Methane Super-Emitters in California's Oil Fields

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Methane Super-Emitters in California's Oil Fields

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Abstract

Methane is a potent yet underestimated contributor to global greenhouse gas emissions. We examined the characteristics of 255 sources of methane super-emitters identified by NASA's Airborne Visible/InfraRed Imaging Spectrometer-Next Generation in 109 California oil fields. Super-emitter events were primarily associated with oil & gas wells, gas gathering pipelines, and storage tanks (73% of sources). Sources with persistence of $\leq 20\%$ and $> 50\%$ comprised 77% and 1% of sources and contributed to 59% and 4% of the total measured emissions, respectively. We estimate total onsite methane emissions from 24 oil fields as 2.3 to 3.4 times the estimated rate by the current official lifecycle assessment model for California's Low Carbon Fuel Standard used for determining carbon intensity of crude oil production. These findings suggest that without considering direct observations of oil field methane super emitters, greenhouse gas emissions policy for the oil and gas sector is likely to underestimate emissions.

Methane (CH₄) is a potent greenhouse gas (GHG) with global warming potential (GWP) of 85 and 30 times of carbon dioxide GWP at a 20-year and 100-year horizon time scale.¹ CH₄ emissions associated with oil and gas production activities play a significant but still uncertain role in the global CH₄ budget ², despite the imperative to reduce emissions to limit climate change ³. Emissions are thought to be increasing, particularly in North America ^{2,4,5}. CH₄ emissions have been suggested as an obvious target for near-term climate mitigation efforts ^{6,7}, particularly fugitive emissions that are leaked unintentionally to the atmosphere during oil and gas extraction and use ⁸⁻¹⁰.

Over the last decade, direct measurements of CH₄ leaks by scientists have shown that the CH₄ emission rates from the oil and natural gas (NG) systems are larger than inventories published by states and federal agencies^{11,12,21,22,13-20}. Detailed studies suggest that one of the explanations for this discrepancy is failure to account for the disproportionate contribution of CH₄ “super-emitters”²³⁻²⁶. CH₄ super-emitters can account for a significant portion of the total CH₄ emissions²⁷, where 5% of leaks are typically responsible for over 50% of the total leaked volume²⁸. The definition of super-emitters is somewhat arbitrary. In a 2017 study of Barnett Shale’s natural gas infrastructure in Texas, the rate of 26 kg CH₄/h was chosen as the threshold to define super-emitters^{25,29}, where 1 % of the sites accounted for 44% of the total CH₄ emissions.²⁵ Super-emitters can occur due to fugitive emissions such as equipment leaks²⁵ and equipment malfunction^{25,30}, or intentional venting such as storage tank venting and compressor depressurization. Super-emitters can be persistent or intermittent, which adds to the complexity of measuring them given their variability in space and time^{22,25,28}. More frequent measurements are necessary to capture the super-emitters associated with occasionally malfunctioning equipment³¹. Investigating the causes of super-emitter behavior is a major challenge requiring detailed local observations and statistically robust sampling at the facility or equipment scales.

In this study, we took advantage of CH₄ plume imaging by the NASA/JPL Airborne Visible/InfraRed Imaging Spectrometer-Next Generation (AVIRIS-NG)³² that enables source-level attribution of CH₄ super-emitters while providing broad spatial coverage of California oil and gas fields. Previous work with AVIRIS-NG in California revealed the existence of CH₄ super-emitters across CH₄ emitting sectors, including oil and gas³³, but did not investigate the specific source infrastructure or temporal characteristics that were needed to inform mitigation policies. Here we present a detailed investigation of CH₄ super-emitters in oil fields in California, a domain where short-lived climate pollutants, including CH₄, are regulated by law^{34,35}.

We studied the characteristics of 255 sources of CH₄ super-emitters which were detected during the AVIRIS-NG aircraft campaign of 2016 to 2018 over 109 California’s oil fields. AVIRIS-NG’s detection limit is 2 to 10 kg CH₄/h³³, depending on environmental conditions. Within California oil fields, the minimum reported CH₄ emission rate was 24±17 kg CH₄/h; hence we referred to all the reported sources of CH₄ emissions as super-emitters. In this study, we considered only sources associated with petroleum production activities, including the production and processing of petroleum-associated NG and the NG-fueled power plants within the boundaries of oil fields.

The California Low Carbon Fuel Standard (LCFS) is one of the state's first GHG emissions regulations which includes CH₄ emissions for determining the carbon intensity of transportation fuels ³⁵. The California Air Resources Board (CARB) adopted Oil Production Greenhouse Gas Estimator (OPGEE), a life cycle assessment (LCA) model, for the California LCFS in 2012 ³⁵. OPGEE is used to estimate the carbon intensity of the production of crude oil as part of the transportation fuels pathway and has been updated several times ³⁵. Carbon intensity is stated in terms of an equivalent mass of carbon dioxide per energy content of the fuel (or fuel volume), including CH₄ and other related GHG emissions. Carbon intensity is an important parameter in developing GHG reduction policies and regulating its economy (e.g., carbon offset or carbon credits trade). The carbon intensity of fuel is calculated based on the many activities and their emission intensity through the fuel production pathway. Underestimating the extent of emission-related activities and their emission factors may result in underestimating the carbon intensity of fuels and ultimately undermining the effectiveness of the GHG reduction policy. It is crucial that the LCA models adopted by state and federal agencies are verified and improved by comparing them to other reliable data sources. Here, we developed a methodology to examine how OPGEE model's estimation of total CH₄ emissions from oil fields compares to new observations of CH₄ super-emitters observed by AVIRIS-NG observed and measured. We used the current version of the model (OPGEE 2.0c ³⁶), but our methodology is applicable to future updates of this model and conceptually to any other GHG LCA models, including CH₄ emissions.

Hereafter we referred to OPGEE as the “model” and to CH₄ emissions as “emissions” unless stated otherwise.

Source Attribution

We grouped the super-emitter sources into 10 general equipment categories (Figure 1a). Wells, pipes, and tanks categories accounted for 32%, 31%, and 19% of the total observed sources, respectively. Oil & gas wells accounted for 90%, and cyclic steam stimulation, water disposal, injection, and multi-purpose wells together accounted for 7% of the sources in the wells category. In the wells category, 50% were active wells, 10% idle wells, and 5% plugged wells. The status of 20% of the sources in the wells category was either active, idle, or plugged, which could not be determined with certainty because several wells with different statuses were located near the reported location of the emissions source. Unmarked wells accounted for 2% of the sources in the wells categories. The pipes category consisted of gathering pipelines, transmission lines, and process piping. Gas gathering pipelines accounted for 85% of the sources from pipes. The tanks

category included storage and processing tanks, with storage tanks accounting for 96% of all tank sources. Table S1 in the supplementary information (SI) document summarizes the equipment categories and subcategories that we determined for all sources.

The average emissions rates for the equipment categories ranged between 150 and 506 kg CH₄/h (Figure 1b). The average rates of emissions from all source equipment categories were of the same order of magnitude, and we observed high variance, with 8 equipment categories having a coefficient of variation (standard deviation divided by the average value) > 0.6. Figure 1b shows, that the average rates of measured emissions are relatively close for most equipment categories.

Expected Rates of Emissions and Detectability

We compared the measured rates of emissions to the expected range of emissions rates based on OPGEE model's adopted emission factors (EFs) at the equipment level. We used this comparison to determine the equipment categories which their emissions were detectable by AVIRIS-NG and to gain insight into possible process drivers of observed emissions (See SI and Methods; Table S2 and Table S3).

The ranges of measured emissions rates for oil & gas wells were close to the model estimated range of venting emissions due to well workover and cleanup activities (Figure 1b and Table S2). The model estimated rate of fugitive emissions from the wells was not detectable by AVIRIS-NG (Table S3). Five sources were identified as plugged oil & gas wells. Two of them were observed emitting in half of the repeated measurements (> 5 measurements), suggesting failing components could be responsible. Most of the sources in the wells categories were, however, active oil & gas wells. For example, Figure 2a shows 13 oil & gas wells in an oil field in Kern County and the average measured emissions rates. Eleven of these wells were active, and 2 could be either active or plugged.

The model estimated range of venting emission rates from cleaning pipelines (pigging) matched the range of the measured emission rates (Table S2). However, satellite images (Google Earth Pro 2016-2018) of the sources do not show any pig launching or receiving facility or any other equipment near the sources which could be responsible for these plumes. For example, the four CH₄ plumes observed along the gas gathering pipelines in Figure 2b, seem to be most likely due to pipe failure (leakage), considering the unlikely involvement of other equipment due to their layout and distance to the sources. According to the model's selected emission factor (EF), fugitive emissions from the gathering pipelines would not be detectable by AVIRIS-NG (Table S3). The

expected rates of CH₄ emissions from the venting of the oil storage tanks might be detectable depending on tank capacity (Table S2). Figure 3 shows CH₄ emissions from storage tanks in dense urban areas in Los Angeles. Venting and fugitive emissions from the gas dehydration and the fugitive emissions from acid gas removal units could be detectable by AVIRIS-NG depending on the volumetric flow rate of natural gas that they process (Table S2 and Table S3). All other modeled fugitive emissions, assuming they are emitted continuously, would not be detectable by AVIRIS-NG according to the model's adopted EFs (Table S3).

Number of Super-Emitters vs. Oil Production Rates

AVIRIS-NG surveyed 109 California oil fields in 2016-2018 and found CH₄ plumes in 37 of those fields. These 37 oil fields were responsible for 85% of California oil production in 2017 (

Figure M1). We focused on oil fields that were flown more than 5 times on different days, comprising 15 fields that had super-emitters and 9 that did not. These 15 oil fields produced 55% of the total crude produced in California and represented 82% of the 255 sources. In contrast, the 9 oil fields without plumes produced 1.5% of the oil in California in 2017. These 24 oil fields produced 20 to 60,000 bbl oil/day.

We calculated the source density of the super-emitter by dividing the number of observed super-emitter sources by the oil fields' infrastructure footprint area covered by AVIRIS-NG for each oil field (see Methods). The infrastructure included wells of all types and statuses, oil & gas processing facilities, storage tanks, and power plants. Figure 4 compares the 24 oil fields' oil production rates with their source density. Out of 9 oil fields with zero source density, 8 oil fields produced less than 600 bbl oil/day. There were only 5 oil fields that produced more than 12,000 bbl/day, of which all contained super emitters, but did not have the highest source densities. The top 5 oil fields in terms of source intensity produced between 1,600 to 12,000 bbl/day, indicating a probable pattern of intermediate rate producing oil fields having the highest source densities.

Temporal Behavior of the Sources

We separated emissions based on their observed persistence by defining a persistence factor (f)³³ for each source as the ratio of the number of CH₄ plume observations over the number of overflights from different days (for ≤ 5 overflights we applied a correction factor, see Methods). The majority of sources (77% of 255 sources) were non-persistent emitters ($f \leq 0.2$), with 180 sources observed were emitting just once. For sources that were flown at least six times, 82% were observed emitting only once or twice (Figure M2). Persistent emitters, emitting more than half of

the time ($f > 0.5$), represented only 1% of the sources (Figure M3). Non-persistent super-emitters also accounted for higher aggregated emissions. To compare the rate of emissions of the persistent and non-persistent sources, we grouped the sources into six persistence categories (based on their f values, see Figure M3). All persistence categories had a relatively close average emissions rate between 213 and 277 kg CH₄/h. When we aggregated the rate data based on f values (see Methods), non-persistent emitters ($f \leq 0.2$) emitted a total of $6,928 \pm 186$ kg CH₄/h, persistent emitters ($f > 0.5$) emitted a total of 452 ± 25 kg CH₄/h, and intermittent sources (with $0.2 < f \leq 0.5$) emitted a total of $4,416 \pm 123$. Thus, the non-persistent sources, both in numbers and cumulative rates, appeared to be more significant than sources in any of the more persistent groups (Figure M3). None of the equipment categories was more significant than others in persistence level (Figure 1c). Nevertheless, when emission rates were aggregated based on f values, pipes, wells, and tanks (storage and process tanks) categories were the only significant emitters with $4,554 \pm 136$ kg CH₄/h, $3,102 \pm 121$ kg CH₄/h, and $2,116 \pm 93$ kg CH₄/h, respectively (Figure 1d).

Modeled Versus Measured Emission Rates

We aggregated the measured emissions rates using two methods: source persistence and time series analysis. We then compared the observed emissions rates from each oil field with the modeled CH₄ emissions rates from OPGEE, separating the portion of emissions that was theoretically detectable by AVIRIS-NG from the total CH₄ emissions (see Methods).

We first compared observations from the Elk Hills oil field, which was flown on 10 different days, to the model estimates (Figure 5). Elk Hills contained most of the sources per oil field (51 out of 255). Figure S1 to Figure S12 show the time series analysis results for other oil fields. In Elk Hills, the average emissions rate (based on observations) over 10 days was 164% greater than the detectable portion of the modeled emissions. The number of the sources and the total rate of emissions in each day from observations varied among days, with 5 days where AVIRIS-NG observed emissions clearly exceeded model estimates (Figure 5a). Some of the observed variations can be attributed to varying coverage of emitting infrastructure, including facilities and oil and gas wells (Figure 5b and Figure 5c). Reviewing the same-day rate data showed that some of the sources were observed both emitting and not emitting during a short period of repeated measurements (intervals of about 10 minutes). We included the zero rates in averaging emissions rates of sources on each day.

Next, we analyzed the approximated emission rates from the 24 oil fields with at least 6 overflights on different days (Figure 6). For all 15 oil fields with detected CH₄ plumes, the

aggregated observed emissions exceeded the detectable portion of modeled emissions when source persistence was used to aggregate the observed rate data. When time-series analysis was used, the aggregated emissions exceeded the detectable portion of modeled emissions for 13 of the 15 oil fields. For 9 oil fields out of 15, aggregated emissions observations exceeded the model estimates for total CH₄ emissions (difference of > 4 standard deviations based on measured data), suggesting that not only the super-emitters observed by AVIRIS-NG were responsible for a large share of total oil field emissions, but they may be the cause of underestimation of oil and gas production emissions in California.

For two oil fields, Wilmington and Torrance, the difference between aggregated observed emissions and the model estimated detectable portion was 28 kg CH₄/h and 5 kg CH₄/h, respectively, which was insignificant (< 3 standard deviations based on measured data). It is notable that for Wilmington oil field, on 6 days out of 12 days of measurements, the field coverage was between 20 to 40%, and the rate of measured emissions was zero (Figure S12). For Torrance oil field, on 2 days out of 6 days of measurements, the field coverage was < 20% and the measured rate of emissions was zero. We have included these zero emissions in our averaging in the time-series analysis. Nevertheless, emissions estimated based on super-emitter observations stood clearly above the detectable portion of the modeled emissions rates and the total modeled CH₄ emissions for most of the studied oil fields with observed CH₄ plumes. Thus, we concluded that the model systematically underestimated the super-emitters of the studied oil fields.

Interestingly, when we added the excess CH₄ emissions associated with super-emitters (difference between the measured rates and model predicted rates of the detectable emissions) to OPGEE model's estimate, the total CH₄ emissions rate from these 24 oil fields became 2.3 times the official model's estimate when time-series analysis was used, or 3.4 times the model's when the persistence factors were used to aggregate the rate data. Using the 20-year time horizon global warming potentials (GWPs) given by the IPCC's Fifth Assessment Report (AR5)¹ for fossil CH₄, the total GHG emissions from the 24 studied oil fields were 1.2 times the model's estimate when time-series analysis was used, and 1.5 times the model's estimate when persistent factors were used. This difference could be due to underestimating the super-emitters of CH₄, both in terms of emission and activity factors.

Conclusions

Based on our study, we found that CH₄ super-emitters in California's oil fields demonstrated a prevalent intermittent and transitory behavior. In our study, none of the equipment categories

could be singled out statistically with a higher average rate of CH₄ emissions or persistence level. The non-persistent emitters (or highly intermittent sources ³⁷) aside from the equipment category were significant contributors to CH₄ emissions (77% of 255 sources). Some super-emitters could be due to abnormal processes that could be repeated but not necessarily from the same equipment or location. Therefore, it is essential to consider studying the oil field super-emitting behavior as an entirety rather than focusing merely on finding individual persistent super-emitting entities. Indeed, the prominence of non-persistent CH₄ super-emitter sources reveals the challenge for GHG mitigation regulation and policy for sectors where such CH₄ emissions sources may be present. Given the challenge of inventorying non-persistent super-emitters by conventional methods, additional observations are needed, including repeated remote sensing surveys such as described here as well as novel approaches using low-cost monitors of active wells and better pipeline leakage monitoring.

Subcategories of oil & gas wells, gas gathering pipelines, and storage tanks constituted 73% of the 255 studied sources. Studying the satellite images of the area where the methane sources were located from the perspective of the oil and gas production process design gave insights into possible reasons for the super-emitting behavior of the identified sources. Intentional venting (by design) or equipment malfunction could be the potential reason for the super-emitting behavior of the wells and the storage tanks. Inoperative vapor recovery systems or lack of such systems could potentially explain the observed methane plumes above storage tanks. Using the satellite images and studying the equipment layouts, distances, and ruling out other technical explanations, suggested that the likely explanation for the detected methane plumes from the gas gathering pipeline be leakage due to pipe failure.

The high number of super-emitters may have implications for health and environmental justice as well as for climate. Many oil production areas are interspersed with residential areas in California, particularly in the Los Angeles Basin, and the negative health impacts of these facilities on local residents are well known³⁸⁻⁴¹. The finding of CH₄ emissions exceeding expected values suggests that hazardous air pollutants, such as benzene, may be co-emitted from storage tanks or wellheads (US EPA)⁴² may also be underestimated and provides additional impetus for detection and prevention of oil and gas super-emitters.

We developed a methodology to examine GHG LCA models for the inclusion of CH₄ super-emitters by separating the detectable and undetectable portion of the modeled CH₄ emissions and calculating the excess measured CH₄ emissions. Using this methodology, we found the current

version of the California LCFS for estimating crude oil carbon intensity, underestimated CH₄ super-emitters.

Acknowledgment and Disclaimer

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Figure 1. Number of the identified sources (a), average rate of CH₄ emissions (b), average persistence factor (c), and aggregated rate of emissions (d) for each oil field equipment categories. Error bars indicate $\pm$ one standard deviation around average rates. Red squares show median values.

Figure 2. Examples of CH₄ emissions from oil and gas infrastructure in Kern County. AVIRIS-NG detected emissions marked by gold circles and gathering pipeline locations marked in magenta. (a) Emissions from oil and gas wells in Poso Creek oil field. (b) Emissions from gas gathering pipelines in Elk Hills oil field. Aerial imagery and street views were obtained from Google Earth and the USDA's National Agriculture Imagery Program (NAIP)⁴³.

Figure 3. Examples of CH₄ emissions detected by AVIRIS-NG from storage tanks located in dense urban areas in Los Angeles. Emissions sources are denoted by gold circles. (a) Storage tanks located next to a parking lot and highway. (b) Storage tanks located next to a car dealership. (c) Storage tanks located next to two baseball fields. (d) Storage tanks in the Wilmington oil field next to a major roadway. Aerial imagery and street views were obtained from Google Earth and the USDA's NAIP⁴³.

Figure 4. Number of observed CH₄ super-emitters per square kilometer of oil fields' infrastructures covered by AVIRIS-NG flights versus oil production rate. Only oil fields that were flown at least six times on different days were considered. The oil fields infrastructures include wells of all types and statuses, oil and gas processing facilities, storage tanks, and power plants.

Figure 5. (a) Time series of CH₄ emissions rate from Elk Hills oil field based on AVIRIS-NG data, (b) flight coverage of oil and gas facilities, and (c) flight coverage of oil and gas wells. Red circles indicate the number of sources. The red dotted line shows the upper and lower bounds of the detectable portion of the modeled emissions within $\pm$ one standard deviation.

Figure 6. Comparing the average rate of CH₄ emissions from oil fields calculated based on measured data with the model estimated rates of CH₄ emission. The measured rates represent the average of the daily rates over the number of oil field visits in different days. Two methods of time series and source persistence were used to aggregate the measured emissions rates of the detected sources on each day for each field (see Methods). The number of oil field visits for measurements that occurred on different days is given in the parentheses. The more the number of visits is, the more credible the result of the comparison is.

Methods

The Model

To model CH₄ emissions from California oil fields, we used OPGEE, an open-source and peer-reviewed model used by researchers and the government.⁴⁴⁻⁴⁷ CARB has adopted OPGEE to determine life cycle carbon intensity of the crude oil used in California since 2012 and maintained and updated the model as a part of the California Low Carbon Fuel Standard (LCFS) re-adoption and amendments in 2015 and 2018.⁴⁷

We re-organized OPGEE version 2.0c to report onsite CH₄ emissions and added a module for uncertainty analysis. We did not change any formulae in the model which were responsible for the calculation of GHG emissions. Therefore, other researchers can reproduce the results presented in this article if they use the same version of the model. The details of the modifications are given in the supplementary information (SI) document.

The boundary of the analysis for modeling the CH₄ emissions included petroleum production, treatment of the produced associated natural gas, and the natural gas-fired power plants (NGPP) within the boundaries of the oil fields.

We ran the model for 145 oil fields which produced 98% of the crude oil in California in 2017. The model estimated the total life cycle GHG emissions from these 145 fields was 18 Tg CO₂ eq. The total life cycle CH₄ emissions estimated by the model was only 7% of the total GHG emissions. We followed CARB in using 2007 IPCC AR4 GWPs (CH₄ GWP = 25).^{35,48}

The model estimated on-site CH₄ emissions (excluding emissions from NGPPs) for 145 oil fields was 5,315 to 6,081 kg CH₄/h (95% confidence interval), 5,669 kg CH₄/h on average, and a median of 5,655 kg CH₄/h. The model estimated total onsite CH₄ emissions from the oil fields in 2017 were approximately equal to CO₂ emissions from 270,000 passenger cars (assuming 4.6 metric tons of CO₂ per car per year and CH₄ GWP = 25).⁴⁹

On average, venting and fugitive CH₄ emissions constituted 44% and 30% of the onsite CH₄ emissions from the oil fields, respectively. The remainder came from fuel combustion and flaring, 22% and 4%, respectively (excluding fuel combustion in NGPPs). If we assume, the power plants present within oil fields operated at their maximum capacity with 60% efficiency and using the CARB's adopted gas-turbine emission factors in the model, the average total onsite CH₄ emissions from the 145 oil fields would increase to 5,741 kg CH₄/h and with EPA's recommended emission factors for gas-turbine to 5,944 kg CH₄/h.^{47,50}

The life cycle CH₄ emission from the 24 oil fields with > 5 visits on different days that we selected for comparing the measured and model estimated emissions rates at the field level constituted 60% of the total life cycle CH₄ emissions from the 145 oil fields.

Sources of Data

CARB published the model's inputs data for 147 oil fields that were used to determine the crude oil carbon intensity baseline in California for 2010.⁴⁷ These input data included the emission factors which were adjusted for California.⁴⁷ We updated the input data for production rates of crude oil, associated natural gas, and water in 2017 based on data from the California Geologic Energy Management Division (CalGEM) for 145 oil fields.⁵¹ In 2017, California produced 174 million barrels of oil.⁵² These 145 oil fields produced 98% of the crude oil produced in California in the same year.

The source of data for super-emitters of CH₄ was NASA/Jet Propulsion Laboratory (JPL)'s AVIRIS-NG published data for the 2016-2018 California airborne measurements ^{32,33,53-55}. The total number of sources in oil fields was 255, of which 244 had quantified CH₄ emissions. 148 sources out of 244 were flown more than 5 times (Figure M2).

Uncertainty Analysis

We followed Vafi et al. (2014) for the uncertainty analysis using the Monte Carlo (MC) methods.⁵⁶ We further improved the technique by using Latin Hypercube Sampling (LHS).⁵⁷⁻⁶³ We considered 93 emission and activity factors in our uncertainty analysis. We adopted the parameters uncertainty levels from API's Compendium of GHG Emissions Methodologies for the Oil and Natural Gas Industry.⁶⁴

Methodology for Examining GHG LCA Models for Handling of CH₄ Super-Emitters

We studied the model's emissions factors and the range of the activity factors (see SI document) to identify if AVIRIS-NG could detect emissions from the different categories of equipment and emissions categories (venting, fugitives, combustion, flaring) based on the measurement technique's CH₄ emissions detection limit. We used the results to estimate the portion of the model estimated emissions that was detectable by AVIRIS-NG. Then, we compared the average aggregated rate of measured CH₄ emissions from super-emitter sources and the model estimated detectable portion of the CH₄ emissions for each oil field. The difference was the excess CH₄ due to super-emitters that the model underestimated (or overestimated if negative). Thus, we could estimate the extent of underestimation of CH₄ and total GHG emissions by the model. More

details of our methodology are given in the following and in the SI document. We used this methodology to evaluate OPGEE v2.0c. However, our methodology can be used conceptually to evaluate other GHG LCA models.

The AVIRIS-NG Detectable Portion of the Model Predicted CH₄ Emissions Rates

The detectable portion of the model estimated CH₄ emissions was determined by the study of the emission factors used in OPGEE v2.0c and the applicable range of the activity factors (Table S3, S4, S5, and S6 in SI document). The detection limit of AVIRIS-NG was 2 to 10 kg CH₄/h.⁶⁵ The minimum measured rate of CH₄ emissions from the oil fields was 24 kg CH₄/h.⁶⁵ To approximate the portion of the modeled rate of CH₄ emissions that AVIRIS-NG could detect, we considered 2 kg CH₄/h as the detection limit, which was one order of magnitude smaller than the minimum reported measured rate in the oil fields. This assumption could cause overestimating the portion of the modeled CH₄ emissions, which were practically observable by AVIRIS-NG. We hypothesized that the total measured rate of super-emitters for each oil field would exceed the detectable portion of the modeled CH₄ emissions. Thus, assumptions that might lead to overestimating the modeled CH₄ emissions would help avoid a confirmation bias for our hypothesis.

Detectability of CH₄ Emissions from the Equipment Based on the Model's EFs

We used EFs from the OPGEE model to estimate the expected CH₄ emission rate of equipment present in oil fields from different processes. The definition of EF, its value, and the gas discharge mechanism from the equipment could give insight into the detectability of the emissions rates from sources with different temporal characteristics (Table S2 and Table S3). For example, gas venting during the well cleanup is not a continuous discharge, and hence its EF is defined (in OPGEE model) as kg CH₄ per event. Assuming a reasonable duration of venting, we could determine if such an event would be detectable by AVIRIS-NG (see SI document).

Aggregation of Emissions Rate Data

We chose two approaches to aggregate rate data: persistence factors and time series analysis. Our intention to aggregate the rate data was not to calculate a precise and accurate number for the total rate of super-emitters from the oil fields. We wanted to show that the estimated rate based on the measured data would stand above the model predicted rates with a statistically meaningful difference. Therefore, we favored assumptions that might underestimate the aggregated measured emissions rate rather than overestimate them to avoid any confirmation bias for our hypothesis.

Persistence factor

This approach utilized a modified version of the method used by other researchers to aggregate the emissions rate data measured by AVIRIS-NG.³³ We defined persistence factor (f_i) for a source is defined by equation 1:

$$f_i = \omega_i \times \frac{M_i}{N_i} \quad (1)$$

M_i is the number of plume observations from source i ,

N_i is the number of overflights,

ω_i is the correction factor for source i and is defined by equation 2:

The rate data were aggregated using equation 2:

$$\omega_i = \begin{cases} \frac{N_i}{N^*} & \text{if } N_i \leq 5 \\ 1 & \text{if } N_i > 5 \end{cases} \quad (2)$$

N^* is the minimum number of overflights that is assumed necessary to make a statistically meaningful judgment about the source emitting frequency. We set $N^* = 6$.

If we do not apply the correction factor ω_i , then the persistence factor for a source seen emitting once and flown over only once would be 1.0, and theoretically, it would be as persistent as a source seen emitting 10 times and flown over 10 times. Without the correction factor, a source seen emitting once and flown over twice, and a source seen emitting 5 times and flown over 10 times would have the same persistence factor of 0.5. Intuitively or based on a practical judgment, the equality of the source persistence in these scenarios is unsound.

We considered a source more persistent when repeated emissions were observed on different days rather than repeated in a short period of measurements on the same day. Repeated plume observations on the same days were counted as one. However, the average of the repeated rate measurements on the same day was calculated and included in the total average for the source

rate. Similarly, the number of overflights refers to those that occurred on different days, and repeated flights on the same day were counted as one. The rate data were aggregated using equation 3:

$$Q_t = \sum_i f_i \times Q_{i,avg} \quad (3)$$

Q_t is the aggregated rate of emissions from the selected sources,

$Q_{i,avg}$ is the average rate of emissions from source i (the average does not include zero-emission rates on days when no CH₄ plume detected),

f_i is the persistence factor for source i ,

Figure M3b shows the persistence factors versus the aggregated rate of CH₄ emissions and demonstrates the significance of the contribution of the less persistent sources to the total CH₄ emissions by the super-emitting sources.

Time series analysis

In the time series analysis, the aggregation of the rate data is not based on the local persistence of the sources but based on the unweighted sum of measured rates of the sources' emissions from the oil field. Therefore, the contribution of all observed sources, persistent or non-persistent, is taken into account equally.

The aircraft carrying AVIRS-NG can fly across an oil field in a short time. For example, it will take 6 minutes for a King Air B200 aircraft flying at half of its maximum economical cruising speed (260 km/h) to travel across the Elk Hills oil field boundaries (27 km).^{66,67} Thus, we can practically assume that the measured rates in each oil field on each day are from the sources emitting simultaneously, and we can aggregate them. When for each source, more than one datum was available in one day (i.e., the field was flown more than once on the same day), we used the daily average value. In time series analysis of an oil field, the days with total measured emissions equal to zero were taken into account to calculate the average total over the number of oil field visits. Equation 4 shows how we aggregate the source emissions rates to calculate the average total emissions from an oil field:

$$Q_t = \frac{\sum_{j=1}^N \sum_{i=1}^P Q_{S_i}(t_j)}{N} \quad (4)$$

Q_t is the average total rate of emissions from the oil field,

P is the number of the sources,

N is the number of days that the oil field visited for measurements

S_i is source i

t_j is the jth day of measurements

$Q_{S_i}(t_j)$ is the CH₄ emissions rate of source S_i at jth day of measurements (kg CH₄/h)

The total of the measured rates of emissions on one day naturally fluctuates about the annual average. Many days of oil field visits are required to establish an average representing annual oil field emissions to compare with the model prediction. Based on the availability of the measured data, we set the minimum required oil field visits to 6 (on different days) and therefore selected only oil fields which were visited > 5 times.

AVIRIS-NG data are collected in daylight. A difference between the rate of emissions measured in daylight and at night is expected.⁶⁵ Some intermittent venting as part of the routine operation and maintenance may be scheduled for the daytime. Emissions from abnormal processes can occur both day and night, with a higher chance of being corrected during a day shift rather than a night shift. The extent of the differences between day and night emissions rates remains uncertain.⁶⁵

Oil Field Infrastructure Footprint

To calculate the density of the number of super-emitter sources per area to compare with the crude oil production rate (Figure 4), we estimated the footprint area of the oil field infrastructure⁵⁴. We included all wells of any type and statuses, oil & gas processing facilities, storage tanks, and power plants. We excluded any large areas of the oil fields where the satellite images showed no infrastructure. However, we included the area between the well pads, representing the extent of the gas-gathering pipeline in the oil fields. To calculate the source density, we used only the portion of the infrastructure footprint which AVIRIS-NG covered. Figure

M4 depicts our methodology in an oil field where AVIRIS-NG coverage of the oil field infrastructure was not complete. Figure M5 shows the implementation of the methodology for the Kern River oil field, and Figure M6 for Wilmington, where the oil field becomes interspersed with the urban area.

Figure M1. Map showing 140 of 145 California oil fields listed by CARB ³⁵. CH₄ super-emitters in California oil field detected by AVIRIS-NG are marked in yellow (37 oil fields). Oil field extents are outlined green (flown, 121 fields) and in red (not flown, 24 fields). We focused on 109 oil fields which were surveyed by AVIRIS-NG in this study. 5 fields which are not shown on this map are located further north, 3 are flown over and 2 not flown over.

Figure M2. Distributions of the number of times AVIRIS-NG detected CH₄ plumes from an identified source location on different days (a), and the number of times plumes from a source location were observed by the number of the overflights on different days (b).

Figure M3. The relationship between the persistence of the super-emitters, the number of the sources, the average rates of CH₄ emissions, and the aggregated rate of CH₄ emissions. Red diamonds show the medians.

Figure M4. Cymric oil & gas field boundary is outlined in black (data from CalGem⁶⁸). Oil & gas infrastructure footprint is outlined in white. Oil & gas facilities are outlined in blue. Oil & gas wells are shown as very small black dots. Power plants are outlined in green. AVIRIS-NG survey coverage is shown as a pink gradient. Aerial imagery was obtained from USDA's NAIP⁴³.

Figure M5. Kern River oil and gas field boundary is outlined in black (data from CalGem⁶⁸). Oil and gas infrastructure footprint is outlined in white. Oil & gas facilities are outlined in blue. Oil and gas well are shown as very small gray dots. Power plants are outlined in green. Aerial imagery was obtained from USDA's NAIP⁴³.

Figure M6. Wilmington oil & gas field boundary is outlined in black (data from CalGem⁶⁸). Oil & gas infrastructure footprint is outlined in white. Oil & gas wells are shown as small black dots. Aerial imagery was obtained from USDA's NAIP⁴³.

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