Measuring Livestock from Space: Global and U.S. Evidence on the Detection, Attribution, and Limits of Satellite Methane*

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Abstract

Livestock are difficult to measure consistently where agricultural statistics are sparse. We ask when satellite methane contains useful information about livestock activity. Combining global 0.1° methane observations with gridded livestock data from 2003 to 2020, we find that nearby areas with more livestock have higher methane concentrations on five of six continents. The relationship survives controls for rice, fossil-fuel, and waste emissions and pollutant placebo tests. Yet the signal has clear limits. Satellite methane does not reliably track local changes in herd size over time and adds little to predicting herd size beyond information contained in geographic location. Detectability instead depends on whether livestock emissions are sufficiently concentrated relative to the local methane background. In the United States, satellite methane tracks concentrated dairy cattle but not dispersed beef cattle, and California cells hosting large dairy facilities show higher methane concentrations even after accounting for terrain-related effects on satellite column measurements. Satellite methane is therefore not a general livestock census from space, but a useful tool for screening and independently verifying large, concentrated livestock activity, as well as filling measurement gaps for facility-level monitoring in countries where official statistics are sparse or outdated.

Keywords: livestock; methane; remote sensing; agricultural measurement; detection envelope; dairy cattle; beef cattle; CAFO.

JEL Codes: Q12, Q51, C81.

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1 Introduction

Reliable measures of livestock activity remain scarce in many parts of the world, limiting efforts to monitor agricultural production and its environmental consequences (Davis et al., 2025). Existing livestock statistics rely primarily on censuses and surveys that are costly to administer, conducted infrequently, and uneven in their spatial coverage and quality. These limitations are particularly consequential for livestock, which accounts for a large share of agricultural output and land use and is a major source of methane emissions (Gerber et al., 2013; Xu et al., 2021; Saunois et al., 2025). Even where official statistics are available, inventories are often reported at administrative scales that obscure substantial variation in the location and concentration of production. Measuring livestock activity more consistently and at finer spatial scales would therefore improve both agricultural statistics and the assessment of environmental impacts. These limitations create demand for independent, spatially consistent measures of livestock activity that do not rely on producer reporting.

Satellite methane observations offer a potential source of such information because livestock activity generates methane emissions that can be observed from space (Jacob et al., 2016; Parker et al., 2020). Yet atmospheric methane is not a direct measure of livestock activity. Livestock numbers first translate into emissions, which then disperse through the atmosphere before appearing in satellite measurements of column methane concentrations. Each step in this mapping can vary across locations and production systems. Emissions differ across animal species and manure-management practices (IPCC, 2006; Gerber et al., 2013), while the spatial concentration of production determines whether those emissions generate a sufficiently strong local enhancement. Satellites also observe methane from wetlands, fossil fuels, waste, rice cultivation, and other sources, making livestock more difficult to distinguish where background methane is high (Saunois et al., 2025). Atmospheric transport and terrain can further alter the relationship between emissions at the surface and concentrations observed from space (Jacob et al., 2016). Whether satellite methane is informative about livestock activity therefore depends on the strength and spatial concentration of livestock emissions relative to the local methane background.

This paper asks when satellite methane contains economically useful information about livestock activity. We distinguish three questions. First, can satellites detect methane emissions associated with livestock activity? Second, when can this signal recover information about livestock activity itself? Third, does satellite methane provide information beyond what can already be inferred from existing agricultural statistics and geography? This measurement capability addresses a significant gap in agricultural economic statistics, particularly for countries where livestock methane relies on models rather than observed facility-level data. These distinctions separate three concepts that are often implicitly treated as equivalent. Detecting methane associated with livestock does not necessarily imply that satellite observations can recover livestock inventories, and recovering a spatial livestock signal does not necessarily imply that satellites improve on existing information. Establishing where these links hold—and where they break down—is therefore necessary for assessing the statistical value of satellite methane. We address these questions by combining global

satellite observations with livestock inventories and administrative records at progressively finer spatial scales.

We begin by testing whether satellite methane contains a detectable spatial signal of livestock activity at the global scale. We combine global 0.1° satellite-based methane concentrations from GHAP with gridded livestock inventories from FAO's AGLW for 2003–2020. Our baseline specification compares grid cells within 5° × 5° neighborhoods, absorbing broad spatial differences in atmospheric conditions and methane backgrounds. Within the same neighborhood, cells with greater livestock activity have systematically higher methane concentrations. The relationship is positive on five of six continents and is robust to alternative measures of livestock activity based on animal counts rather than predicted emissions. These results establish a persistent spatial association between livestock activity and satellite methane, but they do not by themselves show that the observed signal reflects livestock rather than other correlated methane sources or environmental conditions.

We next test whether this spatial relationship reflects livestock emissions rather than competing methane sources or correlated environmental conditions. Controlling for methane emissions from rice cultivation, fossil fuels, and waste leaves the livestock relationship largely unchanged. We then conduct placebo tests using satellite-based ozone and column carbon dioxide, pollutants that respond to atmospheric transport and economic activity but are not directly produced by livestock methane emissions. Livestock activity predicts methane but not either placebo pollutant. The relationship is also stronger where methane is elevated relative to carbon dioxide, a pattern more consistent with biogenic than fossil sources. Together, these tests support interpreting the spatial gradient as a livestock-related methane signal rather than a general feature of livestock-producing locations.

The livestock signal, however, is not uniformly informative about livestock activity. Out-of-sample classification exercises reveal substantial differences in detectability across countries: satellite methane identifies livestock-intensive areas well in the United States but performs much less reliably in Australia and Brazil, where livestock emissions are more dispersed or competing methane sources are important. U.S. administrative data reveal a similar distinction across production systems. Satellite methane tracks dairy cattle, which are concentrated in large operations with substantial manure emissions, but is much less informative about geographically dispersed beef cattle. The limitation also extends to temporal variation: methane captures persistent cross-sectional differences in livestock activity but does not reliably track local changes in herd size over time. These patterns define a detection envelope in which satellite methane is most informative when livestock emissions are sufficiently large and spatially concentrated relative to the local methane background.

Fine-scale administrative data confirm this detection envelope and clarify the statistical value of satellite methane. Within California's Central Valley, grid cells containing large dairy facilities have higher methane concentrations than other cells in the same county, and the difference remains after accounting for column carbon dioxide and terrain-related retrieval effects. Facility-level emissions estimates yield the same pattern, whereas comparable tests for Midwestern hog facilities show

substantially weaker signals. Satellite methane also adds little to predicting continuous herd size once geographic information is known, but it is more informative for identifying exceptionally large livestock concentrations. Satellite methane is therefore better suited to screening and independently verifying large, concentrated livestock activity than to replacing livestock censuses or nowcasting herd size.

Our paper contributes to three strands of literature. First, we contribute to a growing literature that uses remotely sensed data to measure economic activity when conventional statistics are limited (Henderson et al., 2012; Donaldson and Storeygard, 2016; Jean et al., 2016; Yang et al., 2025; Rossi-Hansberg and Zhang, 2026; Wuepper et al., 2025). This literature has shown that satellite observables can recover information about outcomes ranging from economic activity and poverty to agricultural production. Our setting highlights a distinct measurement problem: the physical signal observed by a satellite need not map one-to-one into the underlying economic activity of interest. Livestock activity must first generate emissions, those emissions must produce a sufficiently concentrated atmospheric signal, and that signal must be distinguishable from other methane sources before it becomes informative in satellite observations. We characterize this mapping empirically and show that its reliability varies systematically across production systems and methane environments. Our results therefore shift attention from whether a remotely sensed variable can proxy for economic activity on average to the conditions under which that proxy is informative. More generally, they illustrate the importance of characterizing the detection envelope of remotely sensed measures rather than evaluating them solely by their average predictive performance.

Second, we contribute to the literature that uses atmospheric observations to measure and attribute methane emissions (Jacob et al., 2016; Duren et al., 2019; Lauvaux et al., 2022; Worden et al., 2023; Maasakkers et al., 2025; Hu et al., 2025). Existing work has demonstrated the value of satellite observations for detecting large methane sources, quantifying regional and national emissions, and evaluating bottom-up inventories. We approach the measurement problem from the opposite direction: starting from independently measured livestock activity, we ask when its atmospheric signature can be recovered from satellite methane. This approach allows us to characterize not only where livestock-related methane is detectable, but also where the mapping breaks down. The resulting detection envelope varies systematically with emission intensity, the spatial concentration of livestock production, and the importance of competing methane sources. It helps explain why concentrated dairy production leaves a detectable satellite signature while dispersed livestock systems often do not, and why the same satellite measure performs differently across methane environments.

Third, we contribute to work on agricultural statistics by clarifying the comparative advantage of satellite-based measures (Lobell, 2013; Davis et al., 2025; Wuepper et al., 2025; Proctor et al., 2025). Remote sensing can provide spatially consistent information without relying on producer reporting, making it potentially valuable where conventional agricultural data are sparse, infrequent, or difficult to verify. Our results also show why this advantage should not be interpreted as implying that satellite measures can replace conventional statistics. Satellite methane adds little to

continuous herd-size prediction once geographic information is known and does not reliably recover local changes in livestock inventories over time. Its comparative advantage instead lies in providing an independent physical signal of unusually large and concentrated livestock activity. Satellite methane can therefore complement, rather than substitute for, conventional livestock statistics by screening locations where official data are limited and providing independent verification where concentrated activity is expected to generate a detectable atmospheric signal.

The remainder of the paper is organized as follows. Section 2 describes the satellite methane, livestock, and validation data. Section 3 presents the empirical framework for spatial validation, detection, and prediction. Section 4 establishes the global livestock-related methane signal and assesses its attribution using competing methane sources and atmospheric placebo tests. Section 5 examines when this signal is informative about livestock activity, focusing on variation across methane environments and production systems, facility-level validation, and the incremental information provided by satellite methane. Sections 6 and 7 discuss policy and conclude.

2 Data and Measurement

Our analysis combines global satellite methane observations with gridded livestock inventories, competing methane sources, and U.S. administrative and facility-level records. Satellite carbon dioxide and ozone are used for attribution and placebo tests. Table A2 summarizes the data sources, coverage, resolution, and role in the analysis. This section describes the satellite methane measure, livestock activity and emissions, and the additional data used for attribution and validation.

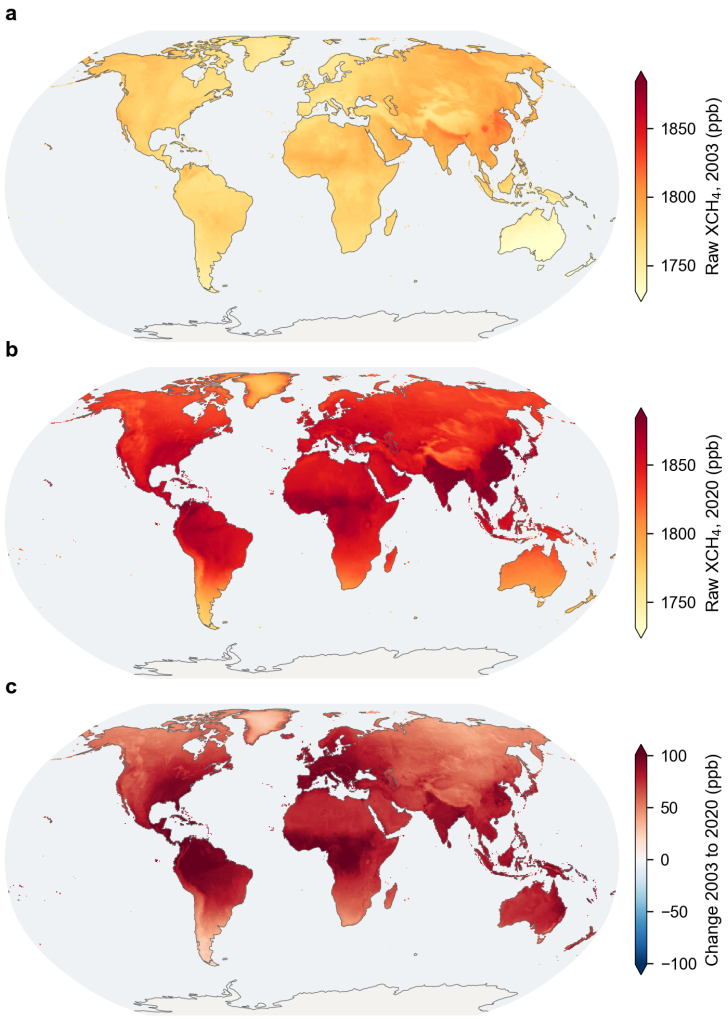
2.1 Satellite Methane

Our satellite measure comes from the GlobalHighAirPollutants (GHAP) column methane product developed by Qu et al. (2025). GHAP integrates satellite observations using a spatiotemporal Transformer model and provides column-averaged dry-air mole fractions of methane (XCH_4) at 0.1° resolution from 2003 to 2020. XCH_4 measures atmospheric methane concentration, rather than emissions, in parts per billion (ppb) of dry air. We construct annual grid-cell means by averaging valid retrievals and excluding fill values.[1] Our primary outcome is raw XCH_4. Across grid cells with livestock data in 2020, mean XCH_4 is approximately 1,848 ppb, with a cross-sectional standard deviation of 21 ppb, as illustrated in Table A3.

Figure 1 shows the raw column methane concentration using GHAP in 2003 and 2020 and the change between them. Column methane is higher in the Northern Hemisphere than the Southern Hemisphere and peaks over the major continental source regions, most visibly East and South Asia, where dense agriculture, wetlands, and industry coincide. Between 2003 and 2020, the concentration rose almost everywhere, consistent with the documented global increase in atmospheric methane (Saunois et al., 2025). Figure A1 summarizes the methane concentration by region and

[1] We considered combining GOSAT and Sentinel-5P TROPOMI observations directly, but inter-sensor differences would introduce a discontinuity large relative to the livestock signal of interest.

Figure 1: Raw column methane, 2003, 2020, and change



Notes: GHAP XCH_4 in parts per billion (ppb) on a fixed color scale. The figure shows the raw column methane concentration using GHAP in 2003 and 2020 and the change between them. Source: GHAP.

year. Because observed column methane combines local emissions with broad atmospheric background and transport, livestock-related variation represents only one component of the observed concentration. The neighborhood comparisons described in Section 3 are designed to isolate this local spatial variation.

2.2 Global Livestock Activity and Methane Emissions

Livestock activity comes from the FAO AGLW gridded livestock dataset compiled by Du et al. (2025), which provides annual animal density at 0.1° resolution from 1961 to 2021 across the globe for the six animal types that dominate enteric and manure methane: cattle, buffaloes, sheep, goats, pigs, and poultry. We convert species-specific densities to head counts using grid-cell area.

Aggregated globally, the gridded product matches FAO census head counts closely.[2] The gridded livestock census is independent of the satellite.

The spatial composition of the herd is shifting, and the shift is regional. Figure 2 maps the 2003 to 2020 change in three ways. Cattle density grew across the Sahel, the East African highlands, and South and Central Asia, and fell across Europe, the Russian steppe, and parts of Australia. Goat density grew over much of the same ground, and more strongly. The third panel combines them: the small ruminant share of the ruminant herd rose across Central Asia, the Sahel, and southern Africa, and fell across parts of South America and Southeast Asia. Figure A2 shows global headcounts by species from 2003 to 2020. All species grew, with the fastest proportional growth in poultry and goats and slower growth in cattle and pigs.

Our baseline measure converts livestock headcounts into predicted methane emissions using IPCC 2006 Tier 1 emission factors (IPCC, 2006). The annual factors for cattle, buffaloes, sheep, goats, pigs, and poultry are 62, 55, 8, 5, 1.5, and 0.02 kilograms of CH_4 per head, respectively, combining enteric fermentation and manure management. These factors differ by more than two orders of magnitude across species, so livestock head counts and predicted methane emissions can differ substantially in their spatial distribution. Figure A3 links the headcount with methane emission and maps the species that contribute the most Tier 1 methane in each cell. Cattle dominate the Americas, much of Africa, and South Asia, buffaloes dominate the Indo-Gangetic Plain, and small ruminants dominate the Sahel and Central Asia. This spatial heterogeneity is one reason the livestock methane relationship need not be homogeneous, which motivates estimating it separately by region.

Figure 3 illustrates the differences in country ranking between headcounts and methane. China leads on head count with 6.2 billion animals, driven by its pig and poultry sectors, but falls to third on methane at 7.4 megatons, because a chicken emits about one three-thousandth and a pig about one fortieth of what a cow emits. India and Brazil, with large ruminant herds, lead on methane at 19.4 and 13.3 megatons. The head count panel is dominated by the pale poultry band, the methane panel by the dark cattle and buffalo bands. The three largest emitters together account for about a third of the global total.

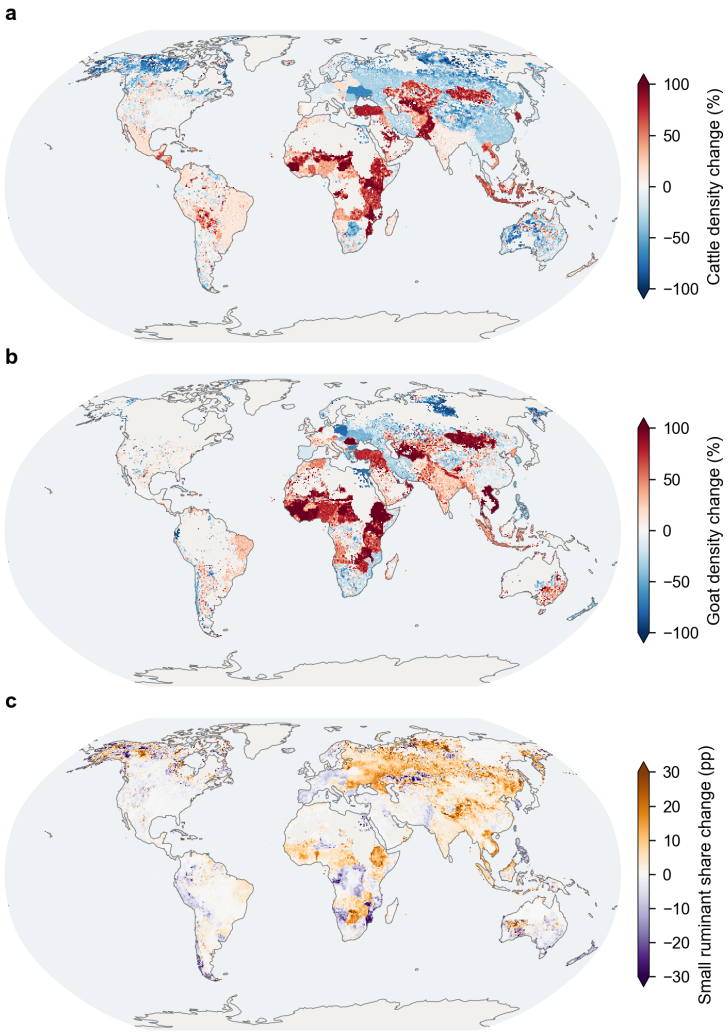
2.3 Other Methane Sources and Validation Data

Rice paddy, fossil fuel, and waste. We use gridded measures of rice cultivation, fossil-fuel methane, and waste methane to account for major non-livestock methane sources. Rice paddy extent comes from the GlobalRice20 product, a 20-meter binary paddy mask that we aggregate to a 0.1° rice fraction by averaging fine-resolution pixels within each grid cell. Because paddy extent is relatively stable over our study period, we treat the 2015 layer as a near-static confounder.

We measure fossil-fuel and waste methane directly using sector-specific gridded inventories.

[2]For example, 1.51 billion cattle in 2020 against an FAO figure near 1.53 billion, and 0.94 billion pigs against about 0.95 billion, which supports its use as an activity measure. We work with the full grid rather than only satellite-observed cells when computing global and species totals, since the full grid is the true global quantity.

Figure 2: Where the herd grew, and where its composition tilted

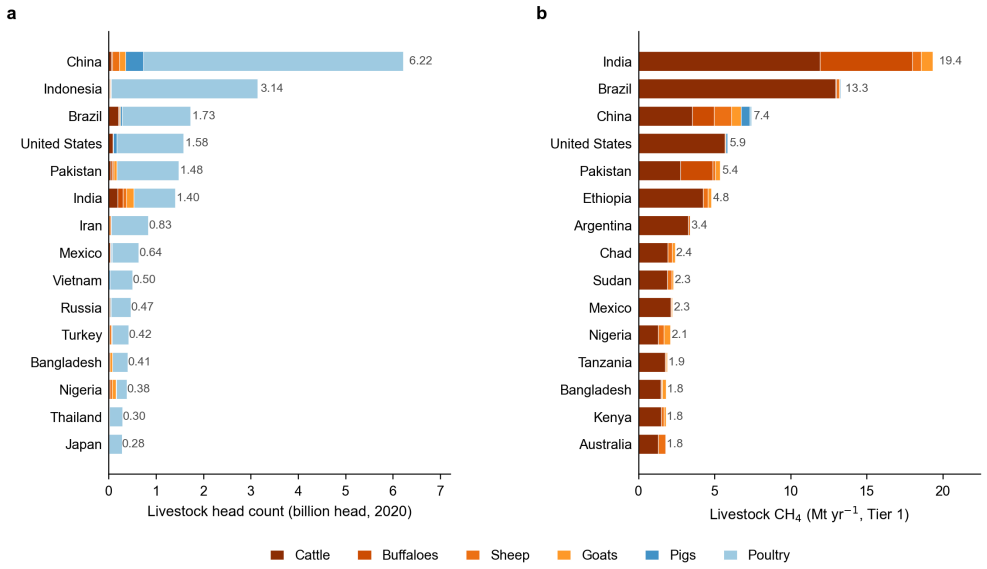


Notes: Change from 2003 to 2020 in (a) cattle density, (b) goat density, both as a percent of the 2003 level and clipped at plus or minus one hundred percent, and (c) the small ruminant share of the ruminant herd, in percentage points. Cattle and goats grew together across the Sahel, East Africa, and South and Central Asia and declined across Europe and the Russian steppe; the composition panel shows where that growth tilted the herd toward goats and sheep. Cells with negligible livestock are left blank. Source: FAO AGLW.

Fossil methane comes from the Global Fuel Exploitation Inventory (Scarpelli et al., 2022), a 0.1° inventory that allocates national oil, gas, and coal methane to infrastructure locations; we sum its oil, gas, and coal layers into a single fossil grid. Waste methane comes from the EDGAR v2025 sector split grids for solid waste landfills and for wastewater, which we similarly combine into a single waste grid. Because the location of oil and gas fields, coal mines, landfills, and treatment plants is spatially stable over our period, we treat both layers as near-static confounders, as we do for rice, using the GFEI reference year and the 2020 EDGAR waste layer. We also retain total methane emissions from EDGAR v2025 (Crippa et al., 2025) as an overall reference.

These gridded measures allow us to condition directly on the spatial locations of major compet-

Figure 3: Weighting animals by what they emit reverses the country ranking



Notes: Top fifteen countries in 2020 by (a) total livestock head count and (b) Tier 1 livestock methane, both stacked by species and computed from the same area-weighted gridded census. China leads on head count but ranks third on methane, while India and Brazil lead on methane; the pale poultry band that dominates panel a all but disappears in panel b, because the emission factors span nearly two orders of magnitude across species. Source: FAO AGLW with IPCC Tier 1 factors.

ing methane sources rather than subtracting them from an aggregate inventory. Section 4.2 uses these measures to assess whether the livestock–methane gradient can be explained by other methane sources. We also use the methane-to-carbon dioxide ratio as a complementary test of whether local enhancements over livestock-producing areas are consistent with biogenic rather than fossil sources.

Placebo pollutants. We use CO_2 and O_3 as placebo outcomes in the tests described in Section 3.1. Column carbon dioxide (XCO_2) comes from GHAP and is observed on the same 0.1° grid and over the same period as XCH_4, providing a closely matched atmospheric comparison. Surface ozone comes from the GHAP global seamless ozone product, also at 0.1° and on the identical grid, for which we use the 2019 layer to match the analysis year.

Neither pollutant should exhibit the same spatial relationship with livestock as methane. Ruminants do respire carbon dioxide, but that carbon was fixed by the plants they ate and returns on a short cycle, so it does not accumulate in the column as fossil carbon does. Ozone is a secondary pollutant formed photochemically from precursors livestock do not emit. A livestock gradient in either would therefore point to our regressor proxying for something other than livestock methane. We merge both to the panel grid cell by cell and restrict the placebo sample analysis to cells in which all three pollutants are observed.

United States ground-truth and market validation data. We use the US to validate the satellite signal against independent livestock records at finer spatial scales. For the United States

application, we use five public sources. First, USDA NASS QuickStats provides state and national cattle and hog inventory, which we obtain from the bulk data files. Second, the Bureau of Labor Statistics provides monthly producer and consumer price indices for cattle, hogs, beef, pork, and dairy from 2003 to 2020, which we obtain through the public application programming interface. Third, FAOSTAT provides Tier 1 livestock methane by country and species, split into enteric fermentation and manure management, and separating dairy from non-dairy cattle. We use the FAOSTAT split to characterize the concentrated manure channel that distinguishes detectable from undetectable operations.

The fourth source is the one that makes the United States test possible. We compile a county-by-year panel of USDA cattle inventories, covering 2000 to 2024 and reporting milk cattle and beef cattle as separate series, to distinguish the two herds at a spatial resolution the state data cannot reach. This matters because the global livestock grid carries only total cattle, so the dairy and beef margin, which our mechanism turns on, is invisible in it. We use the 2017 census year to match the state cross-section.

Last, we use a facility-level point file of confined animal feeding operations with coordinates, production type, and animal population for 37,841 facilities. To put the county counts on the analysis grid, we assign each 0.1° cell to a county by point-in-polygon overlay and distribute each county's dairy and beef herd uniformly across its cells, which is a strong assumption we return to when interpreting the estimates. Grid cells are assigned to states by the same overlay against administrative boundaries.

3 Methodology

We frame the analysis as a measurement validity problem. The object of interest is whether a satellite signal, column methane, tracks an economic quantity and livestock activity. In this section, we first present an empirical design to show the linear correlation through a linear regression, and then use various machine learning models to detect non-linear relationships between livestock and methane emission, considering all kinds of confounders.

3.1 Regression-Based Spatial Validation Design

Let y_i be raw XCH_4 in grid cell i, and let ℓ_i be Tier 1 livestock methane in that cell, area weighted. We estimate

$$y_i = \beta \log \ell_i + \alpha_{n(i)} + \varepsilon_i, \tag{1}$$

where $\alpha_{n(i)}$ is a fixed effect for the 5° by 5° neighborhood $n(i)$ that contains cell i. We work with raw XCH_4 because the neighborhood fixed effects remove the background in a single, transparent step: $\alpha_{n(i)}$ absorbs everything common within a roughly five hundred kilometer block, including the latitudinal background, seasonal and transport structure, and any smoothly varying regional source, so that β is identified from variation in livestock density across nearby cells that share the

same background. We take logs of livestock methane because its density is highly skewed, and we interpret β as a semi-elasticity in parts per billion per log unit.

We use Tier 1 livestock methane, rather than a raw head count, as the regressor because the satellite responds to emissions and the emission factors differ across species by nearly two orders of magnitude, from 62 kilograms of methane per head per year for cattle to 0.02 for poultry (Appendix A5). A total head count would treat a chicken and a cow as equivalent; the emission factor weighting is the physically grounded way to collapse the six heterogeneous species into one methane-relevant quantity, and the weights come from the IPCC inventory guidelines rather than from the satellite, so the regressor is not fitted to the outcome. Section 4.1 confirms that the regression does not depend on this choice.

Identification rests on the assumption that, within a neighborhood, cells with more livestock do not systematically differ in unobserved methane sources in a way correlated with livestock. This is not an assumption of random assignment, and we do not claim a causal effect of livestock on the column. What we claim is narrower and appropriate to a measurement question: that the satellite column carries information about the spatial distribution of livestock once the neighborhood background is absorbed. We estimate Equation (1) separately by continent, because the descriptive patterns and the estimates both indicate that the relationship is heterogeneous, and a pooled coefficient would average over economically distinct regimes.

We assess discriminant validity by adding a vector of controls X_i, the log rice fraction, log fossil methane from the GFEI oil, gas, and coal inventory, and log waste methane from the EDGAR landfill and wastewater sectors, so that the specification becomes

$$y_i = \beta \log \ell_i + X_i'\eta + \alpha_{n(i)} + \varepsilon_i. \tag{2}$$

We report a battery of specification checks based on the specification. A pooled regression adds the controls one at a time and varies the neighborhood block size from three to ten degrees. To confirm that the finding does not depend on how livestock activity is measured, we re-estimate with animal units and with ruminant head counts in place of Tier 1 methane, and we run a species horse race that enters the six species' head counts jointly and tests the ruminant and non-ruminant groups; the results are quite robust, showing the very significant relationship between livestock and methane emissions.

3.2 Detection and Prediction Using Machine Learning Models

We then use machine learning models to detect the non-linear relationship between livestock and satellite methane. To decompose the signal into interpretable drivers, and in particular to see how livestock compares with fossil, waste, and rice, we predict the XCH_4 from twelve features: the six livestock species, rice fraction, GFEI fossil methane, EDGAR waste methane, and three geographic terms, using gradient-boosted trees (Chen and Guestrin, 2016). Trees capture nonlinearity and interactions that a linear model would miss.

A tree ensemble has no fixed effects, so the neighborhood demeaning that identifies Equation (1) inside the regression must here be done before estimation. For each cell i in 5° block $b(i)$ we define the block residual

$$r_i = y_i - \bar{y}_{b(i)}, \qquad \bar{y}_b = \frac{1}{|b|} \sum_{j \in b} y_j, \tag{3}$$

where y_i is raw XCH_4, and the block mean is taken over the cells of the same block with valid retrievals in the same year. This is the within transformation of Section 3.1 computed in advance, and it is the one place in the paper where the background is removed before estimation rather than by fixed effects. Without it, a tree would spend its capacity predicting a roughly 1,800 parts per billion latitudinal level.

We compute Shapley values (Lundberg and Lee, 2017), which allocate the model prediction across features in a way that is additive and consistent, and we rank features by mean absolute Shapley value as a measure of importance. We then rank these factors to identify which are the most important. The unique additive attribution satisfying efficiency, symmetry, and consistency:

$$\hat{f}(x_i) = \phi_0 + \sum_{k=1}^{12} \phi_{ik}, \qquad \phi_{ik} = \sum_{S \subseteq K \setminus \{k\}} \frac{|S|!\,(|K| - |S| - 1)!}{|K|!} \left[\hat{f}_S(x_{iS}) - \hat{f}_{S \setminus \{k\}}(x_{i,S \setminus \{k\}}) \right], \tag{4}$$

where K is the feature set, $\hat{f}_S$ the model's expectation conditional on the features in S, and ϕ_0 the mean prediction. For tree ensembles, the exact values are computable in polynomial time (Lundberg and Lee, 2017), and we use that estimator on a random 60,000-cell subsample of the fitted model. The importance we report for feature k is the mean absolute Shapley value, $\bar{\phi}_k = \frac{1}{n} \sum_i |\phi_{ik}|$, in parts per billion. We measure the importance of each factor as its average absolute Shapley value. This metric represents the average amount, measured in parts per billion, that a specific factor moves the predicted methane level away from the overall average.

Because areas that are close together in our data tend to be very similar, standard testing methods can produce misleadingly high accuracy scores. To prevent this, we use "spatial block cross-validation," which groups nearby areas during testing (Roberts et al., 2017). Finally, we compare six models to demonstrate that the relationships in our data are nonlinear.

4 Global Evidence on Livestock-Related Methane

4.1 Spatial Livestock-Methane Relationship

Our first finding is that, conditional on the local neighborhood, cells with more livestock carry more methane. We first regress the headcount of the livestock on the methane concentration at the grid level. We test two different methods. In Panel A, we use "animal units," which is a way to weight different types of animals based on their size. For example, a cow is weighted more heavily than a

Table 1: Methane concentrations and measures of livestock activity

	(1)	(2)	(3)	(4)
Panel A. Log animal units (tropical livestock units)				
Animal units	0.991***	0.946***	0.975***	0.867***
	(0.085)	(0.080)	(0.084)	(0.076)
Within R^2	0.061	0.075	0.066	0.090
Panel B. Log ruminant head count				
Ruminant head count	0.762***	0.727***	0.749***	0.659***
	(0.076)	(0.073)	(0.075)	(0.070)
Within R^2	0.036	0.051	0.041	0.071
Rice control	No	Yes	No	Yes
Oil/gas control	No	No	Yes	Yes
Waste control	No	No	No	Yes
Neighborhood FE	5°	5°	5°	5°
Observations	647,529	647,529	647,529	647,529

Notes: This table reports pooled OLS estimates of raw satellite methane (XCH_4) on alternative measures of livestock activity. All models include 5-degree by 5-degree neighborhood fixed effects and use the 2019 land sample. Standard errors (in parentheses) are clustered at the neighborhood level. Animal units in Panel A use FAO tropical livestock unit weights. Ruminants in Panel B include cattle, buffaloes, sheep, and goats. All regressors are transformed using $\log(1+x)$. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. Source: FAO AGLW, GlobalRice20, GFEI, EDGAR.

sheep. In Panel B, we use a simple "head count" of all ruminants, such as cattle and goats.

Table 1 presents the results in a single pooled regression that averages across continents using animal units, the standard body mass-based aggregation used in agricultural statistics, and the raw ruminant head count. The results in Panel A show a very strong relationship between satellite methane and animal units. Panel B shows that a simple count of ruminants is also a strong predictor of methane, though the coefficients are somewhat lower. Even after we account for other sources of methane, including rice farming, oil and gas operations, and waste, the coefficient remains high.

The coefficient does not depend on how we measure livestock activity. We then use a species horse race specification to reinforce which animals carry the signal and show why the weighting matters. Table 2 enters the six species' head counts jointly. Cattle and buffaloes, the two largest per-head emitters, load strongly and positively across every control set, and the four ruminant species are jointly significant. The smaller species, however, are spatially collinear with the ruminants and with the confounders, so their individual coefficients are unstable and cannot be read as emissions: sheep even turns negative, while pigs and poultry come out significant only because they proxy for dense agricultural regions, not because these low-emission animals drive methane. That instability is exactly why we prefer the emission factor weighted Tier 1 measure to a data-driven horse race, since the physically grounded weights recover a clean livestock signal that collinear head counts cannot.

Figure 4 shows binned means of raw XCH_4 against log livestock methane, each residualized on 5° by 5° neighborhood fixed effects that remove the background in one step, by continent for

Table 2: Relationship between satellite methane and livestock species

	(1)	(2)	(3)	(4)
Cattle	0.661^{***}	0.637^{***}	0.656^{***}	0.607^{***}
	(0.091)	(0.090)	(0.091)	(0.089)
Buffaloes	0.895^{***}	0.854^{***}	0.892^{***}	0.854^{***}
	(0.243)	(0.240)	(0.241)	(0.237)
Sheep	-0.313^{***}	-0.314^{***}	-0.310^{***}	-0.307^{***}
	(0.095)	(0.094)	(0.095)	(0.093)
Goats	0.327^{***}	0.331^{***}	0.321^{***}	0.299^{***}
	(0.086)	(0.085)	(0.085)	(0.084)
Pigs	0.155^{**}	0.133^{*}	0.154^{**}	0.124^{*}
	(0.070)	(0.068)	(0.070)	(0.067)
Poultry	0.130^{***}	0.126^{***}	0.125^{***}	0.109^{***}
	(0.035)	(0.035)	(0.035)	(0.034)
Ruminants, joint p	< 0.001	< 0.001	< 0.001	< 0.001
Non-ruminants, joint p	< 0.001	< 0.001	< 0.001	< 0.001
Rice / oil-gas / waste	—	R	F	R,F,W
Within R^2	0.095	0.103	0.098	0.116
Observations	647,529	647,529	647,529	647,529

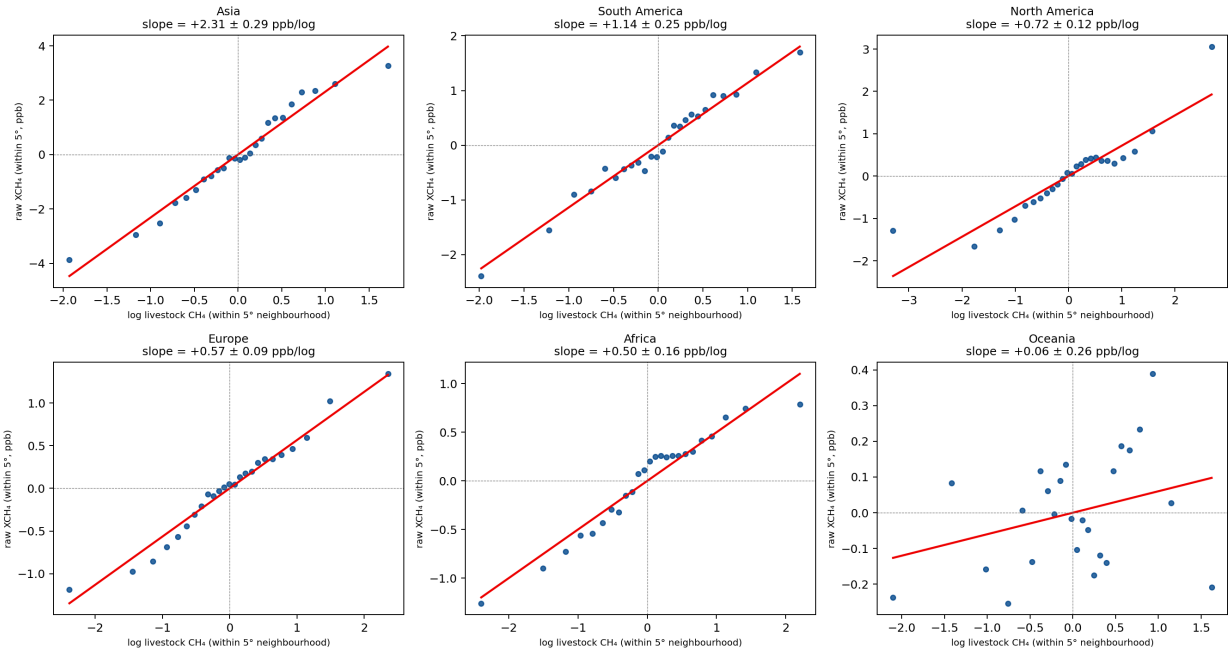
Notes: This table reports pooled OLS estimates of raw satellite methane (XCH_4) on the log of head counts for six livestock species entered jointly. All models include 5-degree by 5-degree neighborhood fixed effects and use the 2019 land sample. Ruminants include cattle, buffaloes, sheep, and goats; non-ruminants include pigs and poultry. The control row indicates the inclusion of rice (R), fossil (F), and waste (W) methane inventories. Individual coefficients for small species may be influenced by spatial collinearity. Standard errors (in parentheses) are clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source: FAO AGLW, GlobalRice20, GFEI, EDGAR.

2019. The relationship is positive on five of six continents. Figure 5 presents the estimated β from Equation (1). The results show that there is a significant relationship between livestock activity and methane emissions, with 2.31 parts per billion per log unit of livestock methane in Asia, followed by 1.14 in South America, 0.72 in North America, 0.57 in Europe, 0.50 in Africa, and a statistically insignificant 0.06 in Oceania (Table A4). Our findings remain consistent across various model specifications and different methods for clustering standard errors, as shown in Panels (b) and (c) in Figure 5. Table A5 presents the results for the pooled sample and replaces the two head-count measures with Tier 1 methane estimates.

A coefficient of 2.31 means that, comparing two nearby Asian cells that differ by 1 percentage in livestock methane, the more intensive cell reads about 2 ppb higher. This is a small enhancement relative to the roughly 1,800 ppb benchmark, which is exactly what one expects from a diffuse surface source seen through a column-integrating instrument, and it is why the signal is invisible in the levels themselves and emerges only once the neighborhood fixed effects absorb the regional background.

The result is robust along two dimensions. First, it survives spatially correct inference. Raw XCH_4 is strongly spatially autocorrelated, so we compute Conley spatial standard errors in addition to neighborhood clustering. The estimation remains significant on five of six continents even under a

Figure 4: Satellite methane and livestock density by continent



Notes: This figure shows average satellite methane levels XCH_4 compared to the amount of livestock methane. Both variables are adjusted to account for differences between 5° by 5° neighborhoods. The dots represent average values for different groups. Data are presented for each continent using 2019 records. Source: GHAP GOSAT XCH_4 and FAO AGLW.

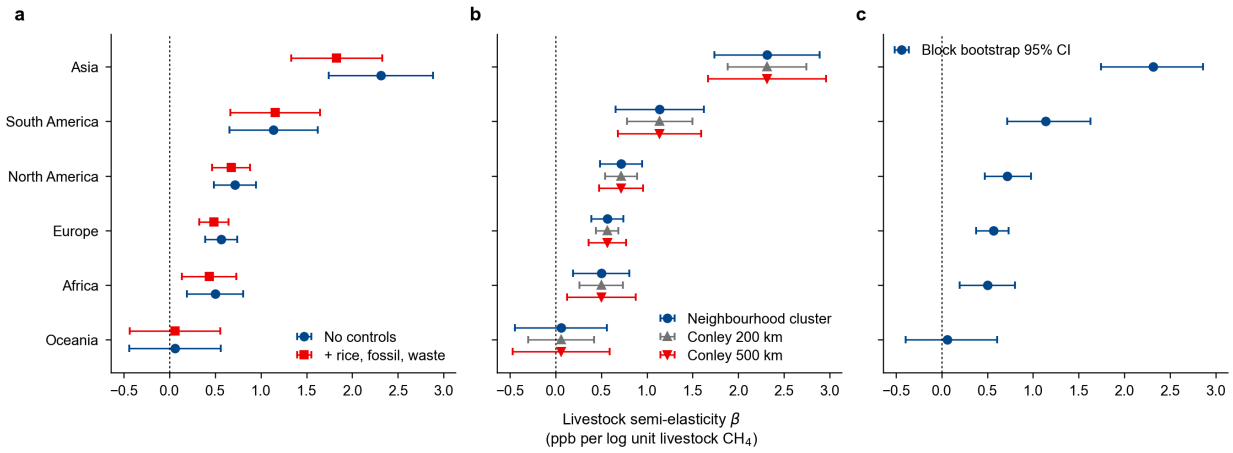
500-kilometer Conley kernel (Figures A5 and A6). Second, it passes a falsification test. Reshuffling livestock density within neighborhoods collapses every continental gradient to essentially zero, which confirms that the estimate reflects the genuine cell-level co-location of livestock and methane rather than a mechanical bias of the fixed effects.

4.2 Attribution of the Livestock Methane Signal

A positive coefficient is necessary but not sufficient for the satellite to measure livestock specifically, because livestock co-locates with other methane sources, biogenic and fossil alike. We address this in two ways. First, within the regression framework, we add three direct controls: rice fraction, oil, gas, and coal methane taken cell by cell from the GFEI fossil fuel inventory (Scarpelli et al., 2022), and landfill and wastewater methane from the EDGAR sectoral grids. These are the actual confounding sources mapped to the grid, not a residual. They attenuate the coefficient only slightly and do not remove it (Table A4). The within-neighborhood livestock signal is not fossil methane, waste methane, or rice in disguise.

Second, and more revealing, the machine learning attribution decomposes the local residual into interpretable pieces. Panel (a) of Figure 6 ranks the features by mean absolute Shapley value using an XGBoost model, with the target the fixed-effect residual, raw XCH_4 minus its 5° block mean. The three geographic terms are the largest features, at 0.61, 0.61, and 0.53 parts per billion for

Figure 5: The livestock semi-elasticity by continent, and its robustness



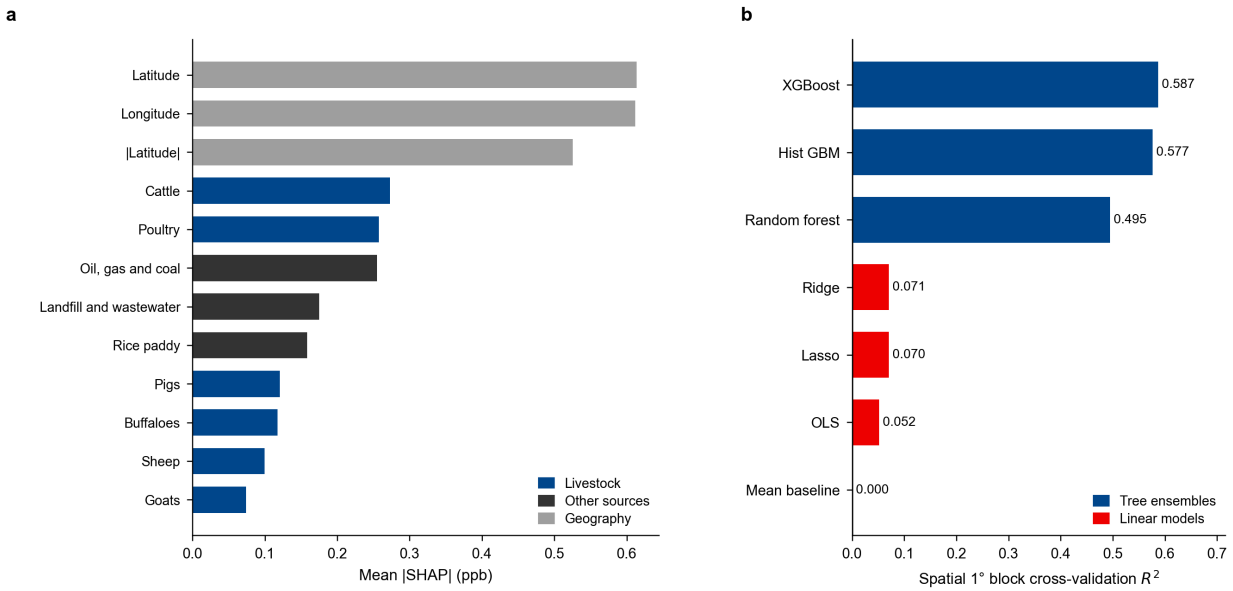
Notes: This figure reports the estimated effects of livestock on methane for each continent in 2019. All results include 95 percent confidence intervals and use a consistent horizontal scale. Panel (a) shows the findings with and without accounting for other methane sources, such as rice farming, oil, gas, coal, landfills, and wastewater. Panel (b) compares different ways of measuring the accuracy of these results using standard regional methods and geographic ranges of 200 and 500 kilometers. Panel (c) shows results from a "bootstrap" test that re-examines the data 400 times by resampling different neighborhoods. The relationship between livestock and methane is positive on five of the six continents studied and remains strong regardless of the testing method used. Accounting for other methane sources slightly reduces the effect, confirming that the signal is driven by livestock rather than by fossil fuels or waste. Sources: GHAP, AGLW, GlobalRice20, GFEI, and EDGAR (version 2025).

latitude, longitude, and absolute latitude, more than twice the largest source feature. Subtracting the average value for each 5° block removes differences between regions, but it does not account for variation within a single block. Factors such as wetlands, terrain, and satellite sensitivity vary within these areas. Since our datasets do not include these factors, the model uses geographic coordinates to represent them.

Livestock, fossil fuels, waste, and rice all have similar effects on local methane levels. For this reason, we cannot link satellite methane to livestock without accounting for these other sources. Our empirical design does exactly this. We use neighborhood fixed effects to remove the influence of large oil and gas fields and regional patterns. We also use specific controls for fossil fuels, waste, and rice to account for other sources found near livestock. Our main finding remains consistent: even after accounting for these other factors, areas with more livestock still show higher methane levels.

We report the predictive performance of each model in Figure 6, Panel B, and Table A7. The most accurate model, the gradient-boosted trees, achieves an R^2 of 0.59 and a root mean squared error of 2.54 parts per billion. Predicting the sample mean everywhere gives 3.95, so the best model improves on a no-skill baseline by 36 percent. Results for the mean absolute error are similar, with an error of 1.81 for the gradient-boosted trees compared to 2.87 for the baseline. The linear models perform poorly, with R^2 values between 0.05 and 0.07, indicating that the relationships in the data are nonlinear. Finally, because every model is nearly unbiased, the remaining errors reflect

Figure 6: What the model learns on, and how well it does



Notes: Both panels describe the results from the same model. The variable we predict is the difference between raw satellite methane and the average for each five-degree block. The model is estimated using 2019 data for areas with livestock and tested on separate one-degree blocks. Panel A shows the importance of each factor based on its average Shapley value. Panel B compares the R^2 of different models against a simple average. Sources: GHAP, FAO AGLW, GlobalRice20, GFEI, and EDGAR.

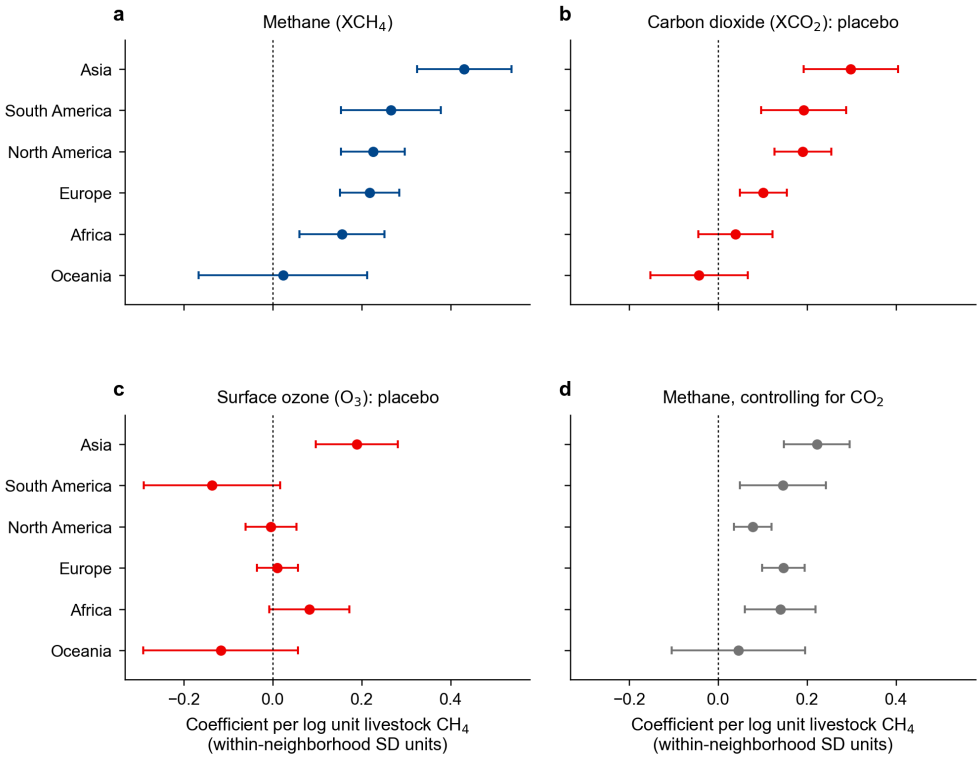
unexplained variation rather than a consistent systematic bias.

4.3 Atmospheric Placebo Tests

We perform an additional test that focuses on other gases in the air rather than other sources on the ground. Statistical controls can only account for factors that we can specifically identify and measure. A broader concern is that livestock are not located randomly. Areas with many animals may differ from areas with few animals in ways we cannot easily observe, such as differences in infrastructure or geography that trap emissions. If our results were driven by these unobserved factors rather than methane from livestock, we would expect to see similar patterns in other pollutants. To test this, we repeat our main analysis but replace methane with other pollutants that livestock do not produce. We use the same locations, years, and fixed effects. Because the units for these gases differ, we report our results in terms of standard deviations to make them comparable.

Figure 7 presents the results, which provide two important insights. First, surface ozone acts as a proper control. Its overall effect is small, only 0.04 standard deviations compared to 0.22 for methane, and it is not statistically significant in North America or Europe. In Asia, we find a positive result, which is likely due to crop burning or local chemistry common in intensive farming areas. Second, carbon dioxide provides a more difficult test, and the results are less clear. Its effect is positive and significant across four continents and is about two-thirds the size of the methane

Figure 7: The livestock coefficient is specific to methane



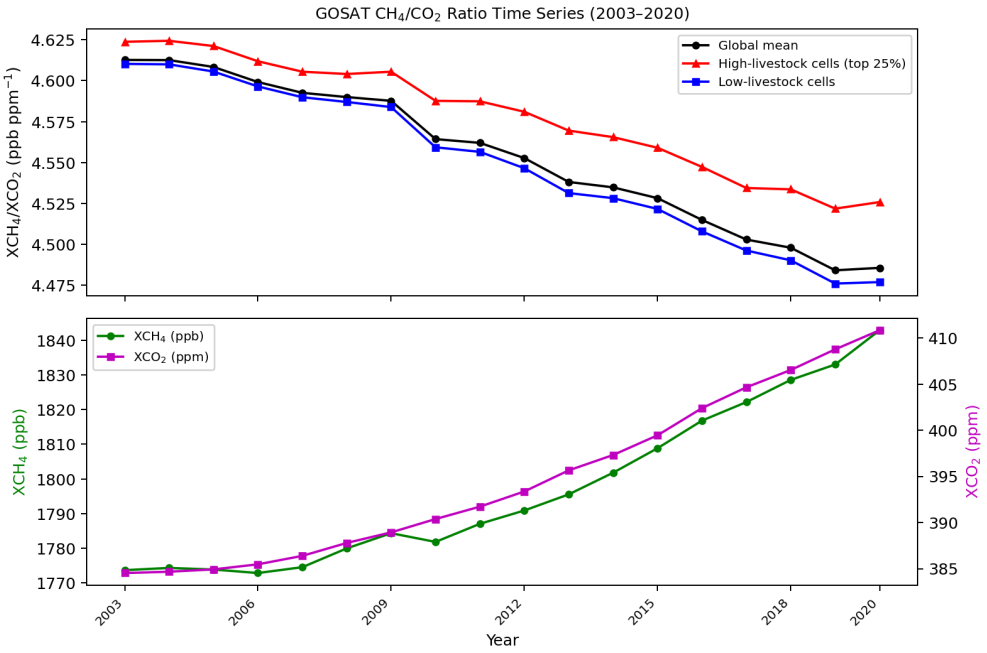
Notes: This figure reports the coefficients of log livestock methane for each continent. Estimates are measured in standard deviations of each gas, with 95 percent confidence intervals shown. Panel (a) displays results for methane. Panels (b) and (c) display results for carbon dioxide and surface ozone, which are pollutants not produced by livestock. Panel (d) shows methane results after controlling for carbon dioxide XCO_2. This accounts for factors that influence both gases simultaneously. Sources: GHAP and AGLW, 2019.

effect. This indicates that areas with many animals also have higher carbon dioxide levels. This could be due to other human activities, crop farming, or the way local geography traps multiple gases. Table A6 provides the detailed results for each continent.

We aim to remove the factors that influence both methane and carbon dioxide. By adding carbon dioxide levels as a control, we can account for external factors that increase both gases and isolate the variation that is specific to methane. The methane coefficient decreases but remains statistically significant in all regions where it was originally present. Specifically, the overall coefficient falls from 0.79 to 0.47 parts per billion. In Asia, it drops from 2.31 to 1.19, while in Africa, it remains nearly unchanged, falling from 0.50 to 0.45. This is because carbon dioxide levels in Africa were already near zero, so accounting for them has little effect. In Oceania, the results remain close to zero across all models.

Overall, 60 percent of the methane coefficient is unique to methane and cannot be explained by general human activity or geographic factors that trap multiple gases. This methane-specific share ranges from about one-third in North America, where the two gases move together, to nearly nine-tenths in Africa. This represents our most rigorous test for identifying factors that influence

Figure 8: The biogenic fingerprint over time



Notes: The top panel displays the ratio of methane to carbon dioxide from 2003 to 2020. The black line represents the global average, the red line represents the 25 percent of areas with the most livestock, and the blue line represents areas with very few animals. The bottom panel shows the individual levels of methane and carbon dioxide used to calculate these ratios. The global ratio falls as carbon dioxide rises faster than methane, but the excess of high livestock over low livestock cells widens from 0.014 to 0.049 ppb ppm^{-1}. Source: GHAP GOSAT XCH_4 and XCO_2.

both gases. North America serves as a reminder that the result is not perfect. In the region where methane and carbon dioxide move most similarly, the largest portion of the initial result is common to both gases.

Our results suggest that livestock methane comes from biological sources rather than from fossil fuels. Further physical evidence supports this conclusion. The process of burning fossil fuels releases both carbon dioxide and methane. In contrast, biological sources produce methane with very little carbon dioxide. Consequently, the methane-to-carbon dioxide ratio should be higher in areas where biological sources dominate. When we group locations by their primary source of emissions, we find that the average ratio is highest in rice-growing areas (4.587) and livestock regions (4.557). The lowest ratio occurs in oil and gas regions (4.553), as shown in Figure A7. This ratio consistently increases in areas with higher livestock density or more rice farming.

This pattern also changes over time. Figure 8 traces the GOSAT methane to carbon dioxide ratio from 2003 to 2020. The global ratio falls steadily, from about 4.61 to 4.49 parts per billion per part per million, because column carbon dioxide rose faster than column methane over the period. Despite this general decline, the gap between areas with the most livestock and those with the least grew significantly. This difference is highly statistically significant. Even as the global ratio moves down, regions with many animals stand out more clearly. We see the same pattern in different locations (Figure A8). The ratio declined the least in South Asia and Sub-Saharan Africa, which

are regions where livestock are common and where herds grew the fastest during this period. These findings are consistent with the idea that increasing livestock activity is leaving a larger biological mark on the atmosphere.[3]

We do not want to overstate the differences between regions. The absolute gaps between different emission sources are small. This is because the satellite measures the entire atmosphere, and methane from the ground is only a tiny part of that total air. However, the order of the results is exactly what science predicts: biological sources like animals have higher ratios than fossil fuel sources. This finding is consistent across three different tests: by emission source, by livestock density, and over time. Therefore, we view this ratio as strong support, though not final proof, that the methane found over livestock and rice regions comes from biological sources. This reinforces our view that these signals are from livestock rather than from fossil fuels.

5 When Satellite Methane Reveals Livestock Activity

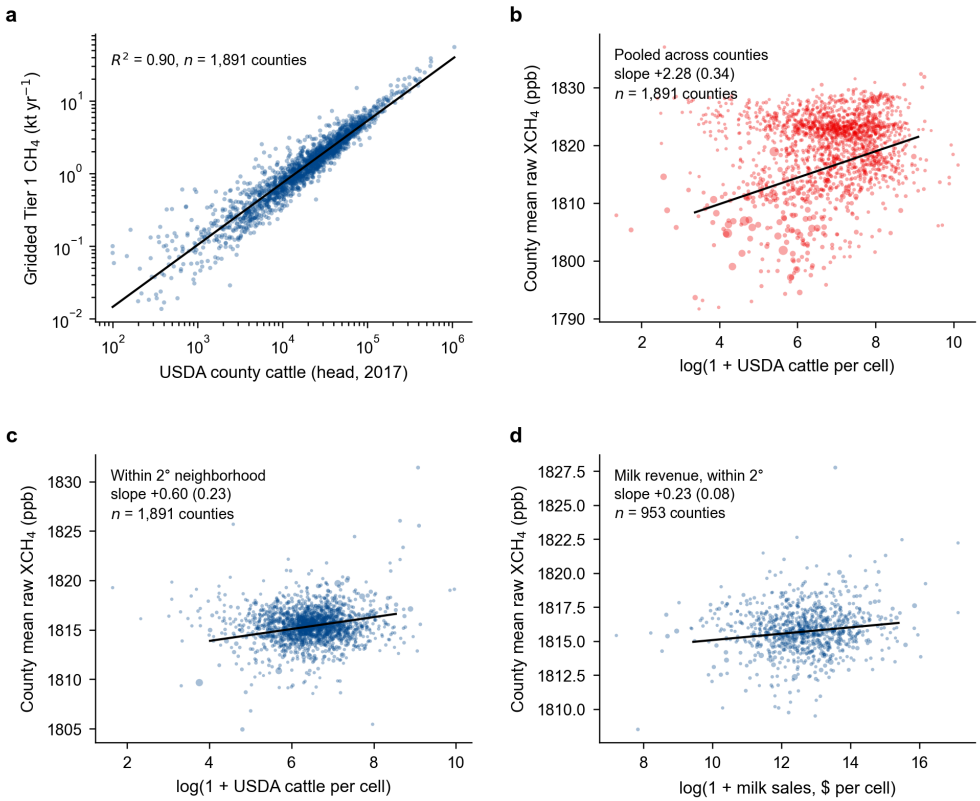
In this section, we discuss what the satellite can detect and why. We use data from the United States for validation for several reasons. The United States has the most detailed and verified livestock data in the world. This is primarily due to the Census of Agriculture and surveys conducted by the United States Department of Agriculture (USDA). These records make the United States the ideal location to test our satellite data against a reliable benchmark. First, we confirm that our livestock data match these official records at different levels of grouping. We then repeat our earlier tests, moving from national results down to the county level.

5.1 Detection across Methane Environments

We first confirm that our gridded livestock product is reliable against that benchmark. We aggregate to counties and reproduce the county census with an R^2 of 0.90 across 1,891 counties (Figure 9a). It is not a test of the satellite, since the gridded product is built from census data. Panels (b) and (c) of Figure 9 show the correlation between cattle and methane emissions at the county level. Regressed on log county cattle across the 50,547 grid cells, the raw column now rises with the herd, at 2.53 parts per billion per log unit, and adding the fossil, waste, and rice controls leaves 2.08. Imposing the 2° neighborhood fixed effects, so that cells are compared only with nearby cells, gives 0.52, and adding the controls on top gives 0.53. Panel (d) of Figure 9 replaces the head count with the value of milk sold, and within the same 2° neighborhoods the column rises by 0.27 parts per billion per log dollar, and by 0.26 once the competing sources are controlled. Table A9 shows that these findings remain strong even after we add more controls.

[3]This analysis compares large groups of data over 18 years. It does not mean we can track changes in specific small areas from one year to the next. Comparing methane to carbon dioxide helps reduce some of the errors caused by wind and weather that usually make it hard to see local signals over time. This evidence supports our biological explanation of the results without changing the known limits of our data.

Figure 9: At county resolution, the satellite tracks the herd



Notes: Panel A shows estimated livestock methane compared to official cattle counts from the United States Department of Agriculture (USDA). Panel B shows satellite methane readings compared to the number of cattle per area across the entire country. Panel C repeats this comparison after accounting for local differences within two-degree neighborhoods. Panel D shows satellite methane compared to the value of milk sales in dollars. Sources: GHAP and the USDA Census of Agriculture.

5.2 Concentrated Dairy and Dispersed Beef Production

United States cattle are overwhelmingly beef, raised on dispersed range where enteric methane is emitted at low density over vast areas, whereas dairy cattle are concentrated in large operations whose manure lagoons release methane from a small footprint. The two should therefore differ sharply in detectability even though both are "cattle." We test this by putting the USDA county census of dairy and beef cattle onto the 0.1° grid and regressing raw satellite XCH_4 on each, with neighborhood fixed effects absorbing the background exactly as in the global specification. Because a single country spans few 5° blocks, we use a 2° neighborhood as the main window and report 1° and 5° alongside it.

Satellite methane tracks dairy cattle, not beef cattle. Table 3 shows our findings. The main result comes from comparing the separate results for each cattle type with the results when they are tested together. When tested one at a time, both types of cattle show a positive relationship with the satellite data. In the 2° specification, the dairy coefficient is 0.43, and the beef coefficient

Table 3: Satellite methane tracks dairy cattle, not beef cattle

	(1) Dairy only	(2) Beef only	(3) Both
Panel A. 1° neighborhood (811 blocks)			
Log dairy cattle	0.229*** (0.045)		0.214*** (0.060)
Log beef cattle		0.266*** (0.060)	0.025 (0.073)
Panel B. 2° neighborhood (240 blocks), main			
Log dairy cattle	0.427*** (0.097)		0.364*** (0.116)
Log beef cattle		0.525*** (0.137)	0.112 (0.150)
Panel C. 5° neighborhood (46 blocks)			
Log dairy cattle	0.485* (0.276)		0.383 (0.412)
Log beef cattle		0.672** (0.310)	0.207 (0.406)

Notes: Raw satellite XCH_4 (2010–2020 mean) on log county cattle per 0.1° cell, with neighborhood fixed effects and standard errors clustered by neighborhood. Columns (1) and (2) enter each cattle type alone; column (3) enters both. Each panel varies the width of the neighborhood comparison window. $n = 50{,}547$ cells throughout. Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

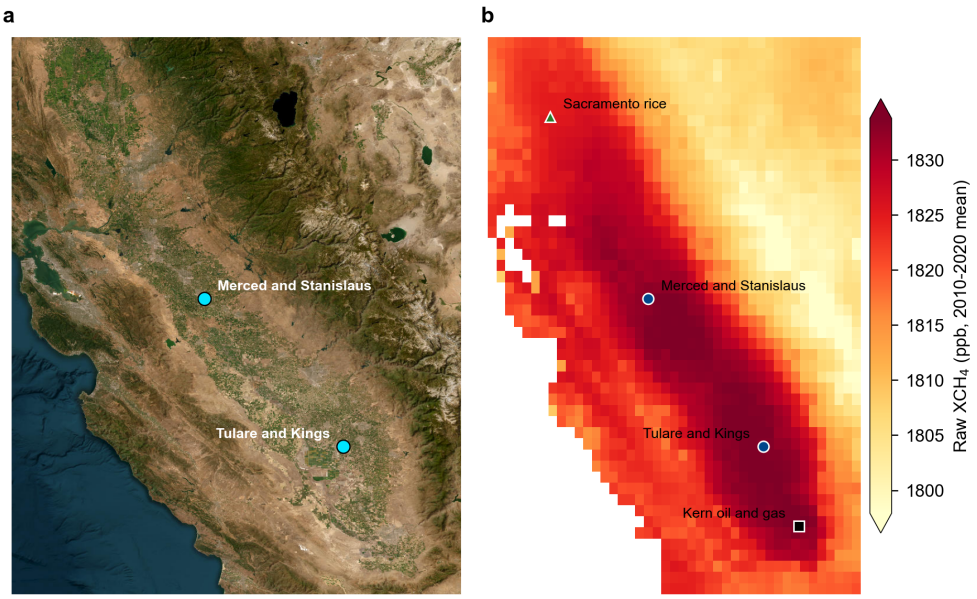
is 0.52. However, when we test them together, the results change. The dairy coefficient remains strong at 0.36, but the beef coefficient falls to 0.11 and is no longer statistically significant. We see the same pattern in the 1° specification. In that case, the dairy coefficient is 0.21, while the beef coefficient is nearly zero at 0.02.

These findings suggest that beef cattle only seem to matter because beef counties are often located near dairy counties. Once we account for both types at once, the satellite data follows dairy cattle and not beef cattle. Figure A14 illustrates this point. When we control for the presence of one cattle type, the relationship for dairy cattle increases while the relationship for beef cattle stays flat. In the largest 5° window, dairy cattle still show a larger effect than beef cattle.

Measurement of local farm economy and livestock activity. The last step converts the result from animals to money, which is what a measurement of the farm economy has to do. This allows us to measure the relationship between methane and the local farm economy. Using data from the Census of Agriculture, we replace the number of dairy cattle with the total value of milk sales at the county level and repeat our estimation. Table A8 presents the results. Among the 953 counties that report milk sales, we find that satellite methane levels increase alongside the value of milk sold. Specifically, methane levels rise by 0.27 parts per billion for every one-log-dollar increase in milk sales. This result is statistically significant at the 1 percent level. These findings show that our satellite data provides information about the size of the local economy, rather than just the number of animals on the ground.

We have two interpretations of these findings. First, milk revenue and the number of dairy cows are very similar. Revenue is calculated by multiplying the number of cows by the amount of milk they produce and the price of that milk. When we include both revenue and the number of cows in the same model, the number of cows accounts for almost all of the effect. This suggests that the

Figure 10: The largest dairy cluster sits on the valley methane maximum



Notes: (a) Esri World Imagery over California's Central Valley with the two dairy cores marked. (b) Raw GHAP XCH_4 over the same window, 2010 to 2020 mean, in absolute parts per billion with no background removed, with the dairy cores, the Kern oil and gas fields, and the Sacramento rice belt marked. The whole valley is elevated because its topography traps emissions; the dairy cores are its maximum, and the margin over the co-located fossil fields is one to two parts per billion. Source: Esri World Imagery and GHAP.

satellite primarily detects the animals themselves, while the monetary revenue is simply another way of measuring those same animals.

Second, this part of our analysis only includes counties that report milk sales, which accounts for about half of our original sample. Therefore, the results for beef cattle in this specific group are not directly comparable to our earlier findings for the full country. Overall, this exercise shows that the signals captured by the satellite match the information found in official government farming records.

The case of California's dairy farms. We examine dairy farms in California to provide further evidence for our findings. California's Central Valley has the highest concentration of dairy farms in the country and is a significant methane hotspot. Figure 10 compares images of this area with the raw satellite data. Within the valley, we measured methane levels across four subregions. In the dairy centers of *Tulare and Kings*, methane levels average 1,833 ppb. The levels in *Merced and Stanislaus* average 1,832 parts per billion. In comparison, the *Kern oil and gas* fields average 1,831 parts per billion, while the *Sacramento rice belt* averages 1,825 parts per billion. The overall average for the entire region is 1,819 parts per billion.

We approach this comparison with caution. Methane levels are high throughout the entire valley because the geography traps emissions. As a result, the areas with many dairy farms represent the highest point of a large methane cloud that covers the valley, rather than a single, isolated source.

The difference in methane levels between dairy areas and oil and gas fields is small, at only one to two parts per billion. This difference is minor compared to the 14 ppb gap between the dairy centers and the regional average.

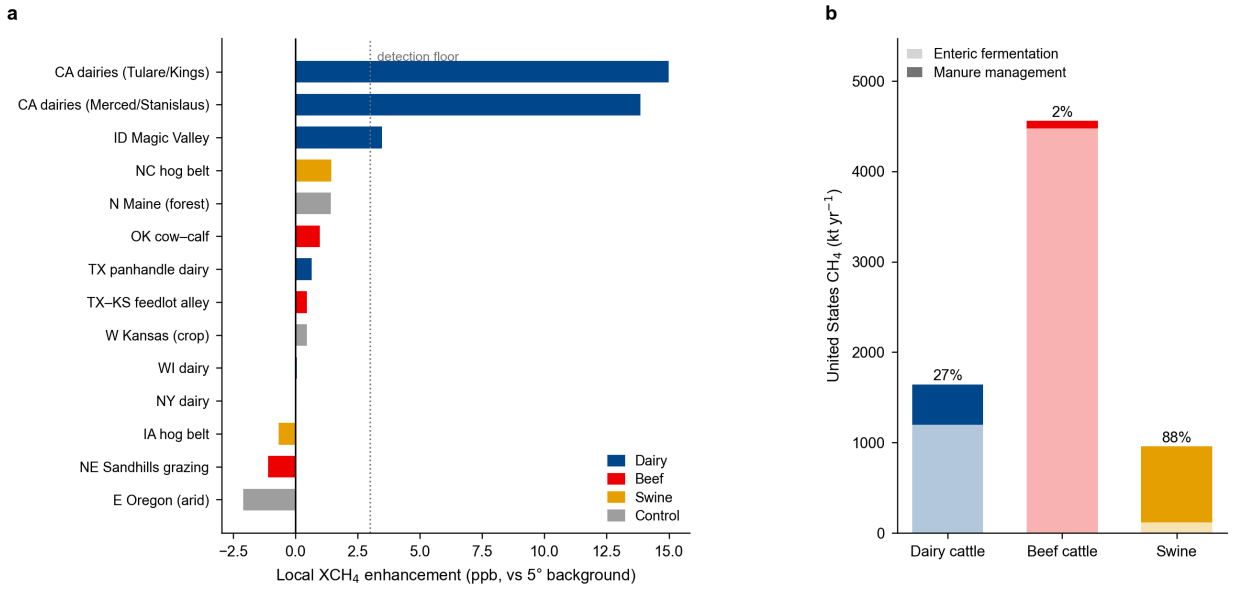
Our data show that the dairy centers have the highest methane levels, while the rice-growing areas have the lowest of the four regions. This finding aligns with previous studies that identify Central Valley dairy farms as a major regional source of methane (Duren et al., 2019). Calculating the exact share of emissions from dairy versus oil and gas would require more advanced measurements, which we do not attempt here.

Satellites measure methane in two very different ways. The first type of instrument measures the entire atmosphere across a large area, about 11 kilometers wide. These satellites can find a slight increase in methane of a few parts per billion. The second type of instrument looks at very small areas, only a few meters wide. These can find specific clouds of methane, known as plumes, if the emissions are large enough. This is how researchers find large leaks in oil and gas pipes (Lauvaux et al., 2022) or monitor specific factories (Varon et al., 2021). These two methods have different limits on what they can see, but they both struggle to find the same things. A satellite that looks for plumes can see a large waste lagoon at a dairy farm, but it cannot see beef cattle spread out across a field. This is because the dairy lagoon is a concentrated source of methane, while beef cattle are too spread out to be detected as a plume. This explains the difference we found between dairy and beef cattle in Table 3. Our finding is supported by research using different measurement methods and by different scientists. A separate study using airplanes in California reached the same conclusion (Duren et al., 2019).

We view these findings as support for our results rather than a replacement. Instruments that look at specific points are only used for small areas and do not provide data very often. Therefore, they cannot provide the worldwide, yearly data that our study needs. At the same time, the instruments we use can measure large areas but cannot see a single waste lagoon. There is a natural way these tools work together. Our method measures methane in areas where livestock is the main source, while specific imagers can link emissions to particular farms. This second type of measurement is exactly what United States law currently prevents from being collected on the ground.

Figure A15 shows the map of these gases. The counties with the highest number of dairy cows are outlined in red. In the southern Central Valley, methane levels are at their highest. These dairy counties reach approximately 1,830 ppb, while the state average is about 1,809 ppb. The carbon dioxide map is more difficult to interpret. Methane and carbon dioxide both reach high levels in the valley because its shape traps all gases released there. Since the valley also contains cities, traffic, and farms, it is hard to tell the two gases apart just by looking at the images. A more formal test is provided in Table A6. That analysis shows that even when we account for carbon dioxide, the link between dairy cows and methane remains strong. This figure proves a simple but important point. The largest group of dairy cows in the country is located in the same place as the highest methane levels in the state. This is true in the raw satellite data before any adjustments are made.

Figure 11: What the satellite can detect, and why



Notes: (a) Local XCH_4 over ten United States livestock regions, GHAP 2010 to 2020, measured against the surrounding 5° background and ordered by magnitude. The dotted line marks the approximate GOSAT detection floor. (b) United States livestock methane by emission channel, FAOSTAT Tier 1, 2020, with the manure share printed above each bar; the solid segment is manure management and the pale segment enteric fermentation. Only the California Central Valley dairy complex clears the floor decisively, at 8.1 ppb, with Idaho's Magic Valley marginal at 3.5, while every beef region and the smaller hog belts sit at or below it. Panel (b) supplies the mechanism. Manure management is a concentrated lagoon source and is 27 percent of dairy and 88 percent of swine methane but only 2 percent of beef, which is dispersed enteric fermentation. Detectability therefore needs both a high manure share and enough scale, which in the United States essentially one region has. Colours denote the production system in both panels. Source: GHAP and FAOSTAT.

Smaller and more dispersed operations are not detectable at GHAP resolution. The North Carolina and Iowa hog belts and the Texas and Kansas feedlot alley are indistinguishable from rural controls (Figure 11a). The mechanism that separates the detectable from the undetectable is the concentrated manure channel. FAOSTAT shows that manure management, the anaerobic lagoon source, is 27 percent of dairy methane and 88 percent of swine methane but only 2 percent of beef methane, which is overwhelmingly enteric and produced by dispersed grazing animals (Figure 11b). Dairies and large hog operations concentrate methane in lagoons, and the very largest such clusters clear the detection floor, while beef does not concentrate methane at all. Detectability therefore requires both a high manure share and sufficient scale, and only the Central Valley meets both at this resolution.

This finding has a policy edge because the United States does not measure facility-level livestock methane. The greenhouse gas reporting program contains no manure management data, owing to a long-standing appropriations rider that bars its collection, so federal livestock methane at the facility level is modeled rather than measured. The satellite already detects the largest clusters, and finer instruments will lower the threshold, so remote sensing could begin to fill a genuine

measurement gap.

5.3 Facility-Level Validation and the Detection Envelope

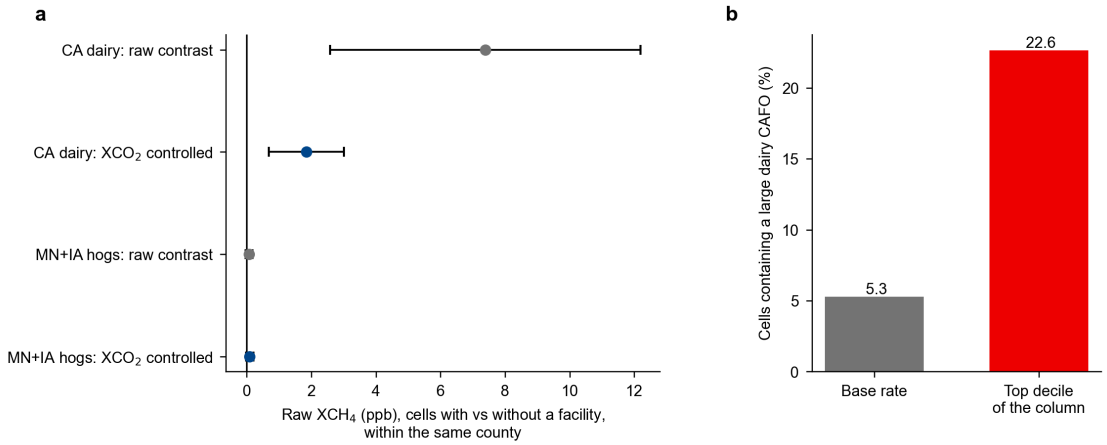
The facility records allow a sharper version of this test, because the mechanism is a claim about facilities, not about counties. If the spatial concentration of livestock is what makes methane visible, then within the same county, holding the census herd fixed, the grid cells that actually host a dairy operation should read higher than the county's other cells. We run exactly that comparison in California, where the permit records cover about two-thirds of the census dairy herd. One adjustment is essential. California counties straddle the valley floor and the Sierra, and a column mixing ratio is mechanically depressed over high terrain, so a naive within-county contrast of 7.4 parts per billion overstates the facility signal badly. Raw XCO_2 from the same instrument shares that column geometry but not the livestock source, and controlling for it cuts the contrast to 1.8 parts per billion with a t statistic of 3.1, with a dose response of 0.23 parts per billion per log head of recorded facility capacity. Three-quarters of the naive contrast was terrain; what survives is a facility-level methane signal, measured rather than inferred (Figure 12a).

The same design in the hog belt returns nothing, and that is the envelope confirming itself at facility level. Minnesota and Iowa hold the densest coverage in the file, more than a thousand treated cells, and hog manure is the most lagoon-intensive channel of all, yet cells hosting hog operations read only 0.09 parts per billion above their county neighbors. Manure share alone is not sufficient; the operations must also be large enough, and midwestern hog sites are an order of magnitude below the California dairies in animal mass per cell. Finally, the facility file lets us score the detector of Section 5.4 against real operations rather than a census proxy: the top decile of the within neighborhood column in California contains a large dairy operation in 22.6 percent of cells against a 5.3 percent base rate, a lift of 4.3 (Figure 12b).

The facility file also lets us replicate, and then test, the structure of the new asset-level inventories. Climate TRACE estimates each operation's methane bottom up, as estimated head times an emission factor (Davitt et al., 2026). We rebuild that object on the permit records with factors implied by the accounting used throughout this paper: FAOSTAT's United States totals for 2020 divided by the NASS herd give 176 kilograms per dairy cow, 51 per beef animal, and 12 per hog, and facility methane is head times factor. Regressed on the column within counties, with the XCO_2 control, California cells gain 0.15 parts per billion per log kilogram of bottom-up facility methane (Table 4, Panel A). Even the hog belt, a null in the presence test, shows a faint dose response in emissions units, 0.014 parts per billion per log kilogram, two orders of magnitude below California's. The detection envelope is a continuum in source strength, not a wall, and the atmosphere ranks the two regions in the same order as the inventory.

Comparing the two inventories teaches something neither shows alone. In animal numbers, they roughly agree where coverage is best: the permit records place 733 thousand head in the Tulare and Kings core against 588 thousand gridded census cattle, a ratio of 1.25 consistent with permits recording capacity rather than standing herds. In methane, they diverge by up to a factor of 3.4,

Figure 12: The spatial concentration mechanism, tested at the facility level



Notes: (a) Within-county contrast in raw XCH_4 between cells that do and do not host a confined animal feeding operation, from state permit records, 2010 to 2020 means; bars are 95 percent confidence intervals, clustered by 2° neighborhood. Grey estimates are the naive contrast; blue estimates control for raw XCO_2 from the same instrument, which absorbs the mechanical depression of any column mixing ratio over high terrain. (b) Share of California cells containing a large dairy operation, 700 or more head, among all cells and among the top decile of the within neighborhood methane column. The California dairy signal survives the terrain control at 1.8 ppb; the Minnesota and Iowa hog signal is absent in both versions, because those operations are an order of magnitude smaller in animal mass per cell. Facility coverage is validated against the USDA herd state by state, and unrecorded facilities bias the contrasts toward zero. Source: state permit records compilation, GHAP, USDA NASS.

and the gap is almost exactly the ratio of the dairy factor to the blended cattle factor, 176 against 62. What the asset inventory adds to a census grid is therefore not mainly location but *typing*: knowing that the animals in a cell are dairy cows nearly triples the methane assigned to it, and the satellite sides with the typed version, since these cores are where the observed column peaks.

5.4 Incremental Information in Satellite Methane

The previous sections examined how livestock numbers influence methane levels. However, a statistical problem often is the opposite, which is using satellite data to estimate the size of a herd that has not yet been counted. We therefore reverse our analysis to predict livestock activity from methane levels. We focus on whether satellite data provide any new information beyond what is already available in existing records.

Our study compares a model that includes satellite data with an identical model that excludes it. The difference between the two represents the specific value added by the satellite. We test this against two benchmarks. The first benchmark includes existing data on other methane sources, such as fossil fuels, waste, and rice farming. The second benchmark adds the specific geographic location of each area. This is a more difficult test because livestock farms are often clustered together, meaning location alone is a strong predictor of where livestock are.

To ensure our results are reliable, we test our models on new areas that were not used during the initial training. We use 10-degree blocks globally and five-degree blocks in the United States. This

Table 4: Replicating the asset inventory and testing it against the atmosphere

Panel A: ppb of raw XCH_4 per log kilogram of facility methane

	California (dairy)		Minnesota + Iowa (hogs)	
	(1)	(2)	(3)	(4)
Log facility CH_4	0.574^{***}	0.148^{***}	0.014^{**}	0.014^{**}
	(0.176)	(0.047)	(0.007)	(0.006)
XCO_2 control	No	Yes	No	Yes
Cells	2,960	2,960	3,094	3,094
Cells with facilities	201	201	1,792	1,792

Panel B: the two inventories inside the California dairy cores

	Animals (thousand head)		Methane (kt yr^{-1})	
	Facilities	Gridded census	Facilities	Gridded census
Tulare/Kings	733	588	122.9	36.7
Merced/Stanislaus	385	736	64.3	46.0

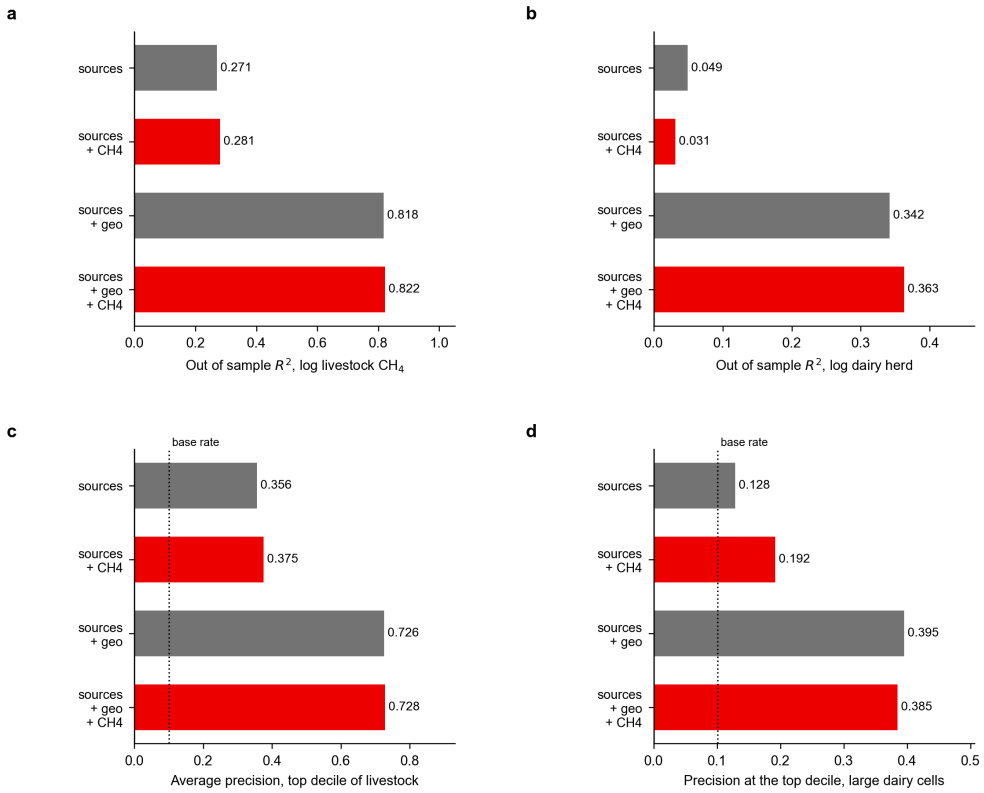
Note: Panel A, raw XCH_4 on log facility methane, where facility methane is reported head times the implied United States emission factor (dairy 176, beef 51, hogs 12 kilograms per head per year, from FAOSTAT 2020 totals over the NASS herd). In Panel B, the animal comparison and the methane comparison disagree by construction, and the wedge is the point. The facility layer types its animals, so the dairy factor of 176 applies; the gridded census layer knows only "cattle" and applies the blended 62. The methane ratio is close to the head ratio times 176/62 in both cores (Tulare/Kings $1.25 \times 2.84 \approx 3.4$; Merced/Stanislaus $0.52 \times 2.84 \approx 1.5$). Facility head counts are permitted capacities and so bound the standing herd from above. Facility records cover about two-thirds of the California census dairy herd. $^{**}p < 0.05$, $^{***}p < 0.01$. Source: Climate TRACE reported facility layer (Davitt et al., 2026), FAOSTAT, USDA NASS, FAO AGLW, GHAP.

prevents the model from appearing more accurate simply because neighboring areas are similar. We perform two tasks: predicting the total number of livestock and identifying the top 10 percent of highest-density areas. This second task helps locate large-scale farming operations. Table 5 and Figure 13 present these results. In the figure, each pair of bars shows the improvement in accuracy gained by adding satellite information.

The results for predicting the exact size of a herd are poor, and we report them as such. Globally, adding satellite methane data to existing records only slightly improves the accuracy of our model. In contrast, simply knowing the geographic location of an area improves the accuracy significantly. For example, knowing where an area is located contributes about 0.55 to the model's accuracy in R^2 while knowing its methane levels contributes only 0.004. In United States counties, the pattern is the same. The satellite data do not provide a reliable way to estimate the size of a herd.

Identifying the largest operations is a more successful task, and the difference between these two results is important. When we try to identify the top 10 percent of dairy farm density in the United States, a model using only existing records is correct about 12.8 percent of the time. This is only slightly better than a random guess. Adding satellite data increases this success rate to 19.2 percent, improving the "hit rate" by about one-half. We see a similar pattern globally. Methane levels help rank the most intensive farming areas, even if they do not improve the overall accuracy of the model. Large concentrations of animals release enough methane to be detected and ranked,

Figure 13: The column detects large operations better than it predicts herd size



Notes: Out-of-sample performance on held-out spatial blocks, ten degrees globally and five degrees in the United States. Grey bars withhold column methane, red bars add it, so each adjacent pair is the increment attributable to the satellite. (a) Predicting log livestock methane, global 2019 cross section of 647,529 livestock cells. (b) Predicting the log dairy herd across 50,547 United States county cells, 2017. (c) Flagging the top decile of livestock density globally, average precision. (d) Flagging the top decile of dairy density in United States counties, precision at an operating point that flags as many cells as are truly positive. Source: GHAP, GFEI, EDGAR v2025, GlobalRice20, FAO AGLW, USDA NASS.

as shown in panels (c) and (d) of Figure 13.

However, geographic location remains the best predictor. A model that only knows where an area is located identifies large dairy farms with 39.5 percent precision. This is twice as accurate as the results from the satellite data alone. Therefore, satellites are not particularly useful for locating herds in countries where farming locations are already well-known and stable. Instead, the value of satellite data is in regions where geographic records are missing, outdated, or disputed. They are also useful for verifying whether reported emissions match the actual atmosphere.

This tool works outside the United States. We use a global database from Climate TRACE to verify our results. This database identifies more than 287,000 cattle farms using images and permits, rather than methane. We checked whether the areas with the highest methane levels actually contain large farms, defined as those with at least 700 dairy cows or 1,000 beef cattle. This provides a separate way to test our tool in every country covered by the database.

Eight countries had enough data to be included in this test, and Figure A16 shows the results.

Table 5: What the column adds, on top of the inventories and on top of geography

Features	Prediction (R^2)		Detection	
	Global	US dairy	Global avg. precision	US dairy precision (lift)
Inventories only	0.271	0.049	0.356	0.128 (1.28×)
+ column methane	0.281	0.031	0.375	0.192 (1.91×)
Inventories + geography	0.818	0.342	0.726	0.395 (3.93×)
+ column methane	0.822	0.363	0.728	0.385 (3.82×)

Note: $n = 647{,}529$ global cells and 50,547 United States county cells. Inventories are GFEI fossil methane, EDGAR waste, and rice paddy fraction; geography is latitude, longitude, and absolute latitude. Column methane enters as raw XCH_4 net of its neighborhood mean, the quantity the gradient regression identifies. The single row where the satellite clearly earns its place is the United States detection task without geography, where it raises the hit rate by half. Source: GHAP, GFEI, EDGAR v2025, GlobalRice20, FAO AGLW, USDA NASS.

As expected, the satellite works best in specific environments. In China, the top 10 percent of methane areas contain a large farm 17.4 percent of the time. This is more than twice as high as the standard chance of 6.7 percent. In India, where large farms are very common, the success rate reaches 35.9 percent. The United States has a success rate 1.6 times better than chance. This is lower than our result for California because the national data include many beef cattle, which the satellite cannot easily detect.

In dry countries like Australia, the satellite is no better than chance. In Brazil, the tool performs poorly because methane from wetlands in the Amazon hides the emissions from cattle. While Russia shows a high success rate, the records for that country are considered unreliable, so we view those results with caution. In summary, the satellite successfully finds large facilities in countries where livestock are the main source of methane. This includes three countries that hold most of the world's poorly tracked herds. However, the tool fails in areas where other methane sources are more common. Both parts of this finding are central to our study.

6 Discussion

6.1 What Satellite Methane Measures

Satellite methane contains a detectable spatial signal of livestock activity, but that signal is informative only under identifiable conditions. Livestock emissions must be sufficiently large relative to the local methane background, and comparisons must be sufficiently local to absorb broad spatial variation in that background. This helps explain why the livestock–methane relationship is strong in some global regions like Asia, weak across U.S. states, and positive again across U.S. counties. Attribution also requires accounting directly for co-located sources, fossil fuels, waste, and rice, since each leaves an imprint comparable to livestock and would otherwise bias the attribution. Beyond those named sources, the pollutant placebos indicate that the coefficient is specific to methane rather than to human activity in general, though not entirely so: carbon dioxide carries a coefficient

of its own, and netting it out removes part but not most of the methane signal.

The limits are equally informative. Satellite methane does not reliably track short-run temporal change at the country scale, and it resolves only the largest concentrated operations. Together with the cross-regional and dairy–beef contrasts, these results define a detection envelope: livestock activity becomes visible when source strength and spatial concentration are sufficiently large relative to competing methane sources and atmospheric background. Outside this envelope, a weak satellite signal should not be interpreted as evidence of little livestock activity.

This detection envelope also clarifies the statistical value of satellite methane. Its comparative advantage is not continuous herd-size prediction or temporal nowcasting, for which existing inventories and geography contain substantially more information. Rather, satellite methane provides an independent physical signal that can help screen for unusually large and concentrated livestock activity and verify patterns recorded in administrative data. Its value may therefore be greatest where livestock emissions are concentrated, and conventional ground data are sparse. Satellite methane is best viewed as a complement to survey infrastructure, not a substitute for it.

6.2 Implications for Policy Analysis

The findings have two immediate implications for agricultural statistics and methane policy. First, satellite methane can provide an independent screening and verification layer where conventional livestock statistics are incomplete, infrequent, or spatially coarse. Its usefulness is inherently selective: the strongest signals arise from large, concentrated sources rather than from livestock production generally. This makes the technology better suited to identifying and monitoring high-emitting clusters than to replacing livestock censuses.

Second, the same selectivity can be useful for methane mitigation. Large confined operations are both among the most detectable sources in our analysis and potential targets for interventions such as feed additives and manure methane capture (Wang et al., 2024; Beach et al., 2015). Satellite observations could therefore complement facility records in targeting and independently verifying mitigation at sufficiently large sources, including monitoring relevant to broader methane-reduction commitments such as the Global Methane Pledge (European Commission and United States, 2021). Such applications should, however, respect the detection limits documented here rather than assume comprehensive coverage of livestock emissions.

The United States evidence illustrates this complementarity particularly clearly. Facility-level information on livestock methane remains incomplete, while the satellite can already identify the largest concentrated dairy sources. Current observations cannot provide comprehensive facility-level monitoring, but higher-resolution sensors may progressively lower the minimum source size that can be detected from space.

Livestock composition remains relevant for interpreting these applications because methane intensity differs sharply across species and production systems. Ruminants account for 120.6 of the 122.6 megatons of Tier 1 livestock methane in our accounting, or 98.4 percent, with non-ruminants at only 2.0 megatons (Table A1). This heterogeneity helps explain why equal numbers of animals

need not generate equally detectable atmospheric signals.

6.3 Beyond Livestock: A Template for Sensing-Based Measurement

The approach generalizes beyond livestock methane. More generally, sensing-based indicators of economic activity should be evaluated as measurement instruments rather than as black boxes. Our analysis suggests four parts. First, that the physical signal covaries with the economic activity after removing broad spatial background variation. Second, distinguish that signal from plausible co-located alternatives, as we do with fossil fuels, waste, rice, and atmospheric placebos. Third, map the detection envelope by identifying the source strength, spatial concentration, and background conditions under which the signal becomes informative. Last, validate the measure against ground truth where such data exist. The same logic can be applied to other agricultural activities that leave observable physical traces, such as irrigation, tillage, and land use intensity. The transferable lesson is to ask not only whether a sensing measure correlates with economic activity, but when that relationship contains useful information.

7 Conclusion

We ask whether satellite methane contains useful information about livestock activity. We answer with a measurement validity design applied to an eighteen-year global panel. The answer is a qualified yes. First, satellite methane contains a robust livestock-related spatial signal: comparing nearby grid cells, within local neighborhoods, methane concentrations increase with livestock activity across five of six continents, and the relationship survives after controls for competing methane sources and atmospheric placebo tests. Second, this signal reveals livestock activity only under identifiable conditions. Detection is strongest when livestock methane emissions are sufficiently large compared to the local methane background, as illustrated by the contrast between concentrated dairy and dispersed beef production and by facility-level evidence. Third, the satellite adds limited information for continuous herd-sized prediction or temporal change, but substantially more for screening and independently verifying large, concentrated livestock activities.

Several limitations bound the interpretation. The estimated livestock–methane coefficient is a conditional spatial association identified within neighborhoods, not a causal effect of livestock on atmospheric concentrations; the placebos and direct source controls strengthen attribution but cannot rule out every unobserved factor specific to methane, and the Tier 1 measure inherits the uncertainty in species-specific emission factors. The instrument imposes further limits. At roughly 0.1° (eleven kilometers), GHAP detects only the largest confined operations, so the Central Valley result does not imply that existing satellites can monitor confined operations generally—finer instruments such as TROPOMI and MethaneSAT will be needed to lower that threshold—and the Central Valley enhancement may partly reflect topographic trapping, with formal source attribution requiring an atmospheric inversion. Finally, the county-level dairy and beef comparison allocates herds uniformly within counties and yields coefficients that move with the comparison window,

so we read it as confirming a mechanism rather than as a precise estimate. These limitations shape how far the measurement can be pushed rather than overturning the detection envelope, and they reinforce reading the estimates as measurement-validation evidence rather than causal or source-attribution estimates.

The broader implication is methodological. Remote sensing technologies can provide information about parts of the agricultural economy that conventional surveys capture incompletely, but their value depends on understanding when the underlying physical signal is observable. For livestock methane, the appropriate role is therefore not a satellite livestock census, but a complementary tool for spatial screening and independent verification within a well-defined detection envelope. As higher-resolution methane instruments become available, that envelope may expand. More broadly, pairing physical signals with economic ground truth and a validity design offers a framework for evaluating when sensing technologies can become useful economic measurements.

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Measuring Livestock from Space: Global and U.S. Evidence on the Detection, Attribution, and Limits of Satellite Methane

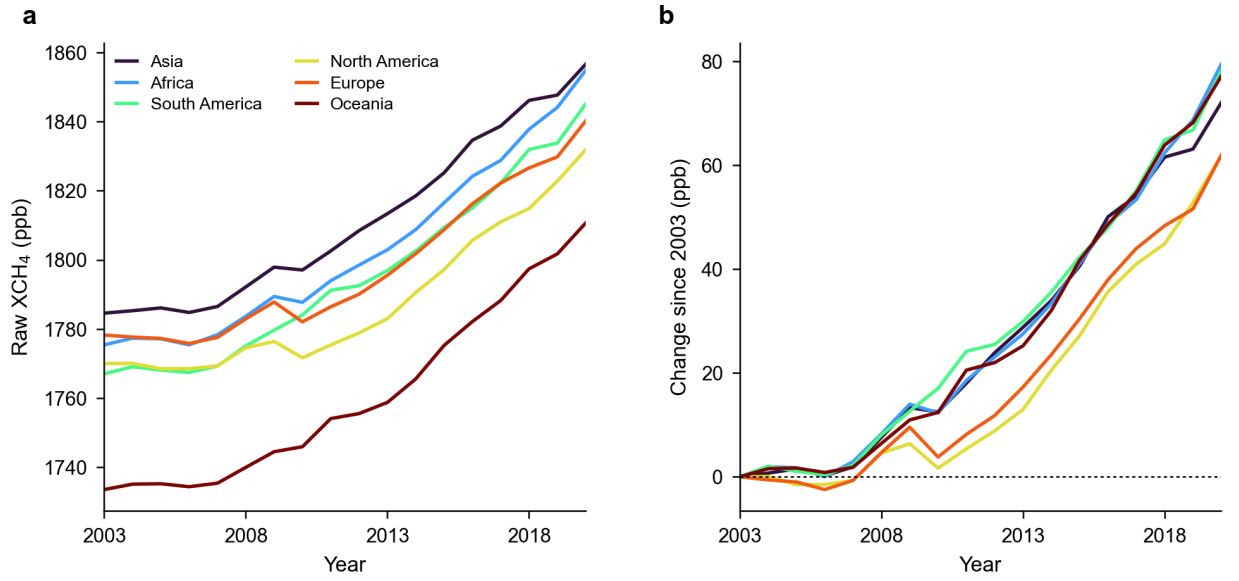
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Online Appendix

A1 Data Construction and Descriptive Evidence

A1.1 Satellite Methane Data

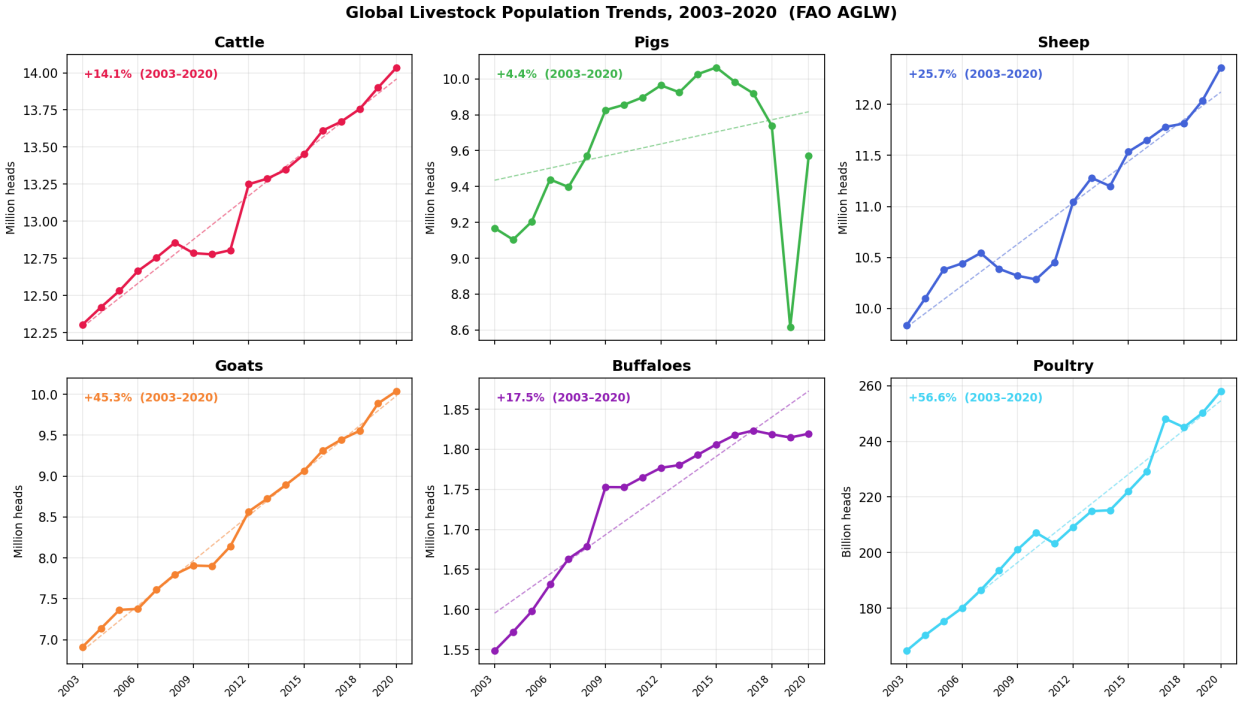
Figure A1: Raw column methane by region and year



Notes: This figure shows the average satellite methane levels for each continent from 2003 to 2020. Panel (a) displays total methane levels. Asia has the highest levels, and Oceania has the lowest levels throughout the entire period. Panel (b) shows the change in methane levels on each continent since 2003. On every continent, methane increased by 60 to 80 parts per billion. The permanent differences in methane levels between continents are caused by general geographic factors rather than livestock activity. Source: GHAP.

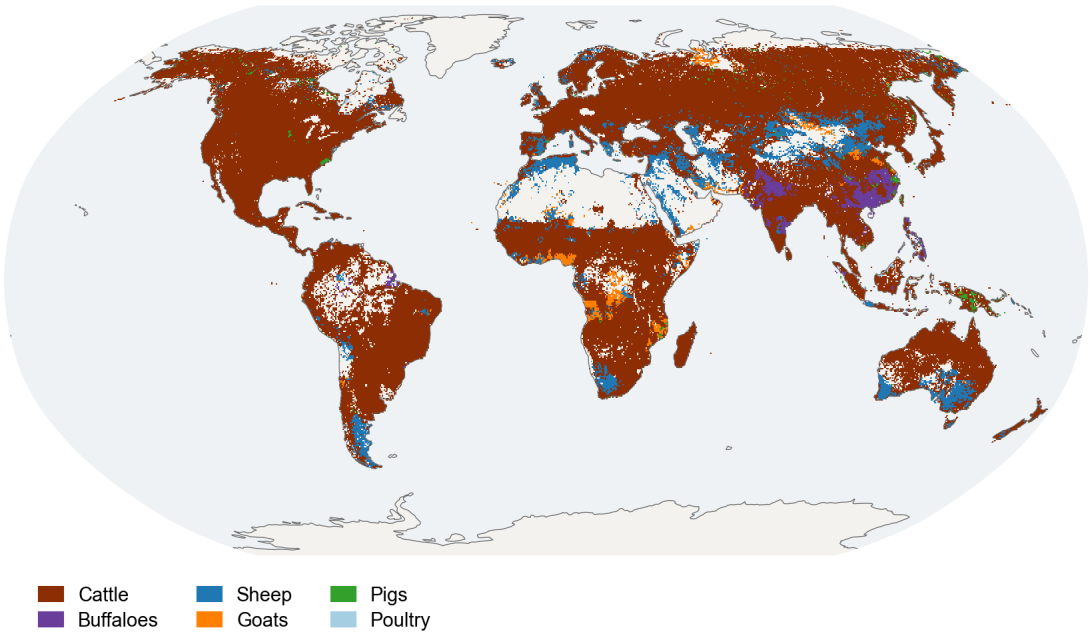
A1.2 Livestock Data and Emission Factors

Figure A2: Livestock head counts by species, 2003 to 2020



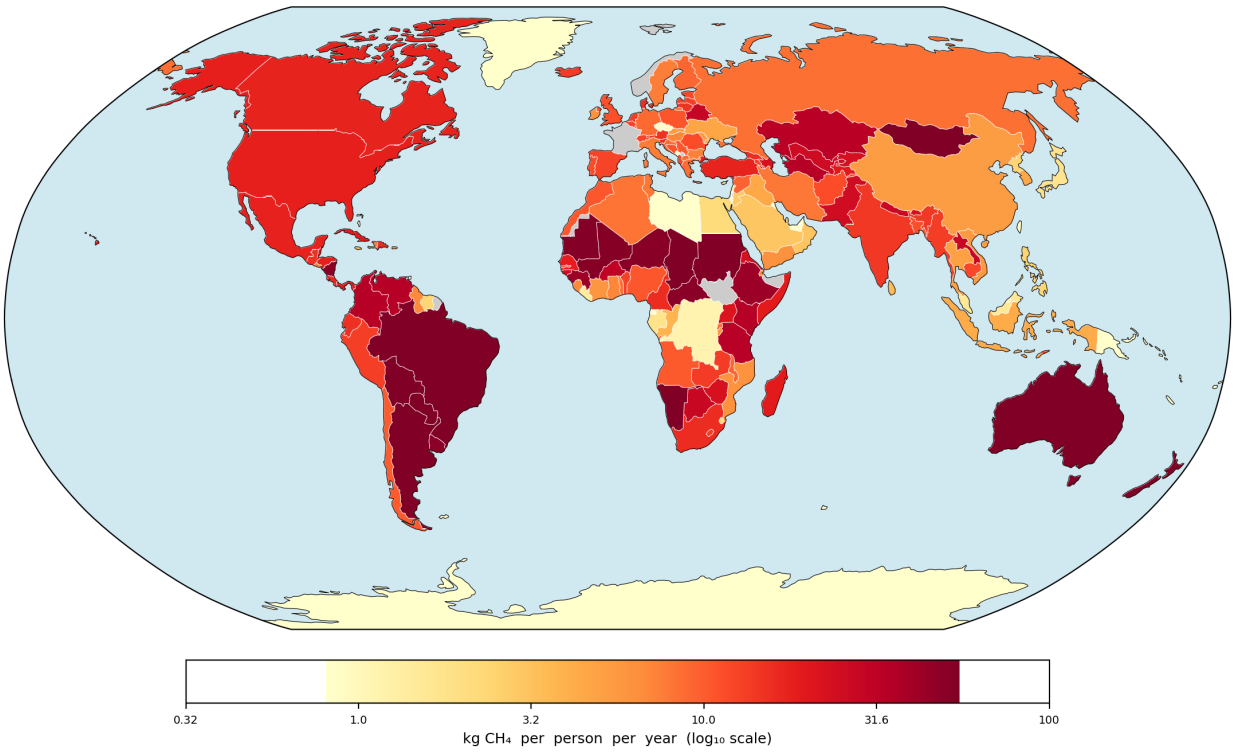
Notes: Global headcounts from FAO AGLW. Poultry and goats grew fastest in proportional terms. Source: FAO AGLW.

Figure A3: Dominant emitting species by cell, 2020



Notes: This figure shows which livestock species produce the most methane in each 0.1° cell. Data are combined into 0.4° blocks to make the map easier to read. Cattle are the primary source of methane in 86 percent of livestock areas. Sheep are the main source in nine percent of areas, primarily in Central Asia, Australia, and Patagonia. Goats and buffaloes are each the main source in two percent of areas. Buffaloes are concentrated in the Indo-Gangetic Plain, while goats are common across the Sahel and Arabia. Sources: FAO AGLW and IPCC.

Figure A4: Livestock methane per person, 2020



Notes: Tier 1 methane divided by national population, on a log scale. Values reflect relative pattern rather than calibrated levels. Source: FAO AGLW and Natural Earth population.

Table A1: Global livestock methane by species, Tier 1

Species	2003 (Mt)	2020 (Mt)	Head count growth
Cattle	80.3	93.8	+17%
Buffaloes	9.5	11.1	+17%
Sheep	7.9	10.1	+29%
Goats	3.8	5.6	+48%
Pigs	1.3	1.4	+5%
Poultry	0.3	0.5	+59%
Total	**103.1**	**122.6**	+18.9%

Notes: Full grid AGLW head counts times IPCC 2006 Tier 1 emission factors. The gridded head counts match FAO, for example 1.51 billion cattle in 2020 against about 1.53 billion. Cattle are 76.5 percent of the 2020 total. Emission factors: cattle 62, buffaloes 55, sheep 8, goats 5, pigs 1.5, poultry 0.02 kilograms of methane per head per year. Source: FAO AGLW and IPCC 2006 guidelines.

A1.3 Additional Data Sources

Table A2: Overview of data sources, coverage, and empirical roles

Dataset	Period	Resolution	Role
GHAP XCH_4	2003–2020	0.1°	Satellite methane, main outcome
GHAP XCO_2	2003–2020	0.1°	Biogenic ratio fingerprint
GHAP surface O_3	2019	0.1°	Placebo outcome
FAO AGLW livestock	2003–2020	0.1°	Livestock activity
GlobalRice20	2015	0.1°	Rice confounder
GFEI oil/gas/coal	2019	0.1°	Fossil confounder (direct)
EDGAR v2025 waste	2020	0.1°	Landfill, wastewater
EDGAR v2025 CH_4 total	2003–2020	0.1°	Total methane reference
USDA NASS QuickStats	2003–2020	State/nation	U.S. cattle and hog inventory
USDA county cattle panel	2000–2024	County	U.S. dairy and beef cattle
BLS price indices	2003–2020	National	U.S. livestock and food prices
FAOSTAT emissions	2003–2020	Country	Enteric and manure split by species

Notes: GHAP is from GlobalHighAirPollutants (GHAP). Sentinel 5P TROPOMI and ECMWF EAC4 were considered but are not used in the main analysis. Source: as listed.

Table A3: Summary statistics for the global livestock–methane sample

Variable	Mean	SD	p10	p50	p90
Panel A. 2019 (main analysis year)					
Satellite outcomes					
Raw XCH_4 (ppb)	1,837.34	19.75	1,815.75	1,836.74	1,860.83
Raw XCO_2 (ppm)	408.90	1.15	407.15	408.87	410.21
Surface O_3 (ppb)	36.16	5.81	30.10	35.30	43.90
Livestock					
Livestock CH_4 (kt per cell)	0.118	0.251	0.000	0.028	0.321
Log livestock CH_4	9.73	2.61	5.71	10.25	12.68
Animal units per cell	1,725	3,571	4	423	4,820
Cattle (head per cell)	1,442	2,953	4	309	4,182
Buffaloes (head per cell)	226	1,774	0	0	2
Sheep (head per cell)	1,169	3,167	0	63	3,541
Goats (head per cell)	1,087	3,850	0	24	2,855
Pigs (head per cell)	715	3,486	0	0	1,127
Poultry (head per cell)	18,898	96,396	0	0	30,809
Confounder controls					
Rice fraction (percent)	16.91	37.48	0.00	0.00	100.00
Fossil CH_4 (Mg km^{-2} yr^{-1})	1.030	26.381	0.000	0.002	0.212
Waste CH_4 (t per cell yr^{-1})	43.00	1,196.85	0.00	0.00	14.67
Observations	647,529 cells				
Panel B. 2020 (most recent year)					
Satellite outcomes					
Raw XCH_4 (ppb)	1,847.98	20.87	1,822.21	1,847.52	1,873.32
Raw XCO_2 (ppm)	410.97	1.14	409.07	411.21	412.08
Surface O_3 (ppb)	35.16	5.85	29.40	34.30	43.30
Livestock					
Livestock CH_4 (kt per cell)	0.126	0.258	0.000	0.032	0.346
Log livestock CH_4	9.85	2.58	5.83	10.39	12.75
Animal units per cell	1,855	3,675	4	489	5,209
Cattle (head per cell)	1,562	3,105	5	357	4,551
Buffaloes (head per cell)	227	1,768	0	0	5
Sheep (head per cell)	1,182	3,249	0	65	3,500
Goats (head per cell)	1,095	3,906	0	26	2,867
Pigs (head per cell)	834	3,841	0	0	1,271
Poultry (head per cell)	20,805	93,321	0	11	36,736
Confounder controls					
Rice fraction (percent)	18.48	38.82	0.00	0.00	100.00
Fossil CH_4 (Mg km^{-2} yr^{-1})	1.030	26.918	0.000	0.002	0.217
Waste CH_4 (t per cell yr^{-1})	45.50	1,172.82	0.00	0.00	17.60
Observations	659,167 cells				

Notes: The sample consists of land cells with positive livestock density and observed satellite methane, corresponding to the sample used in the global livestock–methane gradient analysis. Panel A reports summary statistics for 2019, the main analysis year, and Panel B reports statistics for 2020, the final year of the satellite record. Satellite variables are raw retrieved values without background removal; neighborhood fixed effects account for broad spatial variation in atmospheric background in the regression analysis. Species counts are measured as heads per 0.1° grid cell and are constructed by multiplying AGLW livestock densities by cell area. Livestock CH_4 applies IPCC Tier 1 emission factors to these counts.

A2 Alternative Spatial Specifications

A2.1 Spatially robust inference

Raw XCH_4 is strongly spatially autocorrelated, so inference that assumes independence across cells would be badly miscalibrated. We report three schemes. The baseline clusters standard errors by 5° neighborhood, which allows arbitrary dependence within blocks. We add Conley spatial heteroskedasticity and autocorrelation-consistent standard errors (Conley, 1999), which allow dependence that decays with distance. Writing the residualized regressor as $\tilde{x}_i$ and the residual as $\hat{\varepsilon}_i$, and letting $K(d_{ij})$ be a uniform kernel equal to one when the distance d_{ij} between cells is below a cutoff and zero otherwise, the Conley variance of $\hat{\beta}$ is

$$\widehat{\mathrm{Var}}(\hat{\beta}) = \Big(\textstyle\sum_i \tilde{x}_i^2 \Big)^{-2} \sum_i \sum_j K(d_{ij})\, \tilde{x}_i \hat{\varepsilon}_i\, \tilde{x}_j \hat{\varepsilon}_j, \tag{5}$$

which we evaluate at cutoffs of 200 and 500 kilometers. Because the cells lie on a regular grid, we compute the double sum efficiently by convolving the cell-level score $\tilde{x}_i \hat{\varepsilon}_i$ with a disk kernel, which avoids forming the full pairwise distance matrix. We also report a spatial block bootstrap that resamples whole neighborhoods with replacement, which makes no parametric assumption about the dependence structure, and, as a falsification test, we permute $\log \ell_i$ within neighborhoods and re-estimate, since a valid gradient should vanish when the livestock labels are scrambled.

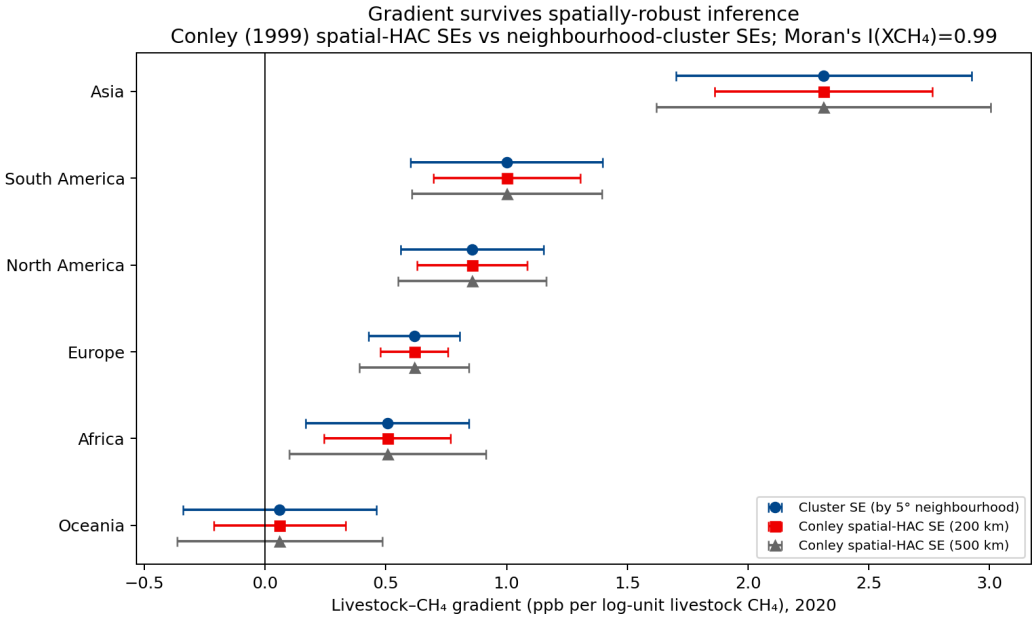
Figure A5 reports the gradient with confidence intervals under neighborhood cluster standard errors and under Conley spatial standard errors at 200 and 500 kilometers. The gradient remains significant on five of six continents even at the 500-kilometer cutoff, and the cluster and Conley 500-kilometer errors are similar in magnitude, which validates the cluster approach used in the main tables.

Table A4: The spatial livestock methane coefficient by continent, 2019

Continent	Coefficient	Cluster SE	Conley 500 km SE	With controls	n
Asia	2.31	0.29	0.33	1.83	114,159
South America	1.14	0.25	0.23	1.16	52,624
North America	0.72	0.12	0.12	0.68	128,455
Europe	0.57	0.09	0.10	0.48	181,317
Africa	0.50	0.16	0.19	0.44	126,451
Oceania	0.06	0.25	0.27	0.06	44,523

Notes: Estimate of β from Equation (1), in parts per billion per log unit of livestock methane. The outcome is raw XCH_4; the 5° by 5° neighborhood fixed effects remove the background in one step. Standard errors: cluster robust by neighborhood, and Conley spatial at a 500-kilometer cutoff. The confounder column adds rice, direct oil, gas, and coal methane from GFEI, and landfill and wastewater methane from EDGAR. A permutation placebo that reshuffles livestock within neighborhoods yields coefficients near zero on every continent. Source: GHAP GOSAT and FAO AGLW.

Figure A5: Conley spatial standard errors

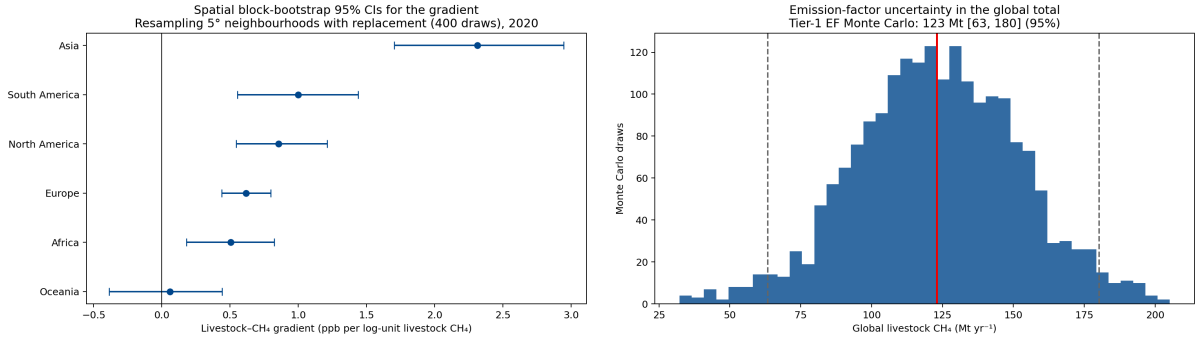


Notes: The gradient with 95 percent intervals under cluster and Conley spatial errors. Source: GHAP and FAO AGLW.

A2.2 Sampling uncertainty

Figure A6 reports the spatial block bootstrap distribution of the gradient and the Tier 1 emission factor Monte Carlo distribution of the global total. The bootstrap confidence interval excludes zero on five of six continents. The emission factor Monte Carlo makes explicit that the absolute total is uncertain, at 123 megatons with a 95 percent interval of 63 to 180.

Figure A6: Bootstrap and Monte Carlo uncertainty



Notes: Left, spatial block bootstrap intervals for the gradient. Right, emission factor Monte Carlo for the global total. Source: GHAP, FAO AGLW, IPCC 2006 factors.

Table A5: The livestock methane coefficient

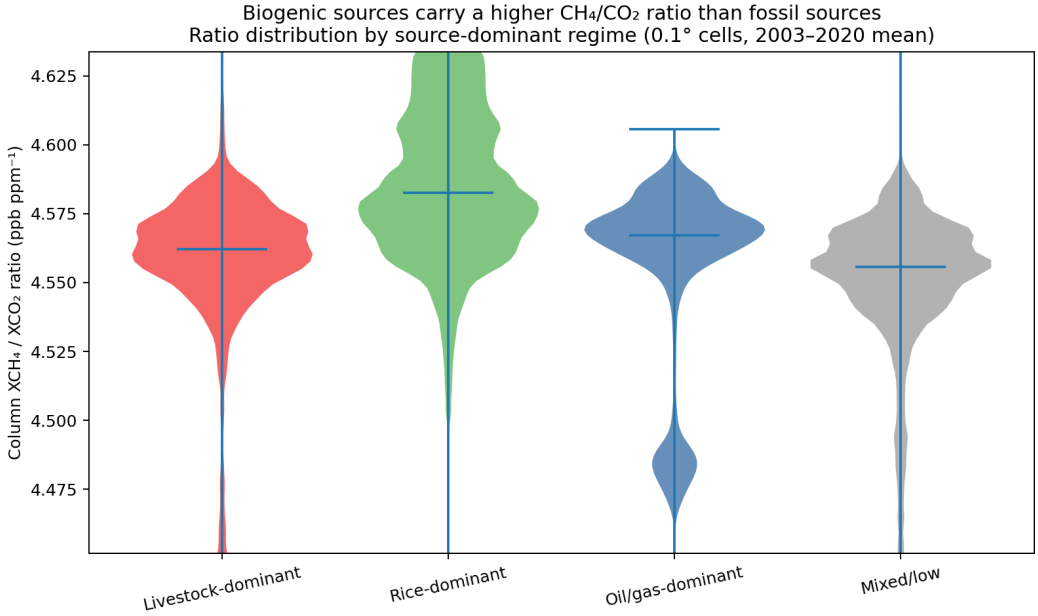
	(1)	(2)	(3)	(4)	(5)
Log livestock CH_4	0.791***	0.753***	0.689***	0.504***	1.239***
	(0.071)	(0.067)	(0.064)	(0.041)	(0.164)
Rice control	No	Yes	Yes	Yes	Yes
Fossil control	No	No	Yes	Yes	Yes
Waste control	No	No	Yes	Yes	Yes
Neighborhood FE	5°	5°	5°	3°	10°
Observations	647,529	647,529	647,529	647,529	647,529
Neighborhoods	754	754	754	1,826	233
Within R^2	0.045	0.060	0.078	0.057	0.132

Notes: Pooled estimate of β on log Tier 1 livestock methane with neighborhood fixed effects, 2019. Column 1 is the baseline; columns 2 and 3 add the confounder controls; columns 4 and 5 vary the fixed effect block size. Pooled OLS of raw XCH_4 on log Tier 1 livestock methane with neighborhood fixed effects, 2019 land sample. Cluster robust standard errors by the neighborhood block in parentheses. Controls are log rice fraction, log GFEI fossil methane, and log EDGAR waste methane. The pooled slope averages across continents; Table A4 reports the heterogeneity by continent. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source: GHAP, FAO AGLW, GlobalRice20, GFEI, EDGAR.

A3 Attribution and Atmospheric Placebos

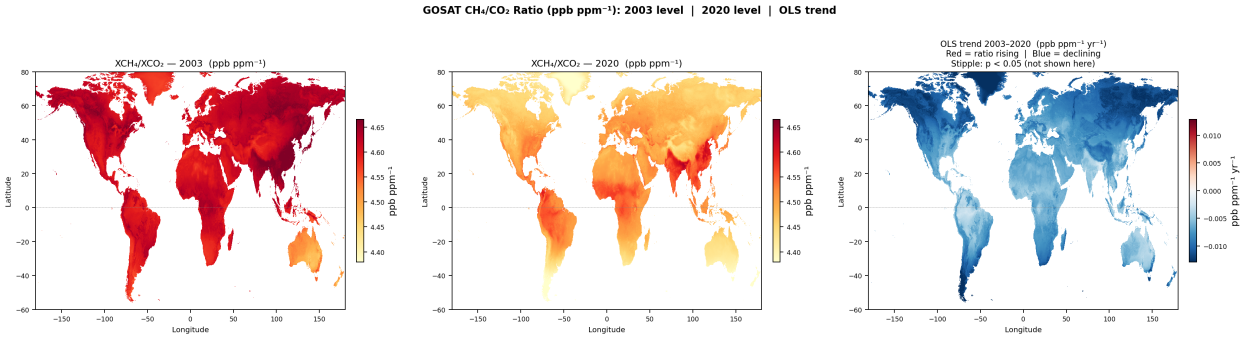
Figure A7 shows the distribution of the ratio across cells classified by dominant source, and Figure A8 maps the ratio in 2003 and 2020 and its change. The ratio is higher over rice and livestock regions, which are biogenic, than over oil and gas regions, consistent with a biogenic origin for the local enhancements, though the absolute differences are small because the signal is column integrated.

Figure A7: Methane to carbon dioxide ratio by source regime



Notes: Distribution of the column ratio across cells classified as rice, livestock, or oil and gas dominant. Source: GHAP XCH_4 and XCO_2.

Figure A8: Methane to carbon dioxide ratio, levels and change



Note: The ratio in 2003 and 2020 and its change. Source: GHAP XCH_4 and XCO_2.

Table A6: Pollutant placebo: the coefficient is specific to methane

	Outcome pollutant (SD units)			Methane
Continent	Methane	Carbon dioxide	Ozone	controlling CO_2 (ppb)
All	0.219^{***}	0.136^{***}	0.037^{**}	0.47^{***}
Asia	0.431^{***}	0.298^{***}	0.188^{***}	1.19^{***}
South America	0.266^{***}	0.192^{***}	-0.137^{*}	0.62^{***}
North America	0.225^{***}	0.190^{***}	-0.004	0.25^{***}
Europe	0.218^{***}	0.101^{***}	0.010	0.38^{***}
Africa	0.156^{***}	0.038	0.082^{*}	0.45^{***}
Oceania	0.023	-0.043	-0.117	0.12

Notes: Each entry is the coefficient on log Tier 1 livestock methane from the main specification, raw concentration with 5° neighborhood fixed effects and neighborhood clustered standard errors, 2019, estimated on the identical sample of 647,508 cells. Coefficients are expressed in within-neighborhood standard deviations of the outcome so that the pollutants are comparable. The final column adds raw XCO_2 as a control to the methane regression.

A4 Machine Learning and Model Performance

Table A7: Predictive skill for the local methane residual is low on every metric

Model	R^2	RMSE	MAE	Median AE	MAPE (%)	Bias
Mean baseline	0.000	3.95	2.87			0.000
OLS	0.052	3.85	2.82	2.10	96.6	0.000
Ridge	0.071	3.81	2.81	2.09	97.1	0.000
Lasso	0.070	3.81	2.81	2.09	97.0	0.000
Random forest	0.495	2.81	2.00	1.42	70.3	0.020
Histogram GBM	0.577	2.57	1.84	1.32	65.0	0.015
Gradient boosted trees	0.587	2.54	1.81	1.30	63.8	0.021

Notes: The variable we predict is a difference centered at zero. Because percentage errors cannot be calculated when the true value is zero, we report the mean absolute percentage error only for areas where this difference is at least one part per billion. We also tested two alternative samples of 300,000 areas, both of which resulted in lower model accuracy. When we include all 18 years of data, the accuracy is 0.45. When we include the 36 percent of land areas that have no livestock, the accuracy falls to 0.37. This decrease occurs because the model cannot use livestock data to explain methane levels in areas where no animals are present. Sources: GHAP, FAO AGLW, GlobalRice20, GFEI, and EDGAR.

A5 Livestock Accounting Detail

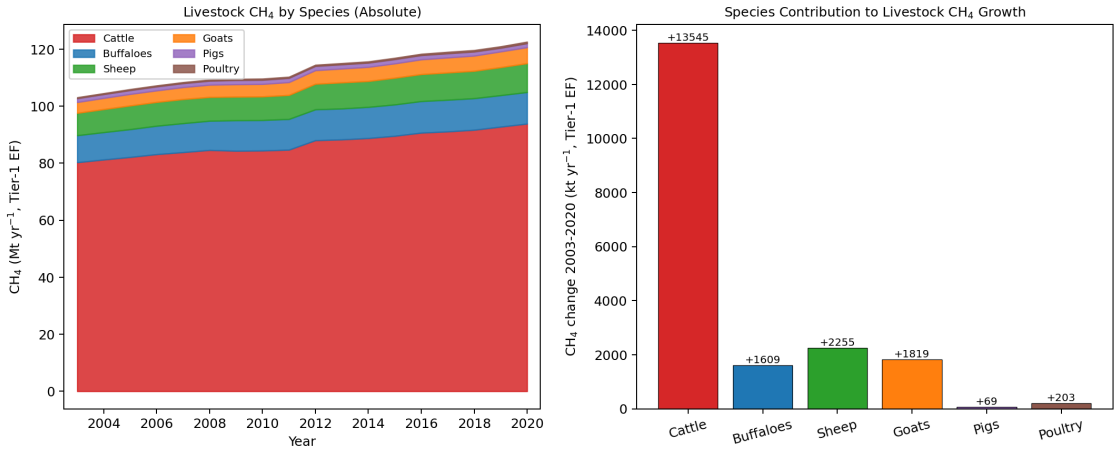
We compute Tier 1 livestock methane from the gridded census as follows. For each 0.1° cell i and species s, the head count is the AGLW animal density times the cell area, $N_{s,i} = D_{s,i}\, A_i$, where $A_i = (111 \times 0.1)^2 \cos\phi_i$ square kilometers corrects for the convergence of the meridians at latitude ϕ_i. Livestock methane in the cell is the head count weighted sum of the IPCC 2006 Tier 1 emission factors,

$$M_i = \sum_s N_{s,i}\, \mathrm{EF}_s, \qquad \mathrm{EF} = (62,\ 55,\ 8,\ 5,\ 1.5,\ 0.02)\ \text{kg CH}_4\ \text{head}^{-1}\ \text{yr}^{-1}, \tag{6}$$

for cattle, buffaloes, sheep, goats, pigs, and poultry, respectively, each factor combining enteric fermentation and manure management (IPCC, 2006). Global and national totals sum M_i over the full grid, and the per capita map divides the national total by population. Equation (6) is the quantity mapped in Figures A4 and tabulated in Table A1.

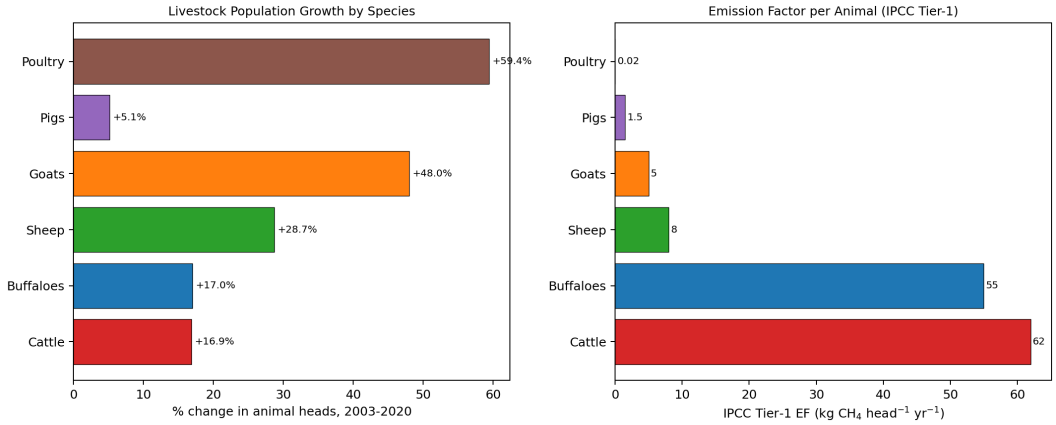
Figure A9 decomposes the growth in Tier 1 livestock methane into the contributions of the six species, and Figure A10 reports the proportional growth of each species. Cattle dominate the level, while goats and poultry grow fastest in proportional terms. These figures use the full grid, so their totals match Table A1.

Figure A9: Livestock methane by species, 2003 to 2020



Notes: Stacked Tier 1 methane by species. Source: FAO AGLW with Tier 1 factors.

Figure A10: Proportional species growth

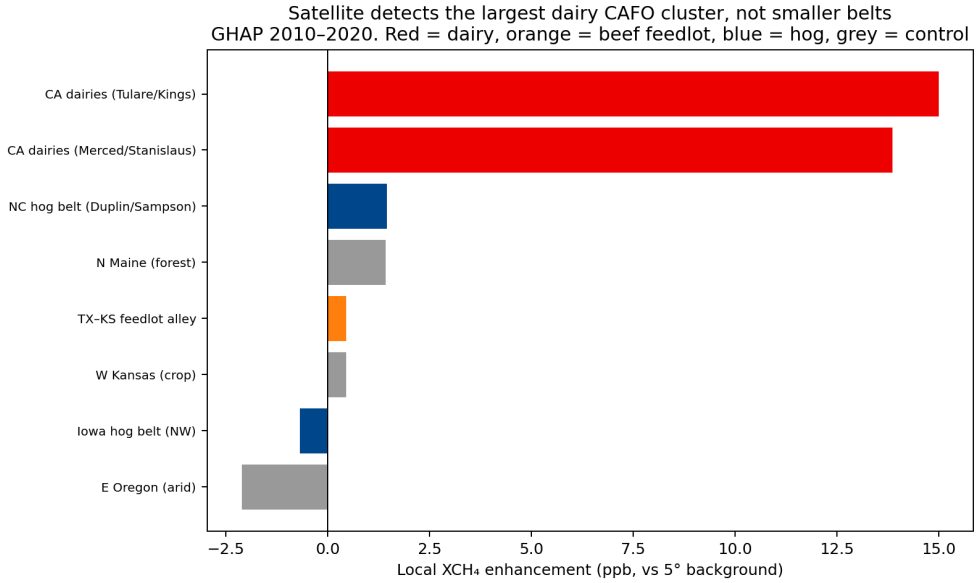


Notes: Head count growth by species, 2003 to 2020. Source: FAO AGLW.

A6 Additional U.S. Validation

Figure A11 reports the local methane enhancement over each United States livestock region, showing that only the California dairy cluster clears the detection floor, and Figure A12 maps the enhancement over the contiguous United States with the major clusters marked.

Figure A11: Enhancement by United States livestock region



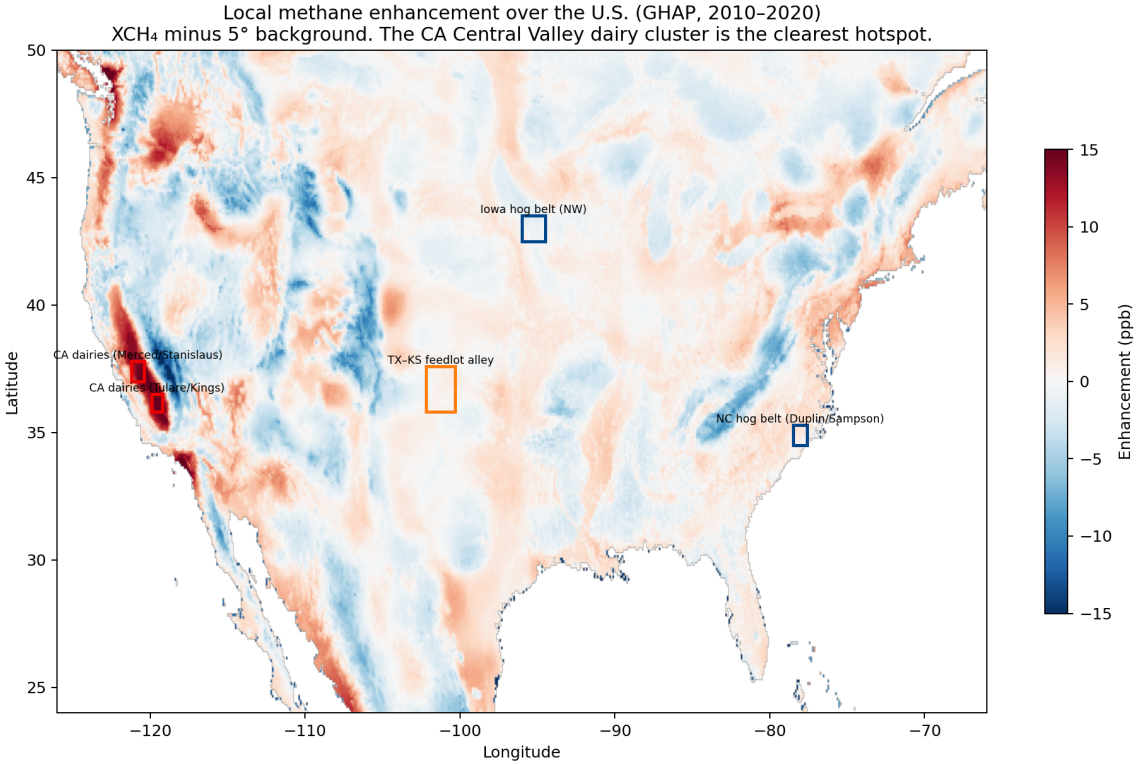
Notes: Local methane enhancement over dairy, beef, and hog clusters and rural controls. Source: GHAP.

Table A8: Satellite methane tracks the value of milk sold

	(1)	(2)	(3)	(4)
Log milk sales ($)	0.273*** (0.064)		0.096 (0.070)	−0.038 (0.121)
Log dairy cows		0.476*** (0.101)		0.521*** (0.180)
Log beef cattle			0.587*** (0.185)	

Notes: Raw satellite XCH_4 on log county quantities, 2° neighborhood fixed effects, standard errors clustered by neighborhood, 2017. Milk sales in dollars come from the Census of Agriculture. The sample is the 953 counties reporting milk sales, 25,208 grid cells. Milk revenue and the dairy herd are close to collinear, so column 4 cannot separate them and should not be read as evidence against revenue. $^{***}p < 0.01$. Source: GHAP and USDA NASS Census of Agriculture.

Figure A12: United States methane enhancement



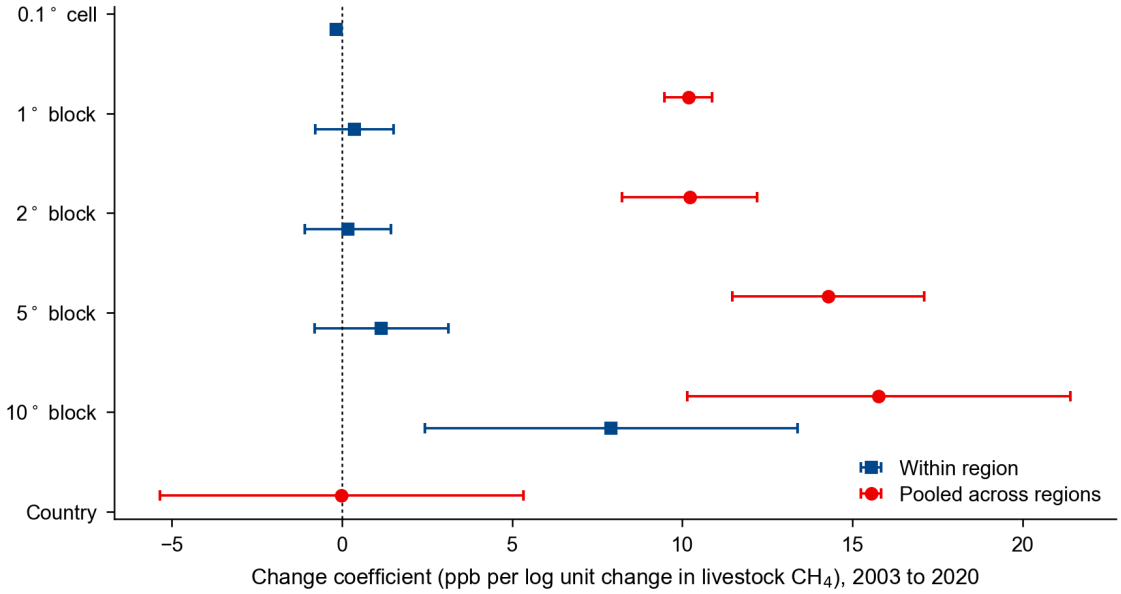
Notes: Local XCH_4 enhancement over the contiguous United States with livestock clusters marked. Source: GHAP.

Table A9: At county resolution, the relationship is positive, and the controls behave

	(1)	(2)	(3)	(4)	(5)	(6)
Log cattle	2.530***	2.075***	0.515***	0.527***		
	(0.294)	(0.238)	(0.134)	(0.122)		
Log dairy cows					0.425***	
					(0.088)	
Log milk sales ($)						0.256***
						(0.056)
Fossil (GFEI)	No	Yes	No	Yes	Yes	Yes
Waste (EDGAR)	No	Yes	No	Yes	Yes	Yes
Rice	No	Yes	No	Yes	Yes	Yes
2° neighborhood FE	No	No	Yes	Yes	Yes	Yes
Observations (cells)	50,547	50,547	50,547	50,547	50,547	25,208
R^2	0.155	0.344	0.027	0.128	0.132	0.140

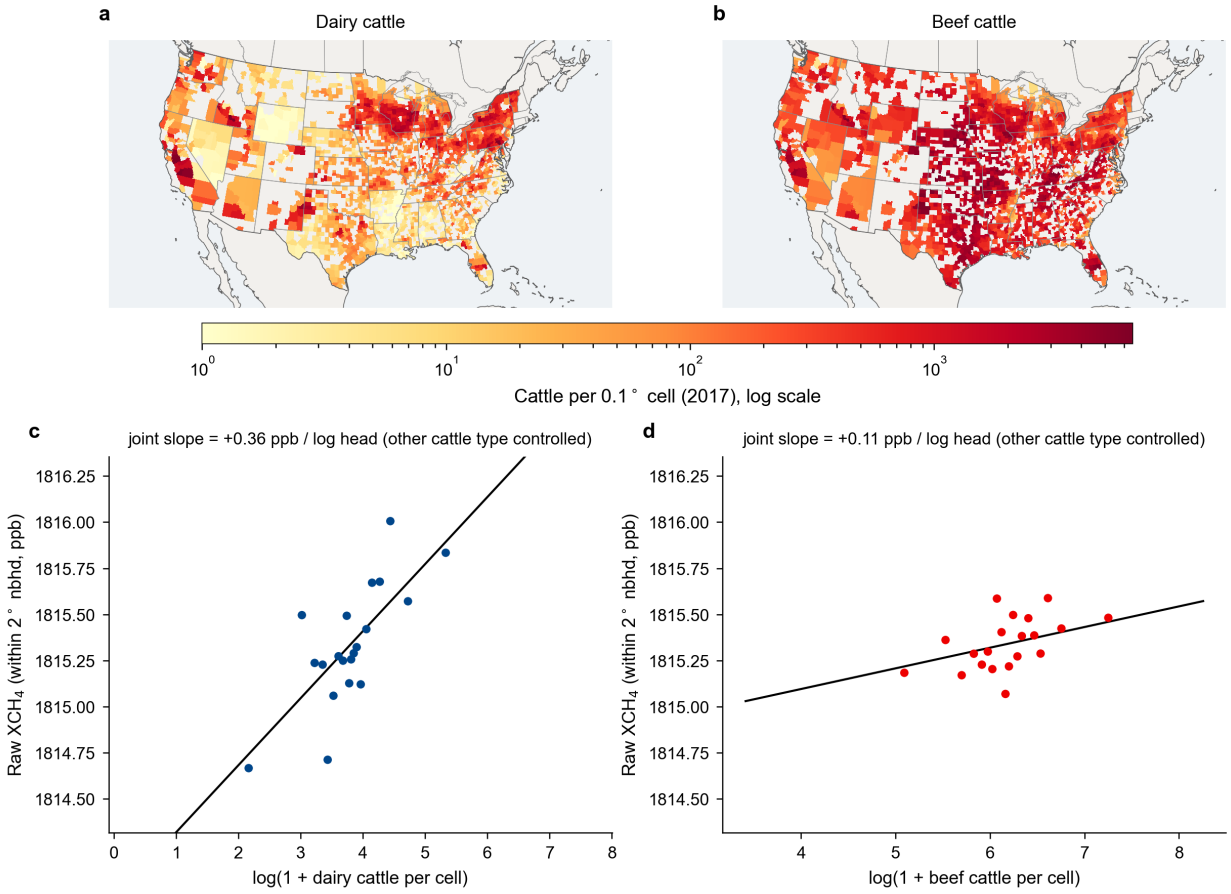
Notes: Column (6) replaces the animal count with the value of milk sold, so the estimate is an elasticity of the column with respect to farm revenue; it is estimated on the counties that report milk sales. The within neighborhood R^2 is small because cell-level column methane is dominated by transport and retrieval noise, which is why the identification rests on the coefficient rather than on fit. $^{***}p < 0.01$. Source: GHAP, GFEI, EDGAR v2025, GlobalRice20, USDA NASS Census of Agriculture 2017.

Figure A13: The satellite does not track change, at any level of aggregation



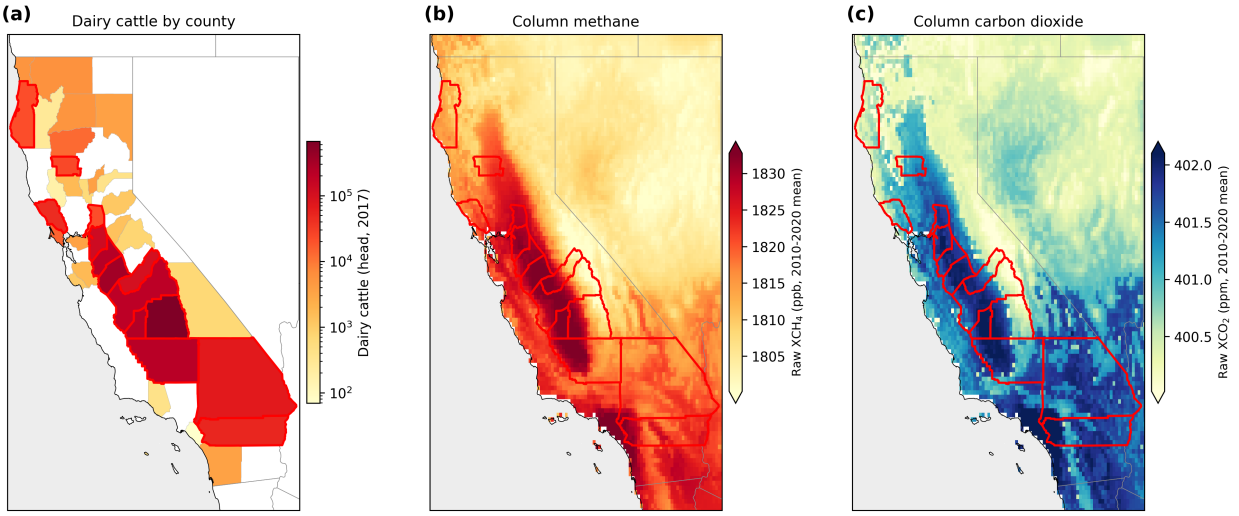
Notes: Change in raw XCH_4 on the change in log livestock methane, 2003 to 2020, by unit of aggregation. Red circles pool units across the world; blue squares compare units only with nearby units.Note: the large pooled coefficients reflect the coincidence that tropical regions grew both their herds and their methane fastest; within a region the coefficient is indistinguishable from zero everywhere except the coarsest block. Source: GHAP and FAO AGLW.

Figure A14: Satellite methane tracks dairy, not beef



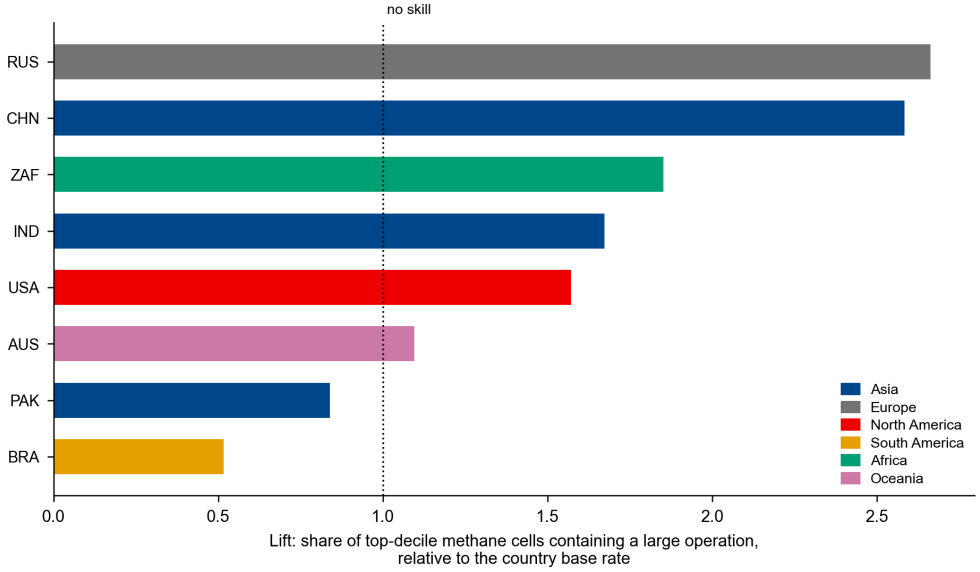
Notes: (a) Dairy and (b) beef cattle per 0.1° cell from the USDA county census, 2017, on a common log scale, so the two herds are directly comparable: beef is both denser and far more widely spread. (c) and (d) plot raw satellite XCH_4 against each cattle type after partialling out the neighborhood fixed effects *and the other cattle type*, so the plotted slope is the joint coefficient of Table 3, column (3). The two lower panels share a vertical scale; the dairy relationship slopes up while the beef relationship is flat. Source: GHAP and USDA NASS.

Figure A15: The California dairy cluster sits on the state methane maximum



Notes: (a) Dairy cattle by county, USDA 2017. (b) Raw satellite XCH_4 and (c) raw satellite XCO_2, GHAP 2010 to 2020 means in absolute units. The national top decile dairy counties are outlined in red in every panel. Source: GHAP and USDA NASS.

Figure A16: The detector against the global asset inventory



Notes: Share of each country's top decile of the within-neighborhood methane column that contains a large Climate TRACE cattle operation, 700 or more dairy or 1,000 or more beef head, relative to the country's base rate. Cells are the 2019 livestock cross section inside each country's asset envelope; countries shown have at least 30 target cells. Facilities are located from imagery and permits, never from methane, so the test is independent; inventory completeness differs by country, which is why lift is computed within country and never pooled. Russia's records carry Climate TRACE's lowest confidence grade. Source: Climate TRACE (Davitt et al., 2026), GHAP, FAO AGLW.