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**Facility scale inventory of dairy methane emissions in California: Implications for mitigation**

Alison R. Marklein[1], Deanne Meyer[2], Marc L. Fischer[3], Seongeun Jeong[3], Talha Rafiq[1], Michelle Carr[1], Francesca M. Hopkins[1]

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[1]University of California Riverside, Department of Environmental Science, Riverside, CA 94611, USA

[2]University of California Davis, Department of Animal Science, One Shields Avenue, Davis, CA 95616, USA

[3]Lawrence Berkeley National Laboratory, Energy Technologies Area, 1 Cyclotron Road, Berkeley, CA 94720, USA

**Corresponding Author**: Alison R. Marklein, 513-479-8926, amarklein@ucr.edu

## Abstract

Dairies emit roughly half of total methane ($CH_4$) emissions in California, generating $CH_4$ from both enteric fermentation by ruminant gut microbes and anaerobic decomposition of manure. Representation of these emission processes is essential for management and mitigation of $CH_4$ emissions, and is typically done using standardized emission factors applied at large spatial scales (e.g., state level). However, $CH_4$-emitting activities and management decisions vary across facilities, and current inventories do not have sufficiently high spatial resolution to capture changes at this scale. Here, we develop a spatially-explicit database of dairies in California, with information from operating permits and California-specific reports detailing herd demographics and manure management at the facility scale. We calculated manure management and enteric fermentation $CH_4$ emissions using two previously published

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bottom-up approaches and a new farm-specific calculation developed in this work. We also estimate the effect of mitigation strategies - the use of mechanical separators and installation of anaerobic digesters - on $CH_4$ emissions. We predict that implementation of digesters at the 109 dairies that are existing or planned in California will reduce manure $CH_4$ emissions from those facilities by an average of 35%, and total state $CH_4$ emissions by 6% (or ~ 47.3 Gg $CH_4$/yr). In addition to serving as a planning tool for mitigation, this database is useful as a prior for atmospheric observation-based emissions estimates, attribution of emissions to a specific facility, and to validate $CH_4$ emissions reductions from management changes. Raster files of the datasets and associated metadata are available from the Oak Ridge National Laboratory Distributed Active Archive Center for Biogeochemical Dynamics (ORNL DAAC; Marklein et al., 2020; https://doi.org/10.3334/ORNLDAAC/1814)

## 1. Introduction

Methane ($CH_4$) is a greenhouse gas with a large influence on the rate of short-term warming due to its high global warming potential, roughly 85 times that of $CO_2$ on a 20-year time frame (Dlugokencky et al., 2011). Climate mitigation policy in California targets a reduction in $CH_4$ emissions by 40% below 2013 inventory levels by 2030 (State of California, 2016). Dairies provide a major opportunity for $CH_4$ reduction, as roughly half of state-total $CH_4$ emissions come from nearly equal contributions of enteric fermentation by ruminant gut microbes and anaerobic decomposition of dairy manure (Charrier, 2016). The primary method by which California currently plans to reduce dairy $CH_4$ emissions is through installation of anaerobic digesters, which capture manure $CH_4$ emissions for subsequent use as a renewable biofuel (State of California, 2016). However, facility-level measurements of both the magnitude of total emissions and relative contributions of enteric fermentation versus manure management is only available for a few dairies in the state (Arndt et al., 2018). Indeed, uncertainty in $CH_4$ emissions from the dairy industry in California and globally makes it difficult to optimize mitigation actions at the spatial scales relevant to policy and to establish an emissions baseline against which mitigation efforts can be measured.

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$CH_4$ emissions are often estimated by bottom-up (calculated activity-based) or top-down (atmospheric observation-based) methods (National Academies of Sciences, Engineering, and Medicine, 2018). Bottom-up inventories, including those used by the U.S. Environmental Protection Agency (US EPA, 2017) and the California Air Resources Board (Charrier, 2016) estimate dairy emission rates at the state level based on the total number of cows and herd demographics, and on the average statewide manure management approach, $CH_4$ emissions factor, and climate. However, livestock emissions, especially from dairies, remain one of the largest uncertainties in these inventories (Maasakkers et al., 2016), as there is no comprehensive information source for the number of cows or manure management strategies. In addition, the lack of spatial and temporal detail in these inventories makes it difficult to verify their accuracy with observational data, particularly given high levels of spatial variability observed for CH4 emissions (NASEM, 2018).

Top-down estimates of emissions measure atmospheric $CH_4$ enhancements at farm to regional scales using one or a combination of ground, aircraft, and satellite observations (Arndt et al., 2018; Cui et al., 2017; Wecht et al., 2014). Top-down studies often report $CH_4$ emissions for dairies up to two times higher than bottom-up measurements (Cui et al., 2017; Jeong et al., 2016; Miller et al., 2013; National Academies of Sciences, Engineering, and Medicine, 2018; Trousdell et al., 2016; Wolf et al., 2017). However, these comparisons are complicated by uncertainties in source attribution, atmospheric transport models, and the spatial and temporal mismatch that commonly exists between top-down estimates and bottom-up inventories.

Previous bottom-up inventories have estimated national (e.g. US EPA 2017 Greenhouse Gas Inventory, US EPA, 2017), and state-wide (e.g. CARB Greenhouse Gas Inventory, Charrier, 2016)) emissions based on the number of cows at the state, and county levels, respectively. These inventories have been downscaled to 0.1 x 0.1° gridded inventories of $CH_4$ emissions using a combination of California Regional Water Quality Control Board data of dairy-specific herd size and county level livestock data in the CALGEM inventory (Jeong et al., 2016; 2012) or county level dairy cow counts from the U.S. Environmental Protection Agency (EPA) Inventory of U.S. Greenhouse Gas Emissions and Sinks alone

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(Maasakkers et al., 2016; USEPA 2017). While these gridded products provide finer spatial detail than state-wide inventories, there are limitations to the livestock maps that distribute dairies within a county. For example, some gridded products estimate $CH_4$ production from dairies in the Sierra Nevada range (Maasakkers et al., 2016), while in reality these animals exist further west in the Central Valley. In another example, although regional-scale top-down studies (Cui et al., 2017; Jeong et al., 2016) suggest bottom-up inventories underestimate dairy $CH_4$ emissions, a comparison of bottom-up and top-down $CH_4$ emissions at the facility scale (two dairies) was much more comparable (Arndt et al., 2018). This facility-scale comparison suggests the discrepancy might be due to spatial scale. Dairy-level inventories of $CH_4$ emissions are also needed to be relevant to management and mitigation actions that are implemented at the facility level.

To improve the spatial distribution of $CH_4$ emissions from dairies, we describe a new, farm-level database called Vista-California (CA) Dairies. In this analysis, we disaggregate the CARB inventory to the facility level by 1) developing a spatially-explicit map of dairy locations, 2) applying facility-level information from regulatory permit data and county-level animal inventories to estimate herd sizes; and 3) estimating enteric and manure $CH_4$ emissions from dairy facilities based on manure management from permit data and regional norms. Vista-CA Dairies, is hence the first spatially-explicit inventory at the scale at which management and mitigation decisions are made. Compared to previous inventories, we significantly improve (1) spatial resolution of dairy $CH_4$ emissions using more accurate farm-level herd demographics and (2) spatial variation in partitioning of emissions between enteric and manure sources by incorporating information on manure management practices at a finer scale than used in typical inventories. These improvements are critical for accurately attributing local to regional scale $CH_4$ emissions to their sources, identifying high-priority areas for mitigation management, and assessing progress towards achieving mitigation goals (e.g. (State of California, 2016)).

To demonstrate the utility of this facility-scale product in monitoring mitigation outcomes, we apply the inventory to address the effectiveness of mechanical separators and anaerobic digesters - two climate mitigation strategies that the state is pursuing - in reducing manure methane emissions (CDFA 2020a;

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CDFA 2020b). Mechanical separators separate out larger-sized solid particles from the liquid manure pathway, reducing the amount of manure entering lagoon treatment systems that are the major source of manure methane (CDFA 2020a). Digesters, as described above, promote the production of methane from liquid manure waste through anaerobic conditions, but capture it for use as a fuel. First, we perform a sensitivity analysis on the efficiency of mechanical separators in removing solids, and quantify the uncertainty in their reduction in emissions. Second, we quantify the projected effect of anaerobic digesters on total $CH_4$ emissions and on the ratio of enteric $CH_4$ to manure $CH_4$ at the farm and regional scale. Since 2015, cap and trade funds have supported 109 anaerobic digesters in an effort to reduce manure $CH_4$ emissions (CDFA 2020b). This dataset provides the facility-level inventory of methane emissions, critical for attributing methane plumes to dairy sources and for monitoring methane reduction strategies.

## 2. Methods

We determined the locations of dairy farms in California and estimated the herd numbers for each farm. We estimated the enteric and manure $CH_4$ emissions in 3 different ways each, and the uncertainty in each parameter affecting emission estimates at the facility and state scales. These data were compiled in the database Vista-CA, and compared to other methane emission maps in the same domain. Finally, we evaluated the efficacy of two manure management $CH_4$ mitigation strategies that are currently being implemented in California: mechanical separators and anaerobic digesters (Meyer 2019).

### 2.1 Dairy Locations

We used Google Earth satellite imagery to determine the locations of 1,727 dairy farms in California, by identifying metal-topped shelters alongside manure lagoons and corrals (further details given in Duren et al., 2019). These dairy locations are publicly available as part of the Vista-CA methane mapping project on the Oak Ridge National Laboratory Distributed Active Archive Center for

Biogeochemical Dynamics (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1726). We validated the number of currently operational dairies using lists of permitted dairies from three sources: the California Integrated Water Quality System Project (CIWQS, California Integrated Water Quality System, 2019), the San Joaquin Valley Air Pollution Control District (SJVAPCD, Roth, 2009; Zhang, 2017), and Regional Water Quality Control Boards (RWQCB). CIWQS provides the facility name, addresses, and coordinates, for all active, permitted dairies in California under the U.S. Clean Water Act (CIWQS Regulated Facility Reports, 2017). Air permits include the maximum herd sizes for dairies with more than ~1954 cows that are located in the San Joaquin Valley under California Senate Bill 700 (State of California 2003; SJVAPCD 2004) . Finally, we used reports for the year 2015 from RWQCBs in regions (5: Central Valley, and 8: Santa Ana) where herd numbers and nutrient management data for individual farms > 500 cows are collected (California Regional Water Quality Control Board, 2007; 2013; Roth, 2009; Zhang, 2017; Carranza et al. 2018; Duren et al. 2019). Of the 1,727 dairy locations determined by satellite imagery, 842 have RWQCB reports, 927 have SJVAPCD permits for a total of 1,107 permitted dairies, with 620 dairies having both permit types (Table S2). We used addresses to determine the approximate location of each dairy, and manually adjusted the location to the center of a dairy farm using satellite imagery in Google Earth (Duren et al. 2019; Rafiq et al. submitted).

We grouped dairies into three geographic categories by county: North Coast (180 dairies), Central Valley (1493 dairies), and Southern California (54 dairies) to account for differences in climate, animal housing and primary manure management styles among these three regions (Meyer, 2019). The North Coast includes Del Norte, Humboldt, Lassen, Marin, Mendocino, Modoc, Monterey, San Luis Obispo, San Mateo, Santa Barbara, Siskiyou, and Sonoma counties; Central Valley includes the counties Butte, Colusa, Fresno, Glenn, Imperial, Kern, Kings, Madera, Placer, Sacramento, San Joaquin, Solano, Stanislaus, Sutter, Tehama, Tulare, Yolo, and Yuba; Southern California includes Imperial, Los Angeles, Riverside, San Diego, San Bernardino, and Santa Ana counties. Counties not listed did not have dairies in the Vista-CA database.

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We assumed that all permitted dairies are currently operational. While this assumption is untrue, it is not possible to determine which dairies are functioning and which are not since dairy closures are not currently tracked by any agency. Milk production statistics show that there are roughly 1400 commercial dairies in CA, including 162 dairies in Northern California (CDFA 2018).

## 2.2 Herd Populations and Demographics

We used data from three sources to estimate herd numbers and demographic categories at each dairy. First, the RWQCB reports provide the number of milk cows, dry cows, heifers, and calves for dairies in the Central Valley and Southern California for the year 2005 (California Regional Water Quality Control Board, 2013). Second, SJVAPCD permits include the maximum number of cattle in each class at a given facility, based on facility housing in 2011, rather than the number of animals. Third, the 2017 United States Department of Agriculture (USDA) National Agricultural Statistics Survey (USDA NASS, 2017) provides the number of farms and the number of cows in different dairy size classes in each county, though the NASS Census data include farms that are not commercial dairies.These data represent our best estimates, but they represent specific points in time that are not consistent between data sources. With these permits, we can account for the location of ~1,321,000 lactating cows (Table S2) in California. Based on milk shipments, we know that at the time of this publication, there are roughly 1.7M lactating cows in California (Ross, 2019).

For dairies with RWQCB reports, we use the number of milk cows, dry cows, heifers, and calves as the number of cattle in each class. Given that we are calculating an annual $CH_4$ emission rate for each farm, we assume the population and demographics of each farm are constant in time, though in reality these fluctuate as cattle are sold or born. The Central Valley RWQCB assumes the population size of the lactating and dry cows varies by 15% or less (California Regional Water Quality Control Board, 2013).

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For the 307 dairies with only SJVAPCD permits, we converted the reported available housing to cattle populations using a scaling factor representing percent fullness of cattle housing facilities. We developed this factor from dairies with both water board and air quality reports (Table S1).

For the (generally smaller) dairies without SJVAPCD permits or RWQCB reports described above (n=620), we estimate the number of cows in each dairy ($n_i$) in the county based on the number of cows reported by the USDA Census ($n_{USDA}$). We subtract the number of cows from farms in each county with a water board ($n_{WB}$) or air quality ($n_{AQ}$) permit from the total number of farms reported in the NASS census to estimate the number of farms without permits. We also subtract the total number of cows accounted for in each of the farms with water board or air quality reports from the total number of cows reported for the county in the census to get the number of cows on farms without permits. We then divide the cows on farms without permits by the number of farms without permits to estimate the average number of cows per farm for each county (Equation (1)).

$$n_i = \frac{n_{USDA},i - n_{AQ,i} - n_{WB,i}}{(nfarms_{USDA,i} - nfarms_{AQ,i} - nfarms_{WB,i})} \ . \quad (1)$$

In addition to large commercial operations, the USDA Census data include small operations with as few as one lactating cow.

For counties without cattle reported in the USDA Census data, but for which the Vista-CA database includes dairies, we assume that the average of all available data was representative of that county (Supplemental Methods S1.1) using RWQCB reports, SJVAPCD permits, and the county-wide California NASS from 2017 (USDA NASS, 2017).

We also estimate the populations of non-lactating animals, though these data are less reliable than data for lactating animals. The RWQCB reports provide the number of dry cows, bred heifers, heifers, calves 0-3 months, and calves 4-6 months (California Regional Water Quality Control Board, 2013). From this data, we determine the median ratio of dry cows to the number of milk cows to estimate the number of dry cows for dairies without RWQCB reports. Calf and heifer populations are less reliable

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than mature cow populations (lactating + dry cows), as these replacement animals may or may not be at the same facility as the animals they will replace. We assume that replacement animal populations are 10% higher than the mature cow populations (Deanne Meyer, personal communication, February 7, 2020), and are evenly distributed among the 0-23 month old animals. For this analysis, we assume that the replacements are on the same dairies as the lactating cows in order to not double count the heifer ranches; these animals do exist, but may not be present on the dairies. We also estimated the effect of this assumption on overall emissions. Enteric fermentation emissions equations also distinguish between replacement heifers <500 lbs and replacement heifers >500 lbs, and calves 0-6 months and calves 6-12 months. We assume the populations are split equally between the size classes. We also assume the same number of calves aged 0-6 months as for calves aged 7-12 months.

## 2.3 Enteric Fermentation Emissions

We estimated enteric fermentation in three ways, which have previously been used to estimate emissions at the state or national levels: (1) according to the method used in California's greenhouse gas emission inventory (E1; Charrier, 2016), (2) a method used for estimating emissions for the continental U.S. (E2; Hristov et al. 2017), and (3) a method suggested by recent research done in California (E3; Appuhamy et al. 2019). These three methods increase in their complexity: method E1 is based solely on the population and a state-wide emissions factor; E2 is based on a statewide emission factor and diets; and E3 is based on diet as well as the quality of milk provided. We performed each of these calculations with lactating cows only (subscript l) and total cattle, including calves, replacement heifers, and dry cows (subscript t).

The first method, E1, is based on the calculations used by CARB for the official statewide greenhouse gas emission inventory (Charrier, 2016). For this method, we estimate total enteric emissions ($CH_{4,e1}$) based on the number of cattle (n) and a standard emission factor for each cattle type (Eq. (2)). Method E1 assumes enteric fermentation emissions ($ef_{1,}$) are 114.61 kg $CH_4$ per lactating dairy cow ($ef_{1,l}$).

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$$CH_{4,e1l} = ef_{1l} * n_l \qquad (2)$$

For all cattle, the total enteric emissions are the sum of the product of the number of cattle (n) and the emission factor (Eq. (3)). Method E1 assumes that the emissions factors are 11.63 kg $CH_4$ per dairy calf ($ef1_c$); 43.53 kg $CH_4$ per replacement heifer aged 7-12 mo; and 65.71 kg $CH_4$ per replacement heifer aged 12-24 months. We use a weighted mean of 58.32 kg $CH_4$ per replacement heifer ($ef1_h$). Here i represents the classes of cattle, including milk cows, calves, and replacement heifers. The CARB inventory does not provide an emission factor for dry cows, so we exclude those from this analysis (Charrier, 2016).

$$CH_{4,e1t} = \sum ef_{1i} * n_i \qquad (3)$$

The second method, E2, is based off of calculations in Hristov et al. (2017). For this method, we estimate the total enteric emissions ($CH_{4,e2}$) as the product of the number of cattle (n), a dry matter intake (DMI), and an emission factor (ef2; Eq. (6))(Hristov et al., 2017). Method E2 assumes DMI are 22.9 kg/day for lactating cows, 12.7 for dry cows, 8.5 for dairy replacement heifers, and 3.7 for calves, and emission factors are 436, 280, 161, and 70 g/head/day for lactating cows, dry cows; dairy replacement heifers, and calves, respectively.

$$CH_{4,e2l} = n_l * DMI_l * ef_{2e,l} \qquad (4)$$

$$CH_{4,e2t} = \sum n_i * DMI_i * ef_{2e,i} \qquad (5)$$

The third method, E3, is based on calculations by Appuhamy et al. (2019). For this method, we estimate the total enteric emissions including the number of cattle (n), a dry matter intake (DMI), neutral detergent fiber (NDF) in the diet, milkfat (mf)(Appuhamy, 2018). We also include factors for DMI ($f_{DMI}$),

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NDF ($f_{NDF}$) and milkfat ($f_{mf}$). Here, emissions are the sum of emissions due to DMI, neutral detergent, and milk fat content (Eq. (6)). .

$$CH_{4,e3l} = n_l * (f_{DMI,l} * DMI_l + f_{NDF,l} * NDF_l + f_{mf} * mf)) \quad (6)$$

Note that Appuhamy et al. (2019) consider mature cows to be dry cows for 60 days of the year (16.4%) and lactating cows the remainder of the year, while we count the dry and lactating cows separately. For the other cattle classes (i, including dry cattle, replacement heifers, and calves), the E3 emissions are the product of DMI and an factor ($f_{DMI}$), as in E2 (Eq. (7)).

$$CH_{4,e3t} = n_l * \left[\left(f_{DMI,l} * DMI_l + f_{dNDF,l} * NDF_l + f_{mf} * mf\right) * 365\right] + \Sigma(n_i * f_{DMI,i} * DMI_i) * 365 \quad (7)$$

## 2.4 Manure Management Emissions

We estimated manure emissions for each dairy three ways: (1) according to the method used in California's greenhouse gas emission inventory (Charrier 2016), (2) a method used for estimating emissions for the continental U.S. (Hristov et al. 2017), and (3) a method suggested by recent manure management research done in California (Meyer et al. 2019; Figure 1). Methods M1 and M2 are based on average statewide manure management, while method M3 is based on facility-level or regional manure management. We perform each of these calculations first with milk cows only and then including calves, dry cows, and heifers. All three methods follow the same general equation, though have differences in the specific variables used in Eq. (8).

$$CH_{4,m,l} = n_l * \rho_{CH4} * VS_{prod} * B_o * \Sigma[MCF_{system} * f_{system}] \quad (8)$$

In this equation, n is the number of cows, $\rho_{CH4}$ is the density of $CH_4$, which is a constant 0.662 (g/cm3), $VS_{prod}$ is the total amount of volatile solids (VS) produced per animal, $B_o$ is the maximum methane

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production capacity, and MCF is the methane conversion factor for each system, and $f_{system}$ is the fraction of manure going into each manure management system. The different systems include pasture, daily spread, solids, liquid/slurry, lagoon, and dry lot. Pasture is manure deposited while grazing; daily spread is collection of manure that is spread onto field or pasture within 24 hours of deposition; solids are dried manure stored in unconfined stacks; liquid/slurry is manure stored with some water added, with a typical residence time of less than 1 year; a lagoon is a designed storage system for stabilizing waste; and dry lot is an open confined area, where manure may be removed occasionally (IPCC 2006).

The first method, M1, is based on the method used in the CARB greenhouse gas inventory. For M1, methane emissions from manure management are calculated for each dairy facility based on the fraction of manure in each management system, the total VS production, the $CH_4$ density, $B_o$, and the methane conversion factor for each system (CARB 2014; Dong et al., 2006; US EPA, 2017). For method M1, we assume that a constant proportion of manure is in each management type on each dairy according to statewide proportions (CARB 2014). These percentages are 0.7% for pasture, 10.6% for daily spread, 9.1% for solids, 20.2% for liquid slurry, and 58.2% for lagoon, and 1.2% for anaerobic digester. For heifers, the state assumes 87.4% of manure is managed ais drylot, 10.8% as daily spread, 0.9% as liquid, and 0.9% as pasture. Volatile solid production and Bo are constant among management types, and the methane conversion factor for each system is 0.015 for pasture, 0.005 for daily spread, 0.04 for solid storage, 0.323 for liquid/slurry and 0.731 for anaerobic lagoon (Charrier, 2016).

The second method, M2, is based on the methodology used by Hristov and colleagues (Hristov et al., 2017). These are the product of the VS excreted, the methane generation potential, the waste management system distribution in the state, the methane conversion factor (MCF) for the state, and the methane density (Eq. (7)). The percentages of waste entering daily spread, solid storage, liquid slurry, and anaerobic lagoon are 10%, 9%, 20%, and 60% respectively, for dairy cows, with corresponding MCFs for cows are 0.005, 0.04, 0.323, and 0.748, respectively. For replacement heifers, the percentages are 11%, 88%, 1%, and 1% for daily spread, dry lot, liquid/slurry, and pasture, respectively, with corresponding MCFs for heifer are 0.005, 0.015, 0.39, and and 0.015, respectively. The VS excreted are

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2799 kg/day for dairy cows, 1251 for dairy heifers and 370 for calves. $B_o$ is 0.24, 0.17, and 0.17 for dairy cows, replacement heifers, and calves, respectively. The MCF for calves is 0.015.

For the third method, M3, we estimate manure management based on data from the SJVAPCD air quality permits and regional differences in manure management as follows below (Eq. (9)) and shown in Figure (1). $CH_4$ emissions for each manure management system were determined according to CARB emission factors described above and summed for each farm. As described previously, only dairies in the San Joaquin Valley with >500 cows in 2011 have SJVAPCD permits. For these dairies, we estimate manure emissions based on the reported dairy management practices documented in permits, though this information represents facilities inconsistently. These permits report the presence of corrals or freestalls as housing types; flush, scrape, or vacuum systems for manure collection; and mechanical separator, settling basin, or weeping wall as solid-liquid separator systems (Table S1). Housing type typically determines the fraction of manure that is processed by the manure handling system, which can be quantified as the percentage of time cows spend on concrete. For dairies with corrals or freestalls present, we assume time on concrete to be 70% (Meyer, 2019). For dairies without freestalls, we assume time on concrete to be 30% (Meyer, 2019). We assume that time in the milking parlor is 12.5% of total time, which is almost always flushed or hosed out into a liquid manure handling system (i.e., liquid/slurry or lagoon). For the remainder of the time on concrete, we assume that for facilities with scrape or vacuum systems reported, the manure is stored as solids; for facilities with only flush systems reported, we assume that this manure is flushed into lagoons. We assume that the remaining manure (time not spent in housing) is not collected, and remains as solids in the open lot or pasture. For dairies with solid-liquid separator systems reported, manure that is flushed to lagoon is diverted to solid storage based on the mechanical separator efficiency (0.05 for mechanical separator; 0.225 for settling basin; 0.25 for weeping wall). We also estimate the effect of using manure solids as bedding. The majority of manure solids are used as bedding, as it is a cost-effective and easily available option to keep the animals comfortable, though some solids are land applied or removed off farm (Chang et al., 2004). Previous research suggests that solid manure loses roughly 33% of it's C as $CO_2$ in the first month (Ahn et al. 2011); we

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assume that on dairies with lagoons, solid manure remains in the manure pile for at least one month to dry out, and that half of the remaining 67% of the manure C returns to the housing facility and ultimately ends up in the lagoon. The fraction of manure entering the lagoon, $f_{bed}$, is therefore 33%. We assume that all heifer manure is scraped, though in reality some heifer lanes may be flushed.

$$CH_{4,m3,l} = n_l * \rho_{CH4} * VS_{prod} * B_o * [(f_{lagoon} + f_{solid} * f_{bed}) * MCF_{lagoon} + f_{solid} * (1 - f_{bed}) * MCF_{solid} + f_{liquid} * MCF_{liquid} + f_{pasture} * MCF_{pasture}] \quad (9)$$

Given that air district data only exist for the San Joaquin Valley, we made assumptions about housing and manure management in the other regions in California for method M3. For the remaining Central Valley dairies without air quality permits, we used the mean partitioning of solid vs. liquids from permitted dairies in each county. In the Southern California dairies, open lot style farms are predominant (personal communication, Deanne Meyer, February 7, 2020), and most do not even flush the feedlane. On these dairies, we assume that only the milking parlor is flushed, at 12.5% of the time, and the rest of the manure is either dry scraped or remains in the open lot. In the North Coast, pasture dairies are prevalent, though many dairies have some housing for cows. Here, we assume time on concrete is 39%: on average 2 months inside in the winter, and 30% of the rest of the year. During the winter months, the manure is scraped into pits. In the summer, the manure is dried and stacked. In the North Coast, we assumed that only the milking parlor was flushed (12.5%).

## 2.5 Uncertainty and Sensitivity Analysis

We estimated facility-level uncertainty in the number of cows as 20%, as suggested by the IPCC (Dong et al., 2006, Supplemental Methods). We estimated facility-scale uncertainty for enteric fermentation emissions for each of the three methods (Table 2, Supplemental Methods). The methods for calculating the standard errors of each variable are shown in the Supplemental Methods section. For E1, we calculated the standard error in $ef_1$ and n. For method E2, we calculated the standard error in DMI, n,

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and $ef_2$. For E3, we calculated the standard error in DMI, NDF, milkfat, $f_{DMI}$, $f_{NDF}$, and $f_{mf}$ for lactating cows, and DMI only for nonlactating animals. We propagated the standard error of each variable through the emissions calculations equations, assuming the errors were uncorrelated (Supplemental Methods S1.2).

We estimate the facility-scale uncertainty in manure management emissions by propagating uncertainty in the terms $n_{cows}$, fraction of time on concrete, $VS_{prod}$, methane conversion factor (MCF), and $f_{bed}$. We did not address uncertainty in maximum methane production ($B_o$) and $CH_4$ density as these are considered to be constants (US EPA 2017). Uncertainty for time on concrete was determined from variance observed in a recent study (Meyer, 2019) that describes four Central Valley dairies: two with freestalls and two without freestalls. We assume for our analysis that the time on concrete is equal to the fraction of manure produced that passes through the lagoon ($f_{lagoon}$). We also assume that the remainder of the manure (1-$f_{lagoon}$) is stored as a solid in the Central Valley, in pasture in the North Coast, drylot in the Southern Dairies. We assumed that the North Coast dairies had freestall or loafing barns for the winter, and the Southern dairies had no barn housing; however, there are exceptions to these generalizations we did not consider as we have little systematic data on dairies outside of the Central Valley apart from expert knowledge. We estimated the uncertainty in the VS production rate based on the variability reported for lactating cattle and heifers over 13 years (2000-2012) in the CARB inventory (CARB 2014). We calculated the mean and standard error for VS production for each of these two populations. We estimated the uncertainty of the MCFs using data reported by Owen and Silver (Owen and Silver, 2014). We estimated the error uncertainty of $f_{bed}$ to be 100%, as this value may range from including no manure as bedding to including all solid manure as bedding. To propagate the errors in total for the manure management system, we rearranged Eq. (8) with two factors to be as follows, where $MCF_x$ is the MCF for either solids, pasture, or drylot, and given that $f_{lagoon} + f_x = 1$.

$$CH_{4,m} = n_l * VS_{prod} * B_o * density_{CH4} * (f_{lagoon} * MCF_{lagoon} - f_{lagoon} * MCF_x + MCF_x) \qquad (10)$$

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We used the sum of the squared partial derivatives of each variable times the variance of that variable to propagate the uncertainty in facility-scale manure emissions (Supplemental Methods S1.2). To determine the relative effect of manure and enteric emissions from E3 and M3 on facility-level emissions, we propagated the uncertainty associated with the two emissions in quadrature.

Due to the large number of dairies, propagating the facility-level uncertainty to the state-level using standard methods produces unrealistically low state-wide uncertainty estimates (<1%). This suggests that the uncertainties at the facility level are not independent. Therefore, we used previously published estimates for state-scale uncertainties for each of the 6 methods, from the EPA (E1, M1 (US EPA, 2017)) , Hristov et al. 2017 (E2, M2 (Hristov et al., 2017)), and the IPCC (E3, M3, (Dong et al., 2006)).

We performed a sensitivity analysis on each of the methods. We calculate sensitivity $(\delta(x|y))$ of emissions (x) to each parameter (y) as

$$\delta(x|y) = \frac{\partial x}{\partial y} * \sigma_y \qquad (11)$$

where $\frac{\partial x}{\partial y}$ is the partial derivative of emissions (x) with respect to each variable (y) in the emissions equation and $\sigma_y$ is the uncertainty in each parameter y (i.e., fractional uncertainty * value). We calculate fractional uncertainty as each uncertainty divided by the sum of all uncertainties, as in Eq. (12) .

$$\delta = \frac{\delta(x|y)}{\Sigma\delta(x|y)} \qquad (12)$$

We also determined the relative sensitivity of total emissions to manure and enteric emissions.

## 2.6 Spatial patterns of $CH_4$ emissions and comparison with existing spatial inventories

We converted the Vista-CA dairy database into a raster image using R (R Core Team 2013). We then convert the image to a 0.1° x 0.1° grid in WGS84 to match CALGEM (Jeong et al., 2012) and the Spatial EPA (Maasakkers et al., 2016) inventories. We subtract the values from the CALGEM, Hristov, and

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Maasakkers emission inventories from the Vista-CA map to observe spatial variations between inventories.

## 2.7 Alternative Manure Management Strategy Assessment

### 2.7.1 Solid Separators

Solid separators, including mechanical separators, weeping walls, and settling basins, are an alternative methane mitigation manure management practice in California (CDFA 2020a). Separating out solids from liquid manure reduces $CH_4$ emissions by removing a fraction of the carbon content by aerobic decomposition prior to entering anaerobic storage. Mechanical separators, settling basins, and weeping walls remove approximately 5%, 22.5%, and 25% of volatile solids, respectively (Meyer et al. 2011).

### 2.7.2 Anaerobic Digesters

We determined the 109 dairies that have installed or are planning to install anaerobic digesters from reports from the CDFA Dairy Digester Reports in 2017-2019 (CDFA 2020b). We used our database to estimate the effects of anaerobic digesters on $CH_4$ emissions from these 109 dairies in the Central Valley. We assumed a 75% efficiency of $CH_4$ capture in anaerobic digesters (Charrier, 2016; US EPA, 2017).

# 3. Results and Discussion

## 3.1 Herd Populations and Demographics

The 2017 USDA Dairy Census reports the number of milk cows in California to be 1,750,329 in 2017. We report a total of 1,749,812 milk cows in VISTA-CA distributed across 1,727 dairy farms. We also report a total of 261,473 dry cows, 1,659,274 heifers, and 514,499 calves. 75% of milk cows, 80% of dry

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cows, 72% of heifers, and 85% of calves were reported in permits Table (1). We assume a 20% error in our uncertainty in the number of cattle, as recommended by the IPCC (2006).

3.2 Enteric Fermentation

Total enteric emissions for all cattle are 355.8 +/- 26.3 Gg $CH_4$/year for method E1; 415.6 +/- 38.7 Gg $CH_4$/year for method E2, and 426.6 +/- 85.3 Gg $CH_4$/year for method E3. We did not find statistically significant differences between the three methods of calculations of enteric $CH_4$ emissions for either milk cows or all cattle in the state (Table 2, Figure 2a). Statewide enteric emissions for milk cows only are 253.0 +/- 18.7 Gg $CH_4$/year for method E1, 277.9 +/- 23.1 Gg $CH_4$/year for method E2, and 258.9 +/- 51.8 Gg $CH_4$/year for method E3. We found relatively consistent proportions of enteric fermentation $CH_4$ emissions of milk cows to total cattle. Milk cows account for 71%, 67%, and 61% of total enteric emissions based on methods E1, E2, and E3, respectively.

3.3 Manure Management Emissions

Total manure management emissions for all cattle are 378.1 +/- 36.7 Gg $CH_4$/year based on M1, and 407.8 +/- 133.4 Gg $CH_4$/year based on M2, and 436.8 +/- 131.0 Gg $CH_4$/year based on M3, the farm-specific method. We did not find statistically significant differences in manure management emissions between the methods of calculations for either milk cows or all cattle (Table 2, Figure 2b). Total manure management emissions for milk cows only are 373.9 +/- 373.9 Gg $CH_4$/year based on M1, 402.7 +/- 131.7 Gg $CH_4$/year based on M2, and 441.3 +/- 132.4 Gg $CH_4$/year based on M3. The fraction of manure emissions that comes from the milk cows is greater than 98% for all three methods. This is because the manure of non-milk cows is primarily managed in ways with very low methane emissions, including daily spread, on dry lots, or on pasture. The difference between the emissions from milk cows alone and emissions from the total dairy herd are smaller than the uncertainties in manure emissions.

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## 3.4 Sensitivity Analysis

Total uncertainty in $CH_4$ emissions at the facility scale (E3+M3) is 14.4%; 84.1% of the uncertainty is due to uncertainty in manure emissions, while 15.9% of the uncertainty is due to enteric emissions. We report the statewide uncertainty in enteric emissions to be 7.4%, 8.3%, and 20% for E1, E2, and E3, respectively (Table 2). The facility-level standard errors for enteric fermentation we calculated are 21.3% for E1, 33.5% for E2, and 35.6% for E3. We find that sensitivities in enteric fermentation differ between the three methods (Table 3). E1 is most sensitive to the number of cows (n) at a facility. E2 is equally sensitive to n and $ef_2$, followed by the DMI of lactating cows. E3 is most sensitive to DMI, followed by n.

We report the statewide uncertainty in manure emissions to be 9.7%, 32.7%, and 30% for M1, M2, and M3, respectively (Table 4). The facility-level standard errors for manure emissions we calculated are 49.6% for M1, 50.5% for M2, and 55.4% for M3. Here, all three methods are most sensitive to the lagoon MCF (74.5% - 82.1%), followed by ncows (12.1% - 16.2%) (Table 4). Method M3 is also very sensitive to the fraction of manure allocated to bedding (12.3%). Our data on MCF for lagoons is only based on 9 observational studies from outside California (Owen and Silver, 2014), so more measurements are needed to reduce this uncertainty. Further, there is little information on the amount of manure used for bedding. Overall, our uncertainty analysis is based on limited data from very few dairies.

## 3.5 Spatial patterns of $CH_4$ emissions

Using the farm-specific method, the two largest sources of $CH_4$ from California dairy farms are enteric fermentation (38.2%) and manure emissions from lagoons (51.0%) statewide. Of manure management $CH_4$ emissions, 97.7% came from lagoons statewide, 1.6% from solid storage, 0.6% from liquid/slurry, and 0.0% from dry lot, pasture, and solid spread. Of the three geographic regions, the majority of manure management $CH_4$ emissions came from the Central Valley (96.1%), with only 2.3% of manure emissions were from the North Coast, and 1.6% from Southern California. Per cow manure

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management emissions were also highest in the Central Valley (0.25 Tg $CH_4$/milk cow/year) due to the predominance of lagoons as manure management practice, compared to the North Coast (1.6 Tg $CH_4$/milk cow/year) and Southern regions (0.12 Tg $CH_4$/milk cow/year). In the 180 North Coast dairies, the 79,974 cows encompassed 1.6% of calculated manure emissions and 2.2% of calculated enteric emissions. The 54 dairies with a total of 42,377 cows in the Southern dairies, made up 2.3% of calculated manure emissions and 1.2% of calculated enteric emissions.

With these emissions data, we also calculated enteric:manure ratios, which can be useful for methane mitigation planning. Mitigation strategies for dairy methane generally target either enteric or manure emissions, affecting this ratio. Manure management emissions per cow are much more variable than enteric emissions regionally, as manure practices vary more than feeding regimes Therefore, differences in enteric:manure are likely due to differences in manure management. The enteric:manure ratio of $CH_4$ emissions in the North Coast is the highest, at 1.9; the enteric:manure ratio in the Southern dairies is 1.5, and in the Central Valley is 0.94 (Figure 4). These differences are primarily due to the differences in manure management and cow housing type across regions: the Central Valley primarily uses flush systems, storing a large percentage of manure in lagoons, while North Coast and Southern California dairies tend to have scrape systems and dry lots, respectively. Because lagoons have the highest MCF, the Central Valley has the highest per-cow emissions and lowest enteric:manure $CH_4$ ratios. The CARB inventory also shows a statewide enteric:manure ratio of 1.08, which is primarily influenced by the large number of dairies in the Central Valley (CARB 2014). The enteric:manure ratio also has implications for verifying mitigation effectiveness, as strategies that reduce either enteric or manure emissions should alter this ratio. If emission signatures of enteric fermentation differ from those of manure management, such as the $^{13}C\text{-}CH_4$ isotopic signature, it may be possible to use downwind or regional measurements of these signatures and their changes with mitigation to quantify enteric:manure ratios.

### 3.6 Comparison with existing spatial inventories

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We compare this spatially-explicit facility-level database with three other existing bottom-up spatial inventories, the spatially-explicit EPA model (Maasakkers et al. 2017; comparable to E1+M1), the Hristov model (Hristov et al. 2017, comparable to E2+M2), and the CALGEM model (Jeong et al. 2012; Jeong et al. 2016), by aggregating these estimates to 0.1° x 0.1° resolution to match the spatial scale of these other products (Figure 4). The EPA model and the Hristov model were both developed for the contiguous United States, while CALGEM was developed for California only. First, we note that there are no significant differences in the statewide total methane emissions or methane emissions on a per cow basis amongst the three products. However, there are differences in how manure is treated. CARB estimates that 76% of manure is stored as a liquid, either in lagoon or liquid/slurry, while Hristov assumes that all manure is in lagoon or liquid/slurry, which are the manure treatments with the two highest emissions factors (Hristov et al., 2017). Thus the Hristov estimates are consistently higher than those of CARB and this farm-scale estimates.

We determined Pearson's correlation coefficients using R to test differences in spatial patterns between inventories. CALGEM is the closest to VISTA-CA emissions (E3+M3), with a Pearson's correlation coefficient of 0.79. Hristov et al. is the second closest, with a Pearson's correlation coefficient of 0.56, but tends to overestimate emissions in the Central Valley, including hotspots of methane emissions. Maasakkers et al. matches the least, with a Pearson's correlation coefficient of 0.30, and tends to underestimate the hotspots of methane emissions in the Central Valley. The other models also have emissions in areas where VISTA-CA does not have dairies (shown in gray in Figure 4). Hristov et al. (2017) includes the largest emissions area where VISTA-CA does not show dairies, mostly in the lower Central Valley and Southern Regions, though also in the North Coast. Maasakkers et al. (2017) follows, with additional emitting areas primarily in the lower Central Valley. CALGEM has the fewest areas that are not in VISTA-CA, mostly in the North Coast and Southern regions of California.

## 3.8 Alternative Manure Management Strategy Assessment

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We found that existing solid separators reduce state-wide manure $CH_4$ emissions by 96.7 Gg/year, (22.9%). This estimate assumes that half of all separated solids are used as bedding, and one third of the C of separated solids are emitted as $CO_2$, rather than $CH_4$, as with other solids. However, there is inconsistency in the applicability of separators as a methane emission strategy (CDFA 2020a, CDFA 2020b): on the one hand the AMMP funds separators to reduce methane emissions, but in the digester program projects include separators prior to their digesters.

We estimated the effects of anaerobic digesters on $CH_4$ emissions at 109 dairies in the Central Valley that have or are scheduled to have anaerobic digesters in 2017-2019 (CDFA 2020b, Figure 5). Following the USEPA, we assume a 75% efficiency in anaerobic digesters (Lory et al., 2010; Charrier 2016). We predict a total reduction of $CH_4$ emissions by 54.5 Gg $CH_4$/year. This represents a 73.2% decrease in manure emissions and a 38.2% reduction in total (manure + enteric) emissions from dairies with these digesters, resulting in a 12.9% decrease in statewide manure emissions and a 6.5% decrease in total (enteric + manure) statewide dairy emissions. However, limited data exist on farm-scale emissions before and after digesters, or on the efficiency of digesters.

Our estimate provides a baseline against which the effectiveness of digester systems to reduce $CH_4$ emissions can be assessed. Current top-down measurements of $CH_4$ emissions in California are associated with large uncertainty, and are not likely to capture signals of this magnitude. Jeong et al. (2016) inversion modeling posteriors suggest a 25% error in $CH_4$ emissions in the California Central Valley, but pixel-by pixel error is much higher. The 95% confidence intervals for the Central Valley are 1020-1740 Gg $CH_4$/year (Jeong et al. 2016), which is an order of magnitude larger than the reduction we expect to see from the digesters.

## 4. Data Availability

Raster files at 0.1° resolution of methane emissions from the Vista-CA Dairy dataset and associated metadata are open access and are available in the Oak Ridge National Laboratory Distributed

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Active Archive Center for Biogeochemical Dynamics (ORNL DAAC) (Marklein et al., 2020; https://doi.org/10.3334/ORNLDAAC/1814).

## 5. Conclusions

The farm-specific Vista-CA Dairies emission product is the first spatially-explicit database of $CH_4$ emissions from dairy at the farm scale. By separately mapping enteric fermentation emissions and manure management emissions, our product is valuable for source attribution and for determining the effects of changes to management on greenhouse gas budgets. State or county-level assumptions by EPA and CARB often do not match on-farm reality (Arndt et al., 2018), particularly given that they use statewide average emissions factors that cannot capture regional differences in climate or management within the state. At the state level, manure and enteric fermentation $CH_4$ emissions from the farm-specific method were not significantly different than previous analyses (Appuhamy, 2018; CARB, 2014; Hristov et al., 2017; Maasakkers et al., 2016), which supports the validity of the farm-specific methodology. Furthermore, by limiting emissions to locations with confirmed dairies, our facility-level database consolidates emissions estimates to point sources rather than regional estimates. For example, using county-level data, dairy emissions are predicted to be evenly spread throughout the county or through areas of active farmland (Maasakkers et al., 2016), but this approach can miss $CH_4$ hotspots and predict emissions in areas without dairies. Hotspots are particularly important to predict and monitor, as prevention and mitigation efforts occur at the facility scale.

The farm-specific data also explicitly include manure management practices, which can vary with climate, geography, and regional policy. The spatial differences in per cow emissions are particularly pronounced because of regional patterns in manure management strategies. When manure is managed as a liquid, including in lagoons, $CH_4$ emissions are higher than for manure managed as solids. The Central Valley primarily uses flush systems, storing a large percentage of manure in lagoons, while North Coast and Southern California dairies tend to have scrape systems and open lots, respectively, that emit

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far less $CH_4$. Thus, the Central Valley has higher per-cow emissions and lower enteric:manure $CH_4$ ratios (Figure 3).

Major uncertainties exist in both bottom up and top down estimates of $CH_4$ emissions from dairies. These include methane conversion factors, the number of cows, the amount of manure entering different waste streams, the time on concrete for the cattle, the functionality and efficiency of solid-separator systems, and the amount of manure solids used as bedding. We are most confident in the estimates in the San Joaquin Valley region, where air quality permits and water board reports exist, providing facility-level information on the herd sizes and manure management practices. However, manure management strategies were not defined consistently in the reports, so permit information may not be directly comparable between dairies. Further, even with accurate accounting, the different climatic, animal housing, manure management, and biogeochemical factors in each dairy affect the actual $CH_4$ emissions at any given time (Hamilton et al. 2006).

Nevertheless, this dataset is the first comprehensive, facility-scale inventory of $CH_4$ emissions, and can be easily updated as more data become available. This includes addition or removal of dairies, updated information on herd demographics, and information on manure management. We can also update the database with new estimates for $CH_4$ emissions as more data emerge and models become more accurate. More facility-scale information could be gained through either policy initiatives that require more detailed reports or thorough data mining of spatial images. For example, including an accounting of different types of feed will improve enteric fermentation emission predictions (NRC report 2018 24987-2). Mitigation activities including digesters, diet changes, and manure management are implemented at the facility scale. With emissions detail at the facility and process level, the Vista-CA database is therefore useful for predicting and verifying the effects of mitigation activities.

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**Tables and Figures**

Table 1. Total number of animals in each demographic class, and number of cows accounted for in permit data. Note that rows 2 and 3 contain some repeated data where farms have both types of permits. *Note that we assume that the population of replacement heifers is 10% greater than the population of milk cows.

| | Farms | Milk cows | Dry cows | Replacement Heifers* | Calves* |
|---|---|---|---|---|---|
| Total | 1,727 | 1,749,812 | 261,473 | 1,659,274 | 514,499 |
| Water board permit | 842 | 1,030,948 | 155,397 | 1,134,085 | 262,742 |
| Air quality report | 927 | 1,184,109 | 178,830 | 1,302,551 | 288,855 |
| Air quality + water board | 662 | 894,187 | 136,037 | 983,638 | 236,729 |
| No permit data | 620 | 428,942 | 63,283 | 471,911 | 77,082 |

Table 2. Enteric and manure CH4 emissions and standard error at the facility and statewide scales.

| | Mean per dairy (milk cows) kg $CH_4$/year | Facility level SE | Statewide estimate (milk cows) Gg $CH_4$/year | Statewide SE (milk cows) | Statewide estimate (all cattle) Gg $CH_4$/year |
|---|---|---|---|---|---|
| $CH_{4,E1}$ | 146.5 | 21.3% | 253.0 | 7.4% | 355.8 |
| $CH_{4,E2}$ | 160.9 | 33.5% | 277.9 | 8.3% | 415.6 |
| $CH_{4,E3}$ | 149.9 | 35.6% | 258.9 | 20% | 426.6 |
| $CH_{4,M1}$ | 210.9 | 49.6% | 373.8 | 9.7% | 378.1 |
| $CH_{4,M2}$ | 234.0 | 50.5% | 402.7 | 32.7% | 407.8 |
| $CH_{4,M3}$ | 252.9 | 55.8% | 436.8 | 30% | 441.3 |

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Table 3. Estimated input variables and standard error as a % of the mean for each of the methods to calculate enteric fermentation at the farm scale, along with sensitivity to each input variable. *Description of SE calculations are provided in the supplemental methods.

| | variable | | Mean value (%SE*) | sensitivity | Source |
|---|---|---|---|---|---|
| E1 (eq. 2) | n | lactating cows | 1125 cows (20%) | 88.0% | |
| | $ef_1$ | lactating cows | 144.61 kg CH4/cow / year (7.4%) | 12.0% | CARB 2017, US EPA 2017 |
| | | | | | |
| E2 (eq. 4) | n | lactating cows | 1125 cows (20%) | 35.6% | |
| | DMI | Lactating cows<br>heifers<br>calves | 22.9 kg/day (18%)<br>8.5 kg/day (15%)<br>3.7 kg/day (15%) | 28.9% | Hristov 2017 |
| | $ef_2$ | Lactating cows<br>heifers<br>calves | 19 g/kgDMI (20%) | 35.6% | |
| | | | | | |
| E3 (eq. 6) | n | lactating cows | 1125 cows (20%) | 29.1% | |
| | DMI | lactating cows<br>dry cows | 22.9 kg/day (38.2%)<br>13.5 kg/day (30.5%) | 32.4%<br>37.1% | Appuhamy 2018 |
| | dNDF | Lactating cows | 15.1 % DM (35.6%) | 0.5% | |
| | mf | Lactating cows | 3.6 % (6.0%) | 0.2% | |
| | $f_{DMI}$ | Lactating cows | 22.1 (3.5%) | 0.3% | |
| | $f_{NDF}$ | Lactating cows | 2.18 (36.7%) | 0.5% | |
| | $f_{mf}$ | Lactating cows | 32.2 (13.0%) | 0.8% | |

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Table 4. Estimated input variables and standard error as a % of the mean for each of the methods to calculate enteric fermentation at the farm scale, along with sensitivity to each input variable. *Description of SE calculations are provided in the supplemental methods.

| | Variable | | Mean value (%SE*) | sensitivity | Source |
|---|---|---|---|---|---|
| M1 | n | lactating cows | 1125 cows (20%) | 16.2% | IPCC |
| | $VS_{prod}$ | lactating cows<br>nonlactating cows | 2654 (1.4%)<br>1219 (0.9%) | 0.1% | CARB 2017 |
| | MCF | Pasture<br>Daily spread<br>Solid storage<br>Liquid/slurry<br>Lagoon<br>Dry lot | 0.15 (245%)<br>0.005 (245%)<br>0.04 (86.2%)<br>0.323 (47.1%)<br>0.748 (52.3%)<br>0.04 (86.2%) | 1.0%<br>0.0%<br>0.0%<br>1.6%<br>82.1% | CARB, Owen and Silver 2014 |
| M2 | n | lactating cows | 1125 cows (20%) | 15.7% | IPCC |
| | $VS_{prod}$ | Lactating cows<br>Heifer<br>calves | 2799 (1.4%)<br>1251 (0.9%)<br>370 (0.9%) | 2.7% | Hristov et al. 2017, CARB data |
| | MCF | Pasture<br>Daily spread<br>Solid storage<br>Liquid/slurry<br>Lagoon<br>Dry lot | 0.15 (245%)<br>0.005 (245%)<br>0.04 (86.2%)<br>0.323 (47.1%)<br>0.748 (52.3%)<br>0.04 (86.2%) | <br>0.0%<br>0.0%<br>1.4%<br>80.2% | CARB, Owen and Silver 2014 |
| M3 | n | 1720 cows per dairy | 1125 cows 20% | 12.1% | IPCC |
| | $VS_{prod}$ | Lactating cows<br>Nonlactating cows | 2654 (1.4%)<br>1219 (0.9%) | 0.0% | CARB data |
| | TOC ($f_{lagoon}$) | Freestall<br>Nonfreestall<br>nonlactating | 74% (5.7%)<br>34% (8.8%)<br>26% (12.3%) | 0.0% | Meyer 2019 |
| | MCF | Pasture<br>Daily spread<br>Solid storage<br>Liquid/slurry<br>Lagoon<br>Dry lot | 0.15 (245%)<br>0.005 (245%)<br>0.04 (86.2%)<br>0.323 (47.1%)<br>0.748 (52.3%)<br>0.04 (86.2%) | 0.3%<br><br>0.1%<br>0.6%<br>74.5% | CARB, Owen and Silver 2014 |
| | $f_{bed}$ | fraction bedding | 0.33 (100%) | 12.3% | Ahn et al. 2011 |

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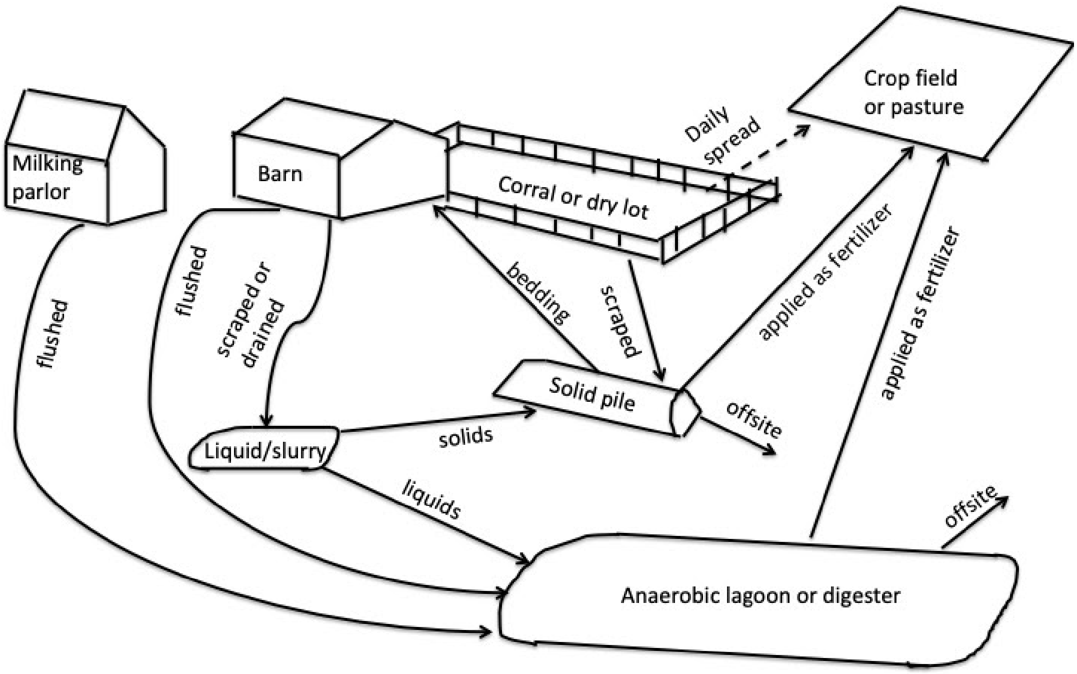


Figure 1. Diagram of manure flows on a dairy farm. Dashed lines indicate North Coast dairies only. Modified from Owen and Silver (2014) and Meyer et al. (2011).

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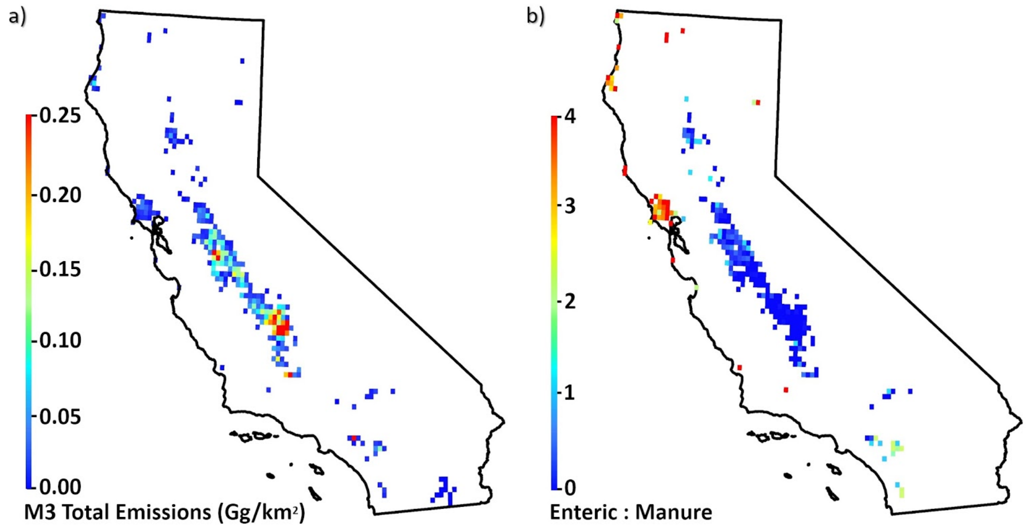


Figure 2. Map of the ratio of (a) total methane emissions and (b) ratio of enteric fermentation emissions to manure emissions. In panel (a), red indicates high total methane emissions and blue indicates low total methane emissions. In panel (b), red indicates relatively high enteric fermentation emissions, while blue indicates relatively high manure management emissions.

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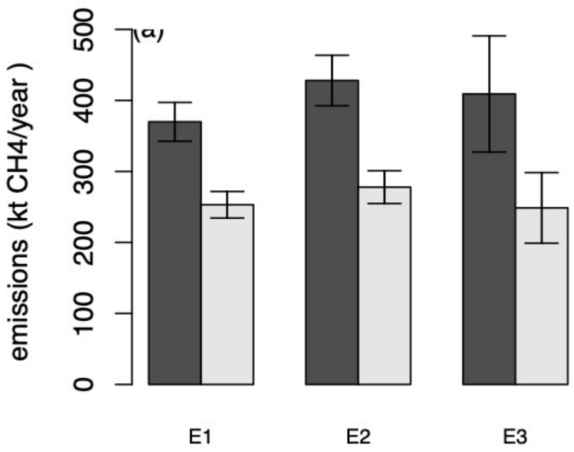


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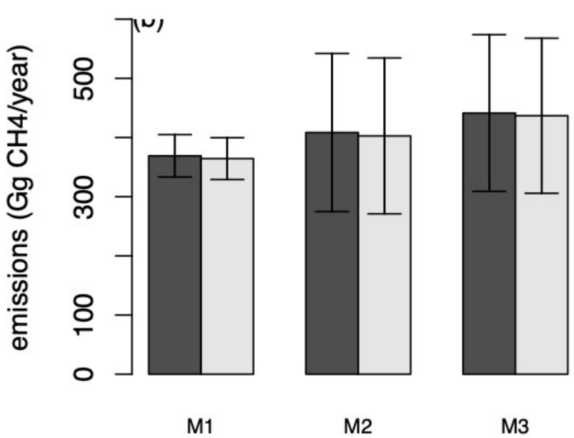


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605 Figure 3. Total state (a) enteric and (b) manure $CH_4$ emissions for each of the three calculations. Dark
606 bars include all cattle, while light bars include only milk cows. The lack of significant difference between
607 the three methods supports the validity of the farm-scale method.

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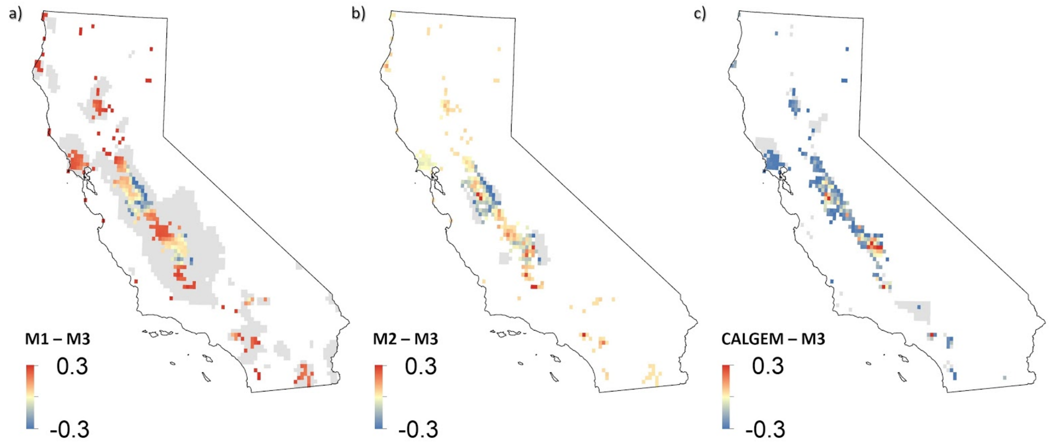


Figure 4. Map of the difference between facility-scale (M3) measurements and (a) M1 (Masakkers et al. 2017), (b) M2 (Hristov et al. 2017), and (c) CALGEM (Jeong et al. 2016). Positive (red) numbers indicate M1, M2, or CALGEM are higher than M3 measurements, while negative (blue) values indicate M3 is higher than M1, M2, or CALGEM. Grey values show where M1, M2, and M3 show dairy emissions but M3 does not.

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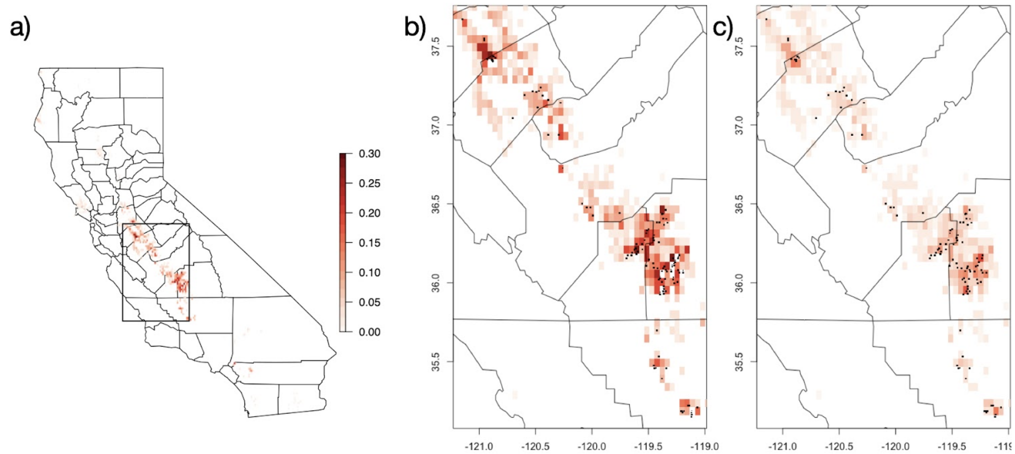


Figure 5. Total methane emissions of California San Joaquin Valley (a,b) before and (c) after installation of anaerobic digesters. Darker red shows higher emissions. The box in panel (a) is expanded in panels (b) and (c).

**Author Contribution:** FH conceived of the presented idea. AM developed the methods and analyzed the data with input from FH, DM, SJ and MF. AM SJ and MF performed the statistics. MC and TF compiled the data. DM provided guidance on the methods and all other aspects of the manuscript. AM prepared the manuscript with contributions from all authors. FH supervised the project.

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