

A multi-platform inversion estimation of statewide and regional methane emissions in California during 2014-2016

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1 **Abstract**

2 California methane (CH₄) emissions are quantified for three years from two tower networks and
3 one aircraft campaign. We used backward trajectory simulations and a mesoscale Bayesian inverse
4 model, initialized by three inventories, to achieve the emission quantification. Results show total
5 statewide CH₄ emissions of 2.05±0.26 (at 95% confidence) Tg/yr, which is 1.14 to 1.47 times
6 greater than the anthropogenic emission estimates by California Air Resource Board (CARB).
7 Some of differences could be biogenic emissions, super-emitter point sources, and other episodic
8 emissions which may not be completely included in the CARB inventory. San Joaquin Valley
9 (SJV) has the largest CH₄ emissions (0.94±0.18 Tg/yr), followed by the South Coast Air Basin,
10 the Sacramento Valley, and the San Francisco Bay Area, 0.39±0.18, 0.21±0.04, and 0.16±0.05
11 Tg/yr, respectively. The dairy and oil/gas production sources in the SJV contribute 0.44±0.36 and
12 0.22±0.23 Tg CH₄/yr, respectively.

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18 **Introduction**

19 California adopted the landmark Global Warming Solutions Act of 2006 to reduce greenhouse gas
20 emissions to the 1990 levels by 2020, and has also enacted several ambitious climate strategies to
21 mitigate the global warming impacts of methane (CH₄), such as Senate Bill No. 1383 which
22 requires a 40% reduction in CH₄ emissions below 2013 levels by 2030. A thorough understanding
23 of CH₄ emission sources is critical to achieve these ambitious emission reduction goals as well as
24 to implement efficient and cost-effective policies that will achieve real reductions.

25 Over the years, researchers have utilized several measurement frameworks, coupled with top-down
26 emission estimation approaches using atmospheric measurements of CH₄ mixing ratios to quantify
27 methane emissions in California and evaluate bottom-up inventories. These top-down studies have

28 included measurement and analysis schemes such as satellite and airborne remote sensing, ambient
29 measurements and inverse modeling, source apportionment, enhancement ratios analysis¹⁻⁸. The
30 top-down studies for statewide CH₄ emissions from 2007 to 2014 are summarized in Table S1,
31 and the derived total statewide emissions have ranged from 1.2-2.3 times higher than the CARB
32 anthropogenic inventory. Similarly, top-down studies have been used to estimate CH₄ emissions
33 in sub-regions of California (Table S2), which contain the largest methane sources in the state,
34 including the South Coast Air Basin (SoCAB), the San Joaquin Valley (SJV), the San Francisco
35 Bay Area (SFBA), and the Sacramento Valley (SV). The SoCAB and SFBA represent the
36 significant urban regions and the SV contains both urban and agricultural sources. The SJV, on
37 the other hand, is predominantly covered by agriculture activities and oil and gas production.

38 Most of current top-down studies rely on data from a single measurement platform. Each platform
39 has its own advantages and limitations in constraining emissions. For instance, aircraft and satellite
40 platforms have good spatial coverage, but aircraft platform deployment is restricted by expensive
41 flight time and is limited to a few days a year, rendering the results as essentially daily snapshots.
42 Similarly, most satellites provide only a once-a-day measurement window, and even the satellites
43 that have better temporal resolution are still limited in spatial resolution and the precision
44 necessary to resolve sources in complicated source domains, such as the SJV. Long-term tower
45 measurements have traditionally played an important role in constraining regional emissions.
46 However, these networks are generally expensive to site, expand, and operate, which renders a
47 dense implementation impractical. Therefore, applying a multi-modal data platform could be a
48 useful approach to obtain more comprehensive information about spatial and temporal resolution
49 of emission sources in a region. Additionally, analysis using a single campaign or one year of data
50 can be affected by year-to-year temporal and seasonal shifts, such as annual rain and drought
51 events. A multi-year study can provide a more comprehensive evaluation of the inventories and
52 help us better understand the emission sources in the state.

53 In this study, we conducted a multiplatform inversion analysis to estimate California annual CH₄
54 emission estimates for a three-year period from 2014 to 2016, using three different datasets. The
55 study framework optimized statewide CH₄ emissions by adjusting CH₄ surface fluxes from the
56 prior inventory to better simulate observed atmospheric CH₄ mixing ratios. The three different
57 datasets include two tower monitoring networks which provide continuous high temporal quality

58 data, as well as a series of aircraft measurement campaigns which provide additional spatial
59 coverage to complement the stationary measurements. We conducted six modeling scenarios to
60 conduct a set of analysis and further derived ensemble inversion estimates with 18 ensemble
61 members by combining the six scenarios with the initializations from three different prior
62 inventories to incorporate the uncertainties in the inverse system. It is the first time that such an
63 analysis has been conducted by using multiple measurement platforms and different prior
64 inventories for multiple years to constrain top-down CH₄ emissions in California.

65 **Materials and Methods**

66 **Tower- and aircraft-based measurements.** This research effort was primarily built around long-
67 term, high quality measurement data collected at a Statewide GHG Monitoring Network operated
68 at multiple regional sites across California by CARB. This network is the first state-operated
69 network of its kind, which provides long-term measurements of atmospheric GHG mixing ratios
70 in California since 2010 with short time intervals (1-5 seconds, depending on site and specific
71 analyzer) and wide spatial coverage (eight towers in the state). The network operates regionally
72 representative monitoring stations throughout the state: two towers in the SV, one in the SFBA,
73 three in the SJV, and two in the SoCAB (Figure 1 and Table S3). All sites of the network conduct
74 continuous ambient air measurements using cavity ring-down CH₄ analyzers with temperature and
75 pressure control (Picarro Inc, Models 1301, 2301 and 2201-i). The systems use permeation tube
76 gas sample driers to dry the intake air and automated drift check and periodic calibration to track
77 accuracy and precision of the instruments. All sites were calibrated with standard reference gases
78 with mixing ratios on the WMO X2004A scale provided by NOAA ERSI's central calibration
79 laboratory⁹. Details about the Statewide GHG Monitoring Network are included in Supporting
80 Information (S1).

81 We also applied other available research measurements to improve the spatial and temporal
82 resolutions, and better quantify the regional and sectoral distribution of CH₄ emission sources in
83 California. This included airborne and tower-based research measurements which occurred during
84 the same time period (Figure 1), including the Megacities Carbon Project (MCP)¹⁰⁻¹², and NASA's
85 AJAX)¹³⁻¹⁴.

86 The MCP network was started in 2012, and now includes 13 tower/rooftop sites to conduct
87 continuous measurements of CH₄ mixing ratios in the Southern California region. Two of these
88 sites (Mount Wilson (WMO) and San Bernardino (SBC)) belong to the CARB's Statewide GHG
89 Monitoring Network. Three of these sites are considered as the background sites including the San
90 Clemente Island (SCI), Victorville (VIC), and La Jolla (LJO). VIC is deployed mainly to track
91 easterly flow impacted by out of state sources. LJO is located nearby the coast and impacted by
92 on-shore and off-shore flows and potentially provides ocean background information after a
93 precision screening. In this study, we used data from the SCI site as the local background in
94 SoCAB for 2015 and 2016, similar to Yadav et al¹². To run the inversion analysis, we used data
95 from six of these sites together with CARB sites which were operational during the time period of
96 interest (2015-2016) (Figure 1 and Table S3). We excluded two sites (Granada Hills (GRA) and
97 Irvine (IRV)) in the inversions considering they were greatly influenced by local landfills.
98 Additional inversion studies with GRA and IRV data could be included in future work after careful
99 data screening.

100 Twelve AJAX flights were deployed and measured CH₄ mixing ratios over the SFBA and the
101 northern SJV during 2013 and 2014. In the study, we focused on the data from six AJAX flights
102 in summer and fall 2014 (15 July, 25 July, 8 October, 15 October, 24 October, and 11 November)
103 (Figure 1). AJAX flights measured CH₄ mixing ratios using cavity ring down spectroscopy
104 (Picarro Inc., model 2301-m) calibrated regularly to NOAA standard gases, and the data were
105 screened for quality and to extract measurements that were taken in or near the planetary boundary
106 layer (PBL) (<2.5 km above ground level). Additional details on the airborne instrumentation and
107 its deployment in the 2014 campaign have been described elsewhere¹⁵⁻¹⁶.

108 The study analysis focused on tower-based CH₄ measurements obtained during afternoon hours
109 (12-17 Pacific Standard Time (PST)) alone. This was driven by the consideration that the
110 atmospheric boundary layer is well developed during late morning and early afternoon hours, so
111 that the measurements result from surface CH₄ emissions which are then well mixed in the
112 boundary layer. Moreover, the meteorological model generally captures the daytime atmospheric
113 boundary layer, but has difficulty simulating the nocturnal boundary layer after the boundary layer
114 collapse¹⁷. Therefore, by focusing on the late morning and early afternoon hours, we reduced
115 uncertainties to simulate back-trajectories in the tower receptors for several hours.

116 We aggregated the hourly tower-based measurements during 12-17 PST into the 3-hour intervals
117 to run the inversions of statewide annual CH₄ emissions for better computational efficiency. We
118 aggregated measurements of airborne-based CH₄ measurements taken from the AJAX field
119 campaign into 30 second intervals for the inversions, similar to Cui et al¹⁸⁻¹⁹ (Figure 2).

120 **Background determination.** We used the zonal averaged CH₄ mixing ratios during 2014-2016
121 between 35° and 43° from NOAA Greenhouse Gas Marine Boundary Layer Reference data²⁰ to
122 define the backgrounds of CH₄ mixing ratios for the tower sites located outside of the SoCAB and
123 for the aircraft receptors (Figure 2). Measurements from a remote site (Trinidad Head (THD),
124 figure 1) were used to determine the background uncertainty in the inversion analysis. Hourly
125 CH₄ backgrounds determined by measurements at the SCI site (Figure 1) were used for deriving
126 mixing ratio enhancements for tower sites in the SoCAB. The details of hourly background mixing
127 ratios determination in the SoCAB are available in Verhulst et al¹⁰. We also used the NOAA zonal
128 mean values to determine the background data for 2014 for the two sites (WMO and SBC) in the
129 SoCAB region before MCP network was fully implemented.

130 **Atmospheric transport.** CH₄ was treated as a passive atmospheric tracer and the transports of
131 CH₄ from the surface fluxes to the ambient atmosphere was simulated by the FLEXible PARTicle
132 (FLEXPART) Lagrangian particle dispersion model²¹ driven by the Weather Research and
133 Forecasting (WRF²², version 3.7.1) mesoscale model. Back-trajectories from FLEXPART-WRF
134 provided the sensitivities of gridded surface CH₄ fluxes to measured CH₄ mixing ratios, which are
135 called the “footprints” (Text S1). WRF model simulations were conducted with three nested
136 domains at the spatial resolutions of 36km, 12km, and 4km, respectively. The WRF configuration
137 (Text S1) is similar to Cai et al. ²³⁻²⁴, which was used for air pollution simulations in California.
138 To conduct the long-term simulations in WRF, we made the following modifications to the WRF
139 configuration: 1) setting the WRF simulation timescale to a 6-day period, with the 1st day as model
140 spin-up; 2) applying the WRF objective analysis for the outermost domain in the study; 3) using
141 the Pleim-Xiu land-surface model²⁵⁻²⁶ to all of WRF domains to improve the first guess fields
142 based on analysis data; 4) turning off the topographic surface wind correction in the innermost
143 domain; 5) modifying the top layer of the vertical structure from 50 hPa to 100 hPa with the same
144 number of the vertical layers; 6) updating sea surface temperature (SST) every 6 hours using time-
145 varying Global Ocean Data Assimilation Experiment High Resolution SST data; and 7) initializing

146 the soil moisture in the Pleim-Xiu land-surface model with surface moisture availability look-up
147 table for April through October, and with analysis data for other months.

148 WRF performance has been evaluated by Cai et al.²⁴ for vertical distribution of temperature,
149 relative humidity, and wind speed using two-day aircraft measurements in the summer of 2008.
150 Good agreement between model and observations was found near surface. Additionally, the same
151 model configuration was used to simulate ozone in the SJV during May-September 2012²⁷, and
152 the long-term model simulations captured the meteorology, i.e. wind speed, temperature, and
153 relative humidity, reasonably well based on observations. Here we further evaluate WRF PBLH
154 simulations using PBLH retrievals using available measurements from radiosondes, radar wind
155 profilers, ground-based LiDAR instruments²⁸, and aircraft soundings during 2014-2016.
156 Additional details are available in Supporting Information (Text S1). The mean biases of simulated
157 PBLH during 12-17 LT were within 13-316 m or 2-65% of the measurement-determined PBLH
158 on average. In addition to model errors, the biases also include the uncertainty from determining
159 PBLH based on these observation platforms.

160 Simulations from the WRF's innermost domain were used to drive FLEXPART and map the
161 footprints to a 0.1 x 0.1-degree spatial resolution consistent with the gridded prior inventories as
162 discussed as below. Each hourly data point from the CARB's Statewide GHG Monitoring Network
163 (2014-2016) and MCP (2015-2016) during 12-17 PST was considered as a receptor. FLEXPART
164 was configured to release 5000 particles at the height of receptors and model the transport of the
165 particles backward in time for 3 days for each receptor of the CARB's Statewide GHG Monitoring
166 Network, and 1 day for each receptor of the MCP. The back-trajectories were also aggregated into
167 the 3-hour intervals for the inversions. For the aircraft measurements, we consider each 30-second
168 averaged data point as a receptor, and we simulated 1-day back-trajectories for each receptor. The
169 duration of backward simulations was chosen based on some sensitivity tests (Text S1).

170 As observed from the footprint analysis, each data platform offers a unique footprint (Text S1).
171 The MCP network focuses on the SoCAB region, and the AJAX flights provided insights in the
172 SFBA and northern SJV regions, while the CARB network provided an overall statewide coverage
173 but has limitations in providing comprehensive regional and local coverage for all source sectors.
174 We ran a variety of cases which combined monitoring data from the different available platforms

175 and identified the dataset in each region which provided the highest footprint coverage (Table S4).
176 These cases were considered as the optimum regional case and we showed their values
177 independently.

178 **Prior inventories.** This study utilized two available gridded CH₄ emission inventories for
179 California for calendar year 2012 as the original prior inventories (Figure S2). The first inventory
180 was obtained from the spatially explicit CALGEM emission model (CALGEM, version 3, 2016),
181 after scaling to match the CARB statewide inventory total by region and emission sector². The
182 second inventory was obtained from a gridded national inventory of U.S. methane emissions²⁹
183 which is designed to be consistent with the 2016 edition U.S. Environmental Protection Agency
184 (EPA) inventory of US Greenhouse Gas Emissions and Sinks (GHGI)³⁰ for the year 2012, from
185 which the emissions data for California region was spatially extracted (hereafter “EPA-GHGI”).
186 Both of these inventories were gridded at 0.1 x 0.1-degree spatial resolution, and the annualized
187 aggregated emissions were extracted for the annual emission analysis in the study. The sectors of
188 wetland and crop agriculture have seasonal variations in CALGEM and the sectors of manure
189 management, natural gas and petroleum production, stationary combustion, and forest fires have
190 monthly/daily variations in EPA-GHGI. However, due to the lack of California-specific seasonal
191 factors for many of the anthropogenic sources, which have been found to have seasonal variation,
192 such as livestock, landfill, and natural gas demand^{12, 31-32}, we thereby did not configure our
193 inversions to include the temporally varied priors. The overall prior simulations were evaluated
194 and the analysis suggested that observations were underestimated by model prior simulations with
195 absolute mean biases ranging between 24-45 ppb, and the coefficient of determination (R²) values
196 ranging from 0.3-0.4 (Figure S3).

197 We also conducted a multivariate analysis by combining the different sector groups from the two
198 inventories in different combinations to construct a hybrid inventory that would provide the
199 additional spatially-resolved prior information. The hybrid inventory which offered the highest
200 R² in simulating CH₄ concentration against the observations was chosen (“Hybrid prior”) (Text
201 S1). Thereafter, the two original inventories and the third hybrid inventory were used as the prior
202 information to initialize the inverse modeling system, and the posterior estimates were compared
203 against the prior to identify the inversion scenario which showed the most improvement. Since

204 CARB publishes a statewide total CH₄ emission inventory, we also compared these posterior
205 statewide estimates against the CARB inventory.

206 Based on the selection of our hybrid inventory, we found the differences between the hybrid
207 inventory and CALGEM were mainly from the dairy livestock (DLS) and the oil and natural gas
208 (ONG) sectors. The optimized hybrid inventory utilized the higher emissions from EPA-GHGI for
209 the DLS and ONG sectors, which are higher than the CALGEM inventory by 19% and 3%,
210 respectively. It should be noted that this analysis does not suggest that the hybrid inventory is the
211 best prior inventory, however, it adds another dimension to reducing the prior inventory
212 uncertainty in the inverse system and can be used to better understand the emission sectors in the
213 region.

214 **Inverse modeling framework.** The statewide CH₄ top-down emissions were derived using a
215 mesoscale Bayesian inverse modeling system. This system was consistent with the framework
216 published by Cui et al.^{18, 33-34} (Text S1). The study implemented a series of inversion cases to
217 conduct inversion analysis for the statewide total CH₄ emissions during 2014-2016. The
218 descriptions of the inversion cases are shown in Table S7. “2014_Inv”, “2015_Inv”, and
219 “2016_Inv” were conducted using CH₄ mixing ratio measurements from the CARB’s Statewide
220 GHG Monitoring Network. These cases were also useful to investigate the capabilities of the
221 current CARB GHG Monitoring Network to constrain the statewide CH₄ emissions.
222 “2015_Inv_urban” and “2016_Inv_urban” were conducted by adding the MCP monitoring
223 network data in the SoCAB to the CARB’s Statewide GHG Monitoring Network data. In addition
224 to estimating the statewide emissions, these two cases were also useful to investigate the utility of
225 a regional intensive urban network in improving the regional CH₄ emission estimates. In addition
226 to the above scenarios, we also tested a case which combined data from the AJAX campaign with
227 the CARB’s Statewide GHG Monitoring Network data for calendar year 2014 (“2014_Inv_flight”)
228 to investigate the utility of adding aircraft measurements with a large spatial coverage to a regional
229 monitoring network.

230 **Results and discussion**

231 **Statewide total CH₄ emission estimates.** We conducted multi-platform inversions to derive top-
232 down statewide CH₄ emissions based on the 18 combinations (6 datasets and 3 prior inputs) of
233 measurement networks and a-priori emission inventories during 2014-2016. Figure 3 shows the
234 inversion results from the 18 individual cases, along with ensemble estimates for each year, as well
235 as the overall ensemble estimate for the 2014-2016 period. The maps of differences between the
236 posterior and prior estimates are shown in Figure S10. We also computed the statewide maps
237 related to the Fisher information matrix¹⁸ to investigate the emissions constrained by the
238 observation platforms within the inverse modeling system (Figure S11). The regions associated
239 with high values of the diagonal of Fisher information matrix represent the areas of the domain
240 that are well constrained by the observations. More ensemble estimates are presented in Table S8
241 from the three types of measurement platform and the three types of prior inventories.

242 For each case, we compared the CH₄ observations used in the inversions (single platform or
243 multiple platforms) against simulated CH₄ concentrations using the prior inventory and the
244 posterior estimates, respectively (Table S9). R² and the mean biases (model minus observation)
245 are used to highlight the improved data-model fit given by the posterior emission estimates. For
246 cases using the tower platforms (“CARB towers”, and “CARB towers + MCP towers”), the R² are
247 improved from 0.1-0.4 based on the prior inventory to 0.3-0.4 based on the posterior estimates. R²
248 values related to the cases of “CARB towers + AJAX flights” fall within the value of ~0.3 using
249 the prior inventory originally and are also slightly improved in the posterior estimates. Moreover,
250 the mean biases in all of cases decreased distinctly using the posterior estimates compared to the
251 cases with the prior inventory in the study as expected.

252 In Figure 3, we compared the study results against the bottom-up annual CH₄ emission estimates
253 from the CARB inventory for the three years (2014-2016), and showed the range of research
254 emission estimates reported in the literature for statewide CH₄ emissions. We also compiled the
255 annual emission estimates from CALGEM and EPA-GHGI for 2012 for comparison. We calculate
256 the top-down statewide CH₄ emission inventory in California to be 2.05±0.26 Tg/yr (at 95%
257 confidence) based on our 18 different inversions in the study. There is no significant change in
258 statewide CH₄ emission estimates from the CARB inventory during 2014-2016, and the three-year
259 averaged statewide CH₄ emissions were 1.57 Tg/yr. This suggests that the inversion analysis of
260 the CH₄ emissions in California are larger than the CARB inventory by a factor of 1.14-1.47. They

261 are also higher than CALGEM estimates by a factor of 1.0-1.4, and slightly higher than EPA-
262 GHGI by a factor of 0.9-1.2. Although there are differences in the total emission estimates for the
263 subsets of ensemble analysis, the overall values are consistent within the uncertainty (Figure 3).
264 Previous top-down studies have estimated statewide total CH₄ emissions to be 1.51-3.70 Tg/yr
265 (Table S1), therefore, the emissions estimated in this study fall within the range of previous studies
266 but are on the lower end of the spectrum, and is also consistent with our conservative assumption
267 in the inversion framework setup (see Text S1).

268 CARB bottom-up CH₄ inventory only focuses on anthropogenic sources, whereas the top-down
269 inversions derive total CH₄ emissions. Emissions from natural sources of CH₄ in California, such
270 as petroleum seeps³⁵⁻³⁶ and wetlands³⁷ could partially contribute to the differences between the
271 bottom-up inventory and top-down estimates. California wetland emissions are estimated to be
272 0.04 Tg/yr³³, while La Brea Tar Pits (the large petroleum seep) were estimated to be emitting 0.06
273 Tg/yr³⁸. Together with other excluded emissions (0.11 Tg/yr) in the CARB inventory² likely
274 contribute 15%-50% of the discrepancies between the CARB inventory and our inversions. In
275 addition, other contributions from “super-emitters”³⁹⁻⁴¹, episodic emission events⁴², other un-
276 inventoried sources, as well as the use of non-region-specific generalized emission factors may be
277 underestimating actual emissions and could contribute to the differences.

278 There are some differences between the results from cases for the three different platforms (Table
279 S8) in terms of the central value of ensemble results. The change between “CARB towers” and
280 “CARB towers + AJAX flights” due to the addition of the measurements from NASA AJAX
281 flights modifies the emission estimates in Northern California. On the other hand, The estimates
282 from “CARB towers + MCP towers” case present higher total statewide CH₄ emissions compared
283 with the cases of “CARB towers”. These differences are primarily driven by changes in CH₄
284 emission estimates in the SoCAB region where the MCP network was deployed. Additional
285 regional differences are explored in detail in the next sections.

286
287 **Sub-regional CH₄ emission estimates.** This study was able to extract CH₄ emission estimates in
288 the sub-regions to analyze their contributions to the statewide CH₄ emissions in California, using
289 spatially resolved inversion estimates (Figure 4 and Figure S14). In general, our ensemble

290 inversion estimates in the study by region fall into the range of previous top-down studies.
291 Comparing inversion estimates in the study with the two gridded inventories, we found CH₄ budget
292 estimates from EPA-GHGI and this study are closer in the Central Valley (SJV and SV) than
293 CALGEM, but CALGEM estimates and this study are closer in the SoCAB region. CH₄ emission
294 estimates for SFBA likely are underestimated by the current two bottom-up inventories.

295 **South Coast Air Basin.** The footprint values in Table S4 show that the “CARB towers + MCP
296 towers” cases provide additional information to constrain SoCAB emissions beyond the “CARB
297 towers” cases. In the maps calculated by the Fisher information matrix for the SocAB (Figure S11),
298 we also can compare the sensitivity of two tower sites (MWO and SBC) used in the “CARB
299 towers” cases against the sensitivity offered by eight towers used in the “CARB towers + MCP
300 towers” cases. The larger coverage associated with the higher values of the Fisher information
301 matrix in the “CARB towers + MCP towers” cases indicate the importance of the MCP deployment,
302 and CH₄ emissions in SoCAB were better constrained by the addition of data from the MCP
303 platform.

304 We estimated CH₄ emissions in the SoCAB during 2014-2016 to be 0.39 ± 0.18 Tg/yr, which is
305 higher than the corresponding estimates from the CALGEM (0.349 Tg CH₄/yr) by a factor of 0.6-
306 1.6, and higher than EPA-GHGI (0.257 Tg CH₄/yr) by a factor of 0.8-2.2.

307 The exceptional gas leak event at Aliso Canyon took place during October 2015 to February 2016⁴².
308 A CARB report quantified the CH₄ emissions from the leak event and estimated that 0.0996 Tg
309 CH₄ was emitted into the atmosphere during the event, with 0.0784 Tg CH₄ released in 2015 and
310 0.0212 Tg CH₄ released in 2016³⁸. We estimated the total CH₄ emissions to be 0.36 ± 0.08 ,
311 0.42 ± 0.22 and 0.38 ± 0.20 Tg/yr for the years of 2014, 2015, and 2016, respectively. We did not
312 specially exclude the measurements during the event period in the inversions, therefore, the higher
313 estimates for CH₄ emissions in 2015-2016 than the value in 2014 may due to the Aliso Canyon
314 event. The difference of estimates in 2015-2016 against estimates in 2014 is comparable with the
315 contribution of the Aliso Canyon event reported by CARB and Conley et al⁴². This also indicates
316 that top-down studies capture all the emissions from all the sources in a region, including episodic
317 events. Therefore, additional caution and caveats should be considered in direct comparisons

318 against generalized bottom-up inventories that are not corrected for regions and time periods of
319 interest.

320

321 **San Joaquin Valley.** According to the ensemble inversions, The total CH₄ emissions in the SJV
322 were quantified to be 0.94±0.18 Tg/yr, which is higher than CALGEM (0.78 Tg/yr) by a factor of
323 1.0-1.4, and higher than EPA-GHGI (0.90 Tg/yr) by a factor of 0.8-1.2. Two independent top-
324 down studies from Jeong et al.² and Cui et al.¹⁹ have quantified CH₄ emissions based on tower
325 network and aircraft measurements respectively in the same region, and our results in this study
326 are within the range of previous estimates.

327 In evaluating the spatial coverage and effective constraints offered by the current monitoring
328 network (Figure S1 and Figure S11), the region with the lowest constraints was observed in the
329 southern SJV, with gaps in Tulare, Kings, Fresno, and Madera counties – all of which contain large
330 agricultural sources. These regions stand out as the highest priority for network expansion in the
331 entire state. Adding additional measurements in SoCAB from MCP did not provide any additional
332 improvement for the SJV domain given the topographical constraints offered by the mountainous
333 region at the confluence of SoCAB and SJV which significantly limit wind flows between the two
334 regions.

335 **Sacramento Valley and San Francisco Bay Area.** We also estimated annual CH₄ emissions for
336 the SV and SFBA areas (Figure 4). Based on the ensemble results, we estimated CH₄ emissions in
337 SV to be 0.21±0.04 Tg/yr, which is 1.0-1.5 and 0.7-1.1 times the CALGEM (0.17 Tg/yr) and EPA-
338 GHGI (0.23 Tg/yr) inventories, respectively. Similarly, the ensemble emissions range of CH₄
339 emissions in SFBA was estimated to be 0.16±0.05 Tg/yr, which is 0.8-1.5 times the corresponding
340 CALGEM (0.14 Tg/yr) and EPA-GHGI (0.14 Tg/yr) inventories. Future work in these areas is
341 necessary, although they are not the largest contributors to the statewide CH₄ emissions.

342 Overall, the multiplatform inversions of the regional CH₄ emissions are consistent with observed
343 regional “hotspots” by SCIAMACHY satellite⁴³⁻⁴⁴ and an aircraft campaign⁴⁵. The suite of
344 inversions compared with previous studies also supports the robustness of our inverse modeling in
345 conducting spatially resolved analysis.

346 **Temporal variation.** We presented the inter-annual and monthly variation of CH₄ emissions based
347 on the posteriors estimates (Figure 3 and Figure S12-S13). First, we did not observe the significant
348 annual variability for the statewide and regional CH₄ emissions during 2014-2016. This flat trend
349 was partly expected, as there weren't any major new regulations or programs in the state during
350 the period of the study, which also were considered in the similar drought condition. For the
351 SoCAB the Aliso Canyon event could explain the enhancements in 2015-2016, especially the year
352 of 2015. The monthly variation of the statewide CH₄ emissions appeared in the posterior estimates,
353 such as the enhanced emissions shown in summer and winter. The enhancements in summer may
354 attribute to the livestock manure management and landfills, and the winter enhancements could
355 attribute to the natural gas demand. For the SV, the rice cultivation could explain the enhancements
356 in summer months. The monthly patterns are relatively complicated and unclear in SoCAB, SFBA,
357 and SJV. Nevertheless, it should be noted that the associated large uncertainties degrade the
358 temporal variation analysis. In the study, the current inversion configuration has limitation to
359 inversely resolve the monthly variability of CH₄ emissions due to the static priors, the large model
360 uncertainty, and the limited sensitivities of the current GHG monitoring network to some of sources
361 which may have the temporal variation.

362 **Sectoral CH₄ emission estimates.** Sectoral emission estimates are very important for accurate
363 emission quantification, robust analysis of emission trends, and effective identification and
364 implementation of mitigation strategies. Although an inversion study encounters substantial
365 challenges in quantifying sectoral emissions due to the uncertainties from the transport model and
366 the prior estimate at such small scales, the processes of inverse modeling studies can provide
367 information to understand sectoral emissions in certain scenarios. For instance, inverse modeling
368 can be used to understand sectoral emissions in sub-regions which have relatively distinct spatial
369 distributions of emission sectors, such as the SJV. Therefore, we further analyzed the data for the
370 SJV to evaluate the sectoral emission distributions in the region. Similar analyses were difficult in
371 SoCAB, SFBA, and SV, where the sectors are collocated within the spatially resolved estimates
372 for the regions.

373 As the two largest emission source sectors in the SJV, emissions from the dairy sector and the oil
374 and natural gas production subsector were estimated individually in the study. Moreover, these
375 sectors in the SJV are relatively isolated geographically. Cui et al.¹⁹ combined the extra spatial

376 information of the two major sources with the inversion results to obtain their contributions
377 independently. In this study, we used the same spatial information and the source contribution
378 analysis as Cui et al.¹⁹ to calculate the sectoral CH₄ emissions in the SJV based on our multi-
379 platform inversions.

380 According to the inversions, we derive the total emissions of the dairy and the production of ONG
381 sectors in the SJV to be 0.44±0.36 and 0.22±0.23 Tg CH₄/yr, respectively (Table S10). Based on
382 the same geographical locations, CH₄ emissions from the dairy and the ONG production subsector
383 are estimated by CALGEM to be 0.66 and 0.05 Tg/yr, while EPA-GHGI estimates them at 0.28
384 and 0.27 Tg CH₄/yr, respectively. As another source of comparison, we note that the analysis of
385 California ONG emissions by Jeong et al.⁴⁶ estimated SJV ONG emissions of 0.17 Tg CH₄/yr,
386 roughly midway between the CARB and EPA-GHGI estimates. The distinct differences in spatial
387 patterns between the two prior inventories account for the large uncertainties in our posterior
388 estimates. Specifically, to evaluate the CARB inventory, we focused on the posterior results
389 against the corresponding prior (CALGEM that is scaled to the CARB inventory), the dairy sector
390 is 100%-115% of the prior, which suggests that emissions from the dairy sector may be
391 underestimated in the CARB inventory, whereas the ONG production subsector is similar to the
392 prior estimates. Overall, the large uncertainties associated with the posterior estimates suggest that
393 the current tower network in the SJV likely limits the sectoral emission analysis.

394 The sectoral emission estimates have been investigated by a previous study (Cui et al.¹⁹), which
395 used airborne measurements to quantify the emissions of the DLS and ONG sources (103 ±29 and
396 24±11 Mg CH₄/hr, respectively) for summer 2010. Within the uncertainties, our results for the
397 emissions from the ONG production sector are comparable with Cui et al.³³. We could not directly
398 compare the annual emission rates derived in the study with the values from the short-time aircraft
399 study. Overall, the results emphasize that additional measurements and studies are required for
400 understanding the dairy emission estimates in the SJV.

401 **Implications.** Long-term measurements of CH₄ mixing ratios play a significant role in developing
402 a consistent and comprehensive analysis of statewide CH₄ emissions, and in tracking the
403 effectiveness of CH₄ emission reduction strategies. Additionally, top-down studies with robust
404 atmospheric measurements can provide a timely review of real-world inventory trends and the

405 effectiveness of emission reduction measures as we reach climate target years. This study used an
406 inverse modeling analysis approach on a multi-year dataset collected from a first-of-its-kind
407 statewide GHG monitoring network and other complementary datasets to evaluate the statewide
408 and regional methane emissions in California. The data and the analysis were useful to provide an
409 independent broad review of the emission estimates in the state and suggest areas of improvement
410 for emissions research as well as network expansion/optimization. The analysis suggests that the
411 total top-down statewide methane emissions are higher than the bottom up anthropogenic
412 emissions estimates by 14-47%, which is consistent with earlier published results in the
413 literature. Some of this discrepancy is likely due to contributions from natural and biogenic
414 sources that are currently not included in the inventory, since they are out of the scope of
415 regulations. Some additional emissions are expected to be contributions from methane super-
416 emitter point sources, and other episodic events. The points to the need for additional source-
417 specific and sector-specific emissions research to better quantify and inform the bottom-up
418 inventories, including research for better California-specific activity and emission factor
419 information for dairy, landfills, and the oil/gas sector, which needs other top-down measurement-
420 based methods or model-based methods with much finer resolution. Overall, a hybrid spatial
421 inventory with landfill and oil/gas sector emissions from EPA-GHGI and the dairy and other sector
422 emissions from CALGEM provided the best optimized model performance. Regionally, the SJV
423 has the largest concentration of methane emission sources with roughly 50% of the statewide
424 CH₄ emissions, followed by the SoCAB, SV and SFBA. The dairy sector is the single largest
425 source in the SJV and is roughly twice as large as the next largest emissions source, the oil and
426 natural gas production subsector. The analysis also identifies the highest priority region to expand
427 the monitoring network, as well as points to additional analytical opportunities to better understand
428 the emission sectors in the state.

429 **Next steps.** CARB has started expanding the GHG monitoring network and plans to add three
430 additional stations in the SJV (Figure S15). CARB is also using the analysis products to add two
431 special monitoring stations in the state, with capabilities to conduct ongoing real-time
432 measurement and analysis of Volatile Organic Compounds and several fluorinated gases. This data
433 is expected to be useful to conduct source apportionment analysis to analyze and track the various
434 GHG emissions source sectors. Additionally, CARB is deploying a statewide ceilometer network

435 to monitor PBLH to evaluate and improve atmospheric transport model simulation. Similarly,
436 continuing airborne measurements will provide valuable data to estimate GHG emissions at
437 multiple spatial and temporal scales for sub-regions, and will be useful to investigate individual
438 source sectors.

439

440 **Supporting Information**

441 Additional information about the CARB GHG monitoring network, the WRF configuration,
442 FLEXPART-WRF footprints, inverse modeling framework, PBLH evaluation, simulating time in
443 FLEXPART-WRF, hybrid prior inventory, sectoral analysis for San Joaquin Valley, sub-region
444 CH₄ emission estimate, and acknowledgement; Figures S1-S17; Table S1–S10.

445

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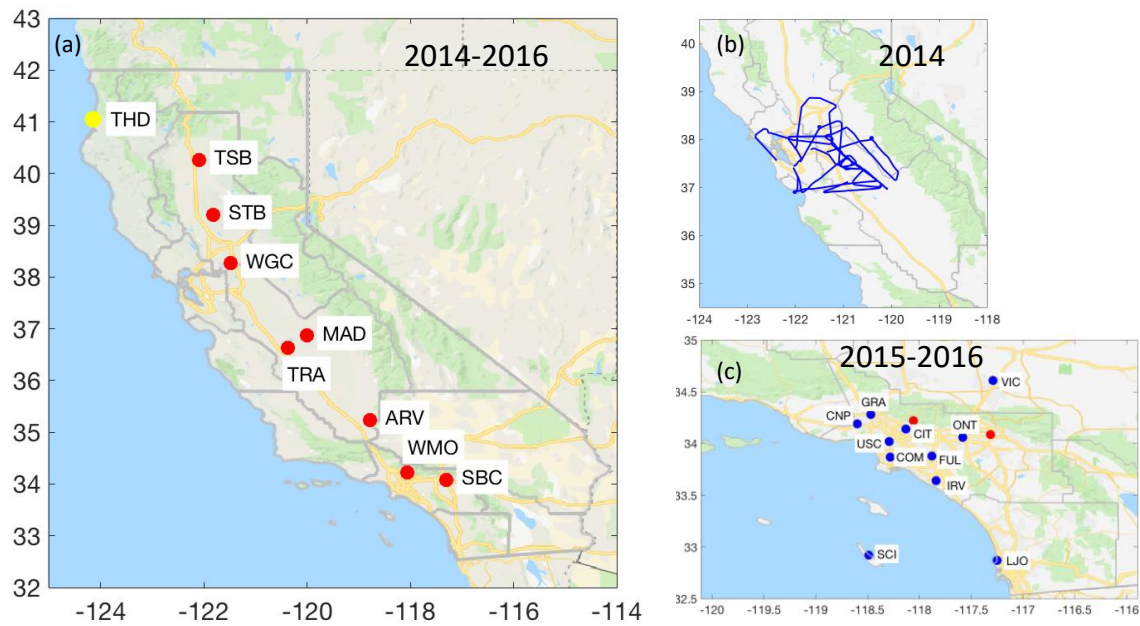


Figure 1. The maps with the locations of the stationary network sites (blue and red dots) and flight path (blue lines) where CH₄ measurements were obtained for the 2014-2016 period.

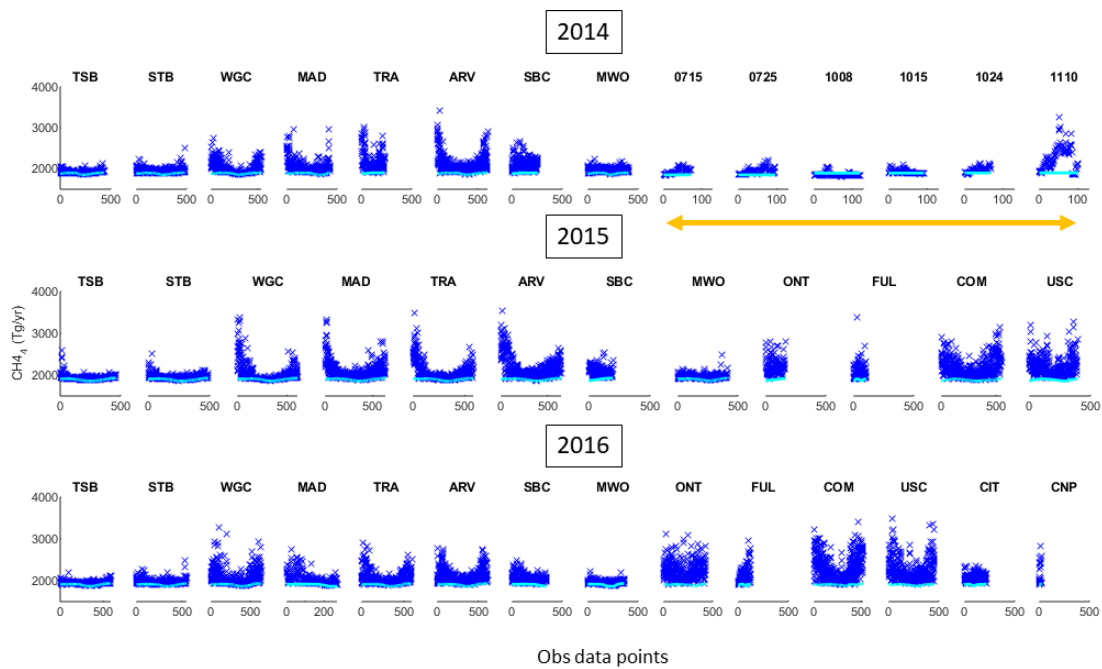


Figure 2. Combined 3-hour averaged CH₄ mixing ratios used in inversions from up to 14 tower sites (blue) and aircraft measurements for 2014-2016 respectively, together with the background values determined in the study (green). Data points marked by the double-headed orange arrow are aircraft measurements.

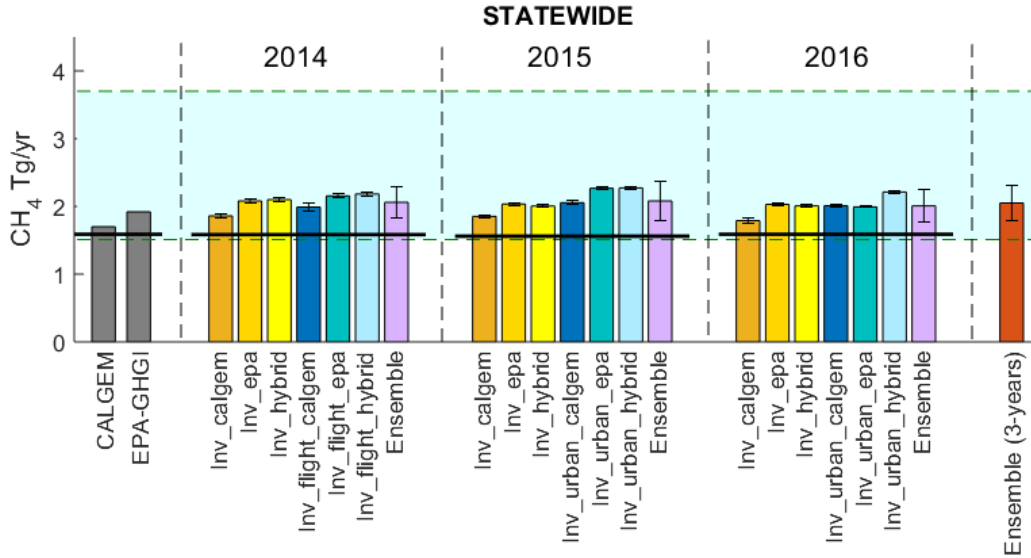


Figure 3. The annual CH₄ emission estimates during 2014-2016 in California derived from this study. The bottom-up inventories (CALGEM version3 and EPA-GHGI) for 2012 are shown as well. The shaded region in light-green represents previous top-down studies listed in Table S1 within the uncertainty analysis (lower and upper bounds are marked as green dashed lines). In addition, the values of black lines are annual CH₄ emission estimates from the CARB inventory. Ensemble values are from 6 members for each year and the 18 members for 3 years. The uncertainty calculated in each inversion case is structured in 1-sigma, and the uncertainties of ensemble results are presented at 95% confidence (2-sigma).

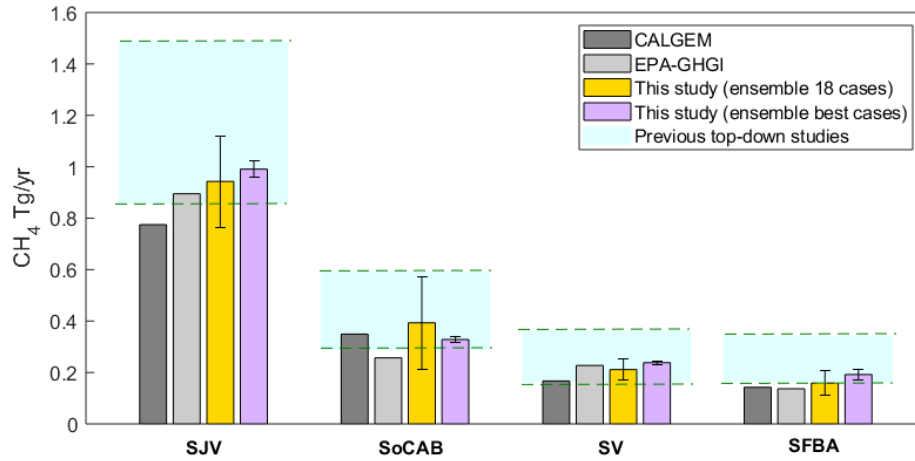


Figure 4. Sub-regional CH₄ emission estimates from our ensemble inversion results of all cases or of cases associated with best footprint coverages, respectively, compared with two gridded bottom-up inventories used in the study. The shaded region in light-green represents previous top-down studies. Inversions in the study include estimates of the exceptional gas leak event at Aliso Canyon. The uncertainties of ensemble results are presented at 95% confidence (2-sigma).

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