leakages or pulses might also occur during
43 nighttime (Plant et al., 2022; Poindexter et al., 2016). In these events, the LIDAR-equipped ones (involving satellites, e.g.,
44 MERLIN) can allow to retrieve methane fluxes at all-latitudes, all-seasons, and all-weather (involving nighttime) as they are
45 not relying on sunlight. Fourth, better characterizing methane vertical profile would in principle help to optimize our analysis,
46 like minimizing the uncertainties in tropospheric air mass factors and subsequent methane enhancements.

47 **Added/rewritten part in Sect. 3.4:** Note that such a multi-tiered framework based on multifarious satellites, aircrafts,
48 and UAVs keeps pursuing wider coverages and faster revisits. We would thus derive the next objective in this manner, i.e.,
49 how to achieve effective, efficient, and economic monitoring of global methane pledges, in which how to make better coverage-
50 resolution balance between instruments is crucial. This will be the topic of the next separate study.

51 Third, nighttime methane monitoring is important because abnormal leakages or pulses might also occur during nighttime
52 (Plant et al., 2022; Poindexter et al., 2016). In these events, the LIDAR-equipped ones (involving satellites, e.g., MERLIN)
53 can allow to retrieve methane fluxes at all-latitudes, all-seasons, and all-weather (involving nighttime) as they are not relying
54 on sunlight. Fourth, better characterizing methane vertical profile would help to optimize our analysis, like minimizing the
55 uncertainties in tropospheric air mass factors and subsequent methane enhancements.

56

57 **Cosmetics:**

58 Spacing between text and references. In Line 57, 59, 136, 223, 225, 244, 312, 343, 360.

59 **Response:** Thanks. We have supplemented these necessary blank spaces.

60

61 Reference in line 117, is this correct format for the current article? In contract to the one in line 145. Is it need to have
62 same info twice?

63 **Response:** Thanks. We have checked the format of the reference. Besides, in Line 117 and Line 145, we have deleted the
64 repetitive references.

65

66 **Reference**

67 Plant, G., Kort, E. A., Brandt, A. R., Chen, Y., Fordice, G., Gorchov Negron, A. M., Schwietzke, S., Smith, M. and Zavala-
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70 Poindexter, C. M., Baldocchi, D. D., Matthes, J. H., Knox, S. H. and Variano, E. A.: The contribution of an overlooked
71 transport process to a wetland’s methane emissions, *Geophys. Res. Lett.*, 43(12), 6276–6284,
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73