SUPPLEMENTAL:

S1. Supplemental Methods

S1.1 Population Sizes and Demographics

Housing "percent fullness" Scaling Factor

For dairies with both water board reports and air quality reports (n=662), we calculated an average percent fullness (pf) of dairy housing. This number is calculated as the number of reported cattle (n_{WB}) over the number of cattle housing available ($nhousing_{AQ}$), for each housing class i:

$$pf_i \;=\; n_{WB,\,i}\,/\,nhousing_{AQ,\,i}\ . \qquad (1)$$

We use the percent fullness as a scaling factor to convert the cattle housing available into estimates of the number of cattle in each class, for dairies with air quality reports but without water board reports (n=265).

$$n_i \;=\; nhousing_{AQ,i} * pf_i\ . \qquad (2)$$

Dairies without USDA Census data

For the counties which do not have cattle reported in the USDA Census data, but have dairies with air quality and/or water quality reports, we assigned the number of cows to be the average number of cows in the farms with water or air quality permits in that county. This assumes that the farms with reports are representative of all farms in the county; however, the water board data are skewed towards farms with over 500 cows and that were established before 2009, and air quality data are only available in the San Joaquin valley.

$$n_i \;=\; mean(n_{AQ,county,i},\ n_{WB,\,county,i})\ . \qquad (4)$$

We used data from the county-wide California NASS from 2017 year to estimate the number of cows in the counties did not have any farms with water board, air quality, or estimates from the USDA Census data (35 counties: Butte, Colusa, Del Norte, Fresno, Glenn, Humboldt, Imperial, Kern, Kings, Lassen, Los Angeles, Madera, Marin, Mendocino, Merced, Modoc, Monterey, Placer, Riverside, Sacramento, San Bernardino, San Diego, San Joaquin, San Luis Obispo, San Mateo, Santa Barbara, Siskiyou, Solano, Sonoma, Stanislaus, Sutter, Tehama, Tulare, Yolo, and Yuba). For these dairies, we individually assessed the number of dairies of each size and estimated the number of cows as the average of each range in the county (see supplemental methods and Supplemental Table 2).

For the counties that didn't have any farms with water board, air quality data, and do not have cow estimates from USDA census data (e.g. Santa Barbara and San Mateo), we determined the number of farms with different levels of cows. Mono county had one dairy with 10-19 cows, so we assigned 15 cows to that dairy. The Santa Barbara dairy had 1600 cows, which we determined from an internet search. In Yolo county, we determined that the UCD farm had 105 cows. The remaining 3 dairies in Yolo county had 11 total cows, so we assigned 4 cows to each of these dairies. In Imperial County, the USDA states that there are 2 dairies with 500+

cows; however, the VISTA database states that there are 22 farms. We assumed that this dairy was divided into separate farms, and divided 1000 by 22 to estimate 45 cows per farm. For Los Angeles county, the USDA states 1 dairy with 500+ cows, while the VISTA database includes 2 farms. To assign cow counts to these two farms, we divided 500/2 to estimate 250 cows per dairy. In Modoc county, there were 2 dairies in the USDA Census with 1-9 cows; we assigned the average, 5 cows, to each of the dairies in this county.

S1.2 Uncertainty analysis

S1.2.1 Facility level uncertainty

n: We assume that the uncertainty in the cattle populations is 20%, as recommended by the IPCC. For dairies with cattle permits, the water quality board assumes 15% uncertainty in population (California Regional Water Quality Control Board, 2013). This uncertainty is likely an underestimate, as there are likely dairies in VISTA that are no longer extant, due to the declining dairy industry, and it is possible that there are dairies that exist that are not included in the database. We do not expect the uncertainty to follow a normal distribution; rather there are likely a few dairies where the estimates are far from correct.

E1: The EPA 2017 reports the 95% confidence bounds as -11 to 18% of the mean enteric emissions uncertainty at the national level (US EPA, 2017). We assume this is the same uncertainty as the uncertainty in ef_1 at the facility level, as this is the only factor besides the number of cows in this model. We convert 95% CI into SE by assuming that 95% CI = 3.92 * SE.

E2: Hristov et al. 2017 provides the 95% confidence bounds as a % of the mean for the parameters in the model (Hristov et al., 2017). For DMI, The confidence bounds are 34.4-35.1% for DMI and 38.3-39.0% for ef_2. We convert 95% CI into SE by assuming that 95% CI = 3.92 * SE. Hristov:

E3: CARB provides the minimum and maximum of DMI, NDF, and mf (Appuhamy, 2018). We assume the range rule, which assumes a normally distributed population, such that SD = (max-min)/4 and SE = SD/sqrt(n), and calculate SE based on n=77. The range rule works best when data are normally distributed and n ~ 30. Error ranges are also provided for f_{DMI}, f_{NDF}, and f_{mf}, which we assume to be standard error.

M1: The IPCC states that the uncertainty range for emissions using regional MCF, Bo, and VS is 20%. We therefore assume 20% uncertainty in $CH_{4,m1}$ (Dong et al., 2006).

M2: Hristov *et al.* (Hristov et al., 2017) report the 95% confidence bounds for manure management to be 65%-63.3%, though their estimate includes swine and poultry in addition to cattle. We convert 95% CI into SE by assuming that 95% CI = 3.92 * SE.

M3: For manure method three, we assess the uncertainty in time on concrete, volatile solid production, and methane conversion factors as described below. We propagate the error using partial derivatives.

Time on concrete: We estimated the standard error for time on concrete for freestall, nonfreestall dairies, and for nonlactating animals from a report that provided time on concrete at four dairies in the Central Valley (Meyer, 2019). We calculated standard error as the standard deviation divided by the square root of the number of samples. For the freestall dairies (n=2), one dairy had 78.2% time on concrete and the other dairy had 69.8% time on concrete. We calculated the mean and standard error of these two measures of time on concrete, which were 74.0 +/- 26.2. For the nonfreestall lanes (n=2), the two dairies had 31.0-37.0% time on concrete, which is the mean of 34.0% +/- 12.0 . For the nonlactating cows, the average time on concrete from the four facilities were 26.5 +/- 7.6.

Volatile solid production: To estimate the standard error in volatile solid production, we calculated the mean and standard error of the VS production by lactating lactating cows and replacement heifers using data from 2000-2012 from the CARB inventory (US EPA, 2017).

Methane Conversion Factor: Owen and Silver 2014 report a field-derived methane conversion factor of 84%+/- 44 (confidence intervals) from a total of 9 observations for lagoon storage and 2.9 +/- 2.5 from a total of 4 observations for solid storage (Owen & Silver, 2014). We convert the confidence intervals into standard errors, and fractional uncertainty by dividing the error by the estimate.

f_{bed}: We estimate the standard error in the fraction of manure solids that are used as bedding to be 100%, as some dairies may not use any manure solids for bedding, and others may use all manure solids as bedding.

S1.2.2 Statewide uncertainty

Because of the large number of dairies, propagating the error throughout the state calculates an improbably small statewide error. Therefore, we use previously published estimates for E1, E2, M1, and M2. We use IPCC recommendations for E3 and M3 (Dong et al., 2006).

E1: The EPA 2017 reports the 95% confidence bounds as -11 to 18% of the mean enteric emissions uncertainty at the national level (US EPA, 2017). We assume this uncertainty is the same in California as in the national scale. We convert 95% CI into SE by assuming that 95% CI = 3.92 * SE.

E2: Hristov et al. 2017 (Hristov et al., 2017) report the 95% confidence intervals of average annual enteric emissions from the continental United States to be 15.6-16.9%. We assume this uncertainty is the same in California as in the national scale. We convert 95% CI into SE by assuming that 95% CI = 3.92 * SE.

E3: The IPCC suggests using +/- 20% using Tier 2 methodology, which we assume is the uncertainty for our statewide assessment (Dong et al., 2006).

M1: The EPA reports -18 to 20% uncertainty for manure management CH4 emissions, which we use here (US EPA, 2017). We assume this uncertainty is the same in California as in the national scale. We convert 95% CI into SE by assuming that 95% CI = 3.92 * SE.

M2: Hristov et al. 2017 (Hristov et al., 2017) report the 95% confidence intervals of average annual manure emissions from the continental United States to be -65.0 to 63.3%. We assume this uncertainty is the same in California as in the national scale. We convert 95% CI into SE by assuming that 95% CI = 3.92 * SE.

M3: The IPCC suggests using +/- 30% as confidence intervals using Tier 2 methodology, which we assume is the uncertainty for our statewide assessment (Dong et al., 2006).

S2. Supplemental Glossary

S2.1 Classes of animals

calf: 0-6 month old cattle
dry cow: cattle that have calved that are not lactating; includes mature cows 15% of the time
heifer: 6-24 month old cattle
lactating cow: cattle that have calved that are lactating; includes mature cows 85% of the time
mature cow: cattle that have calved that may or may not be lactating

S2.2. Types of manure management

anaerobic digester: large containment system or covered lagoon designed for capturing methane and carbon dioxide for use as fuel
anaerobic lagoon: designed storage system for stabilizing waste
daily spread: the collection of manure that is spread onto field or pasture within 24 hours of deposition
dry lot: an open confined area, where manure may be removed occasionally
pasture: land covered in grass that the animals eat
solid storage: dried manure stored in unconfined stacks
liquid/slurry: manure stored with some water added, with a typical residence time of less than 1 year

S2.3.Variables

B_o: maximum methane production capacity
$CH_{4,density}$: density of methane
CH_4: methane
DMI: dry matter intake
dNDF: digestible neutral detergent fiber
ef_1: emission factor associated with method E1
ef_2: emission factor associated with method E2
f_{bed}: fraction of manure that is used as bedding

f_{DMI}: emissions factor for dry matter intake
f_{lagoon}: fraction of manure that enters the lagoon
f_{mf}: factor associated with milkfat
f_{NDF}: factor associated with dNDF
i: class of animal
mf: milkfat content:
MCF: methane conversion factor
n_{AQ}: population of cattle included in AQ permits
n_i: population of animal class i
n_{USDA}: population of cattle in USDA NASS census
n_{WB}: population of cattle included in RWQCB reports
TOC: time on concrete
TOMP: time in milking parlor
VS: volatile solids

Table S1. Manure partitioning. The time on concrete number includes the time in milking parlor. San Joaquin Valley, with air quality data

MCF		SJV: with freestalls	SJV: No freestalls	North Coast	Southern
	Time in milking parlor (tomp)	0.125	0.125	0.125	0.125
	Time on concrete (toc)	0.70	0.34	0.34	0.34
0.04	**Solid**	1-toc	1-toc	0	0
0.015	**Pasture**	0	0	1-toc	0
0.731	**Lagoon**	toc	toc	tomp	toc
0.323	**Slurry**	0	0	toc-tomp	0
0.015	**Drylot**	0	0	0	1-toc

Table S2. Number of farms and milk cows in database with permits, usda reports and in total database for each county (USDA NASS, 2017).

County	npermit farm	Nvista farm	Nusda farm	Npermit cows	Nvista cows	Nusda cows
Butte	1	3	10	350	468	(D)
Colusa	0	1	4	0	80	80
Del Norte	0	8	7	0	6448	6452
Fresno	69	81	65	97006	102790	102796
Glenn	18	36	28	10908	15534	15533
Humboldt	0	63	96	0	23877	23894
Imperial	0	16	2	0	0	(D)
Kern	50	53	41	129743	129794	116605
Kings	123	153	101	142929	173409	173404
Lassen	0	2	8	0	22	22
Los Angeles	0	1	1	0	0	(D)
Madera	41	46	34	67636	67661	66038
Marin	0	26	31	0	10894	10895
Mendocino	0	5	13	0	1180	1182
Merced	224	289	202	219505	272545	272534
Modoc	0	1	2	0	0	(D)
Monterey	0	1	7	0	1445	1445
Placer	1	2	25	340	946	946
Riverside	0	33	36	0	38049	38033
Sacramento	21	36	34	9351	16026	16027
San Bernardino	0	76	40	0	52592	52554
San Diego	0	4	9	0	4328	4330
San Joaquin	93	129	97	74326	106366	106375
San Luis Obispo	0	1	16	0	256	256
San Mateo	0	1	-	0	10	-
Santa Barbara	0	1	3	0	1600	(D)
Siskiyou	0	3	15	0	1194	1193
Solano	1	2	8	610	611	22
Sonoma	0	68	125	0	33048	33059
Stanislaus	191	255	190	149032	183464	183496
Sutter	0	1	4	0	5	5
Tehama	3	12	35	787	3253	3249
Tulare	269	312	235	416932	500395	500402
Yolo	0	2	4	0	105	(D)
Yuba	2	4	6	1415	1417	(D)

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