Agriculture sector: Cattle Operations- Asset-level Enteric Fermentation and Manure ManagementEmissions

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This methodology reflects version 5.2.0 data release. See the changelog for additional information.

1. Introduction

According to the Food and Agriculture Organization (FAO) data (FAOSTAT), beef and dairy milk production systems are the largest contributors of greenhouse gas (GHG) emissions in the livestock sector, representing more than 60% of emissions in the sector and 14.5% of all anthropogenic sources (FAO 2013). Beef and dairy sector emissions are driven by two sources. The primary source is enteric fermentation emissions which consists of methane (CH_4) gas produced in the digestive systems of ruminants and to a lesser extent non-ruminants. The secondary source is GHG emissions from manure management, producing both methane (CH_4) and nitrous oxide (N_2O) emissions via aerobic and anaerobic decomposition of livestock manure, including the microbially-driven processes of nitrification and denitrification (Waldrip et al., 2016; Waldrip et al., 2020). These emissions occur within manure storage facilities common to beef and dairy systems, as well as in-field where manure has been applied, or deposited by livestock.

FAOSTAT is the current de facto beef and dairy cattle emissions estimates inventory which is based on country-level official, implicit, or estimated activity data and an indication of global cattle emissions in each country. While an indication of emissions at a global scale, such information is coarse and varies in data quality based on the country, and does not have specific facility attribution of emissions. Generally, facility-level information is reported in academic studies, and, at times, the location information has been removed or kept vague (Harper et al., 2009; Costa et al., 2014; Zhu et al., 2014). However, while some jurisdictions have permit databases that contain location data for cattle production data, the location of most cattle operations worldwide is unknown. As such, understanding source-level emissions and contribution to regional and global GHG emissions is a difficult process. Discrepancies between top-down and bottom-up assessments of methane emissions may be explained in part by these significant gaps in facility level assessments of livestock operations (Wolf et al., 2017).

To better understand individual beef and dairy production systems emissions, the Climate TRACE coalition has generated a first-of-its-kind cattle operation database that unifies disparate government permit data, and identifies additional, non-reported, operations via artificial intelligence (AI) models with remote sensing data. This database contains cattle operations, here defined as a location that raises cattle which includes, but not limited to, animal feeding operations (AFOs), feedlots, dairies, and cow-calf-operations. This database contains individual cattle operation emissions estimates in the top emitting countries globally.

This understanding of cattle operation emissions involves the following: once individual operations were identified, total head of cattle was estimated using reported cattle numbers, mean values, or, if the operation area footprint was delineated, regression modeling was applied. Once each operation's total head of cattle was determined, the Intergovernmental Panel on Climate Change (IPCC) 2019 equations and emission factors (EFs) from “Chapter 10: Emissions from Livestock and Manure Management” and “Chapter 11: N_2O Emissions from Managed Soils, and CO_2 Emissions from Lime and Urea Application” were applied (IPCC 2019a; IPCC 2019b). The shift to IPCC 2019 approach helps account for global shifts and changes in commercial cattle breeding and production practices which can impact enteric fermentation and manure management emissions derived for these sectors (IPCC 2019a). Lastly, updating to IPCC 2019 allowed for emission reducing solutions (ERS) to be applied to understand how changing and adjusting certain practices, and retrofitting equipment can reduce enteric fermentation and manure management methane emissions. The data and information generated for this emitting sector provides a first of its kind global cattle operation dataset needed to improve emissions monitoring globally.

2. Materials and Methods

This sector utilized a combination of reported total head of cattle by type, AI models, remote sensing imagery, modeling, and IPCC EFs and equations to estimate cattle operation emissions four times per year (quarterly) for years 2015 to 2024 (Figure 1). Quarterly emissions data was generated since the U.S., Canada, and Australia produce quarterly cattle reports every year.

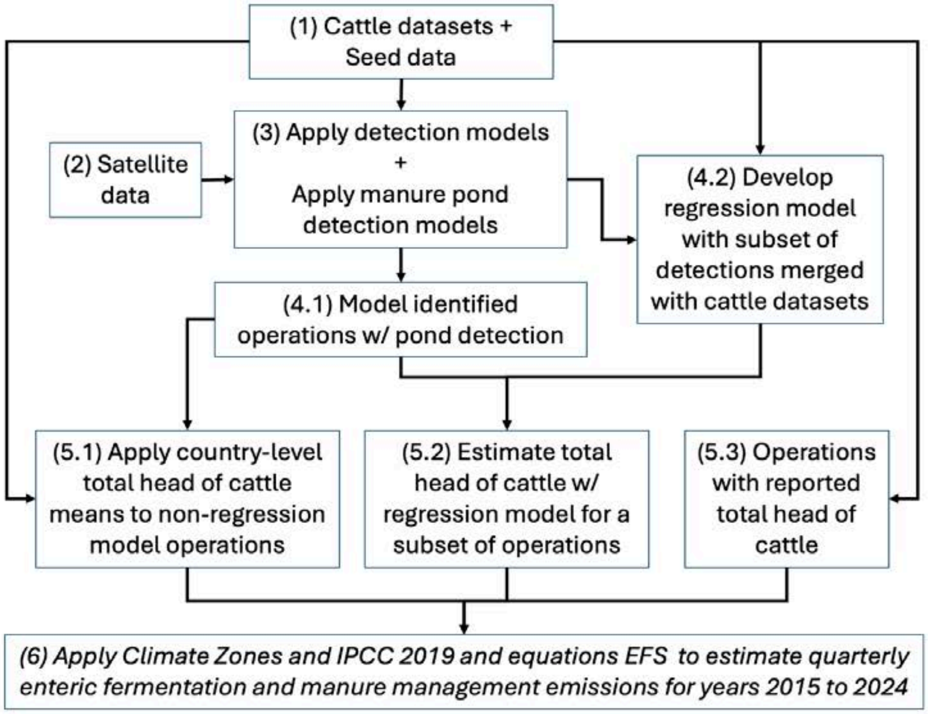

Figure 1 Overview to identify and estimate cattle operation emissions. (1) Cattle datasets and seed data were used with (2) Sentinel-2 or PlanetScope satellite data to (3) train AI models to detect cattle operations and to identify manure ponds in various countries. The model results created two sets - (4.1) point locations of cattle operations with and without ponds detected and (4.2) a subset of cattle operations and without ponds detected used for regression modeling to estimate total head of cattle using footprint areas. (5.1 to 5.3) represent the final three cattle operation types used to estimate emissions. (6) IPCC 2019 EFs and Tier 1 and 2 equations were applied to estimate CH_4 and N_2O from manure management emissions and CH_4 from enteric fermentation, respectively, for each quarter for 2015 to 2024 for each cattle operation. More detailed information can be found in the following sections.

2.1 Datasets

To create the Climate TRACE cattle operations dataset, the following data sources were accessed and employed for facility identification, model development, and to attribute ancillary information and specific emission factors by cattle type at individual locations.

2.1.1 Reported cattle operations

Reported cattle data formed the basis for the Climate TRACE cattle operation dataset. These provided an initial set of data that included: geolocation, cattle type, total head of cattle, and manure management types (in some cases). This information provided the basis to estimate emissions and seed data to the AI models. Reported data included individual U.S. state' CAFO data, shown in Table S1. Additionally, the U.S. Environmental Protection Agency (EPA) Enforcement and Compliance History Online (ECHO) provided additional state coverage where state CAFO data could not be shared to the public, not reported, or not reporting not required (accessed February, 2024; https://echo.epa.gov/). Lastly, the Australian cattle operations were accessed via non-profit Farm Transparency Project map (https://www.farmtransparency.org/, accessed 2023). These reported cattle operations were used directly to estimate emissions and to develop a regression model to estimate total head of cattle for cattle operations with footprint areas (see Figure 1, 4.2 and 5.2 boxes).

2.1.2 Seed data - identifying cattle operations in non-reporting countries

Cattle operations exhibit substantial visual variability across countries—differing in size, infrastructure, management practices, building materials, and cultural context—which limits the transferability of AI models trained on one region (e.g., the United States) to others (Figure 2). Detecting operations globally requires region-specific calibration and seed data generation.

For countries not previously included in the detection pipeline, the first step involved identifying high-confidence seed locations for both the Earth Index and TDX models. Publicly available high-resolution basemaps (e.g., Google Maps, Bing Maps, Mapbox) and ancillary tools such as Google Street View were used to visually confirm cattle operations, including verifying publicly listed farm types where available.

At sub-meter resolution, individual cattle are often directly visible in imagery and can typically be distinguished from other livestock such as horses, sheep, or poultry—operations that may share similar structural features. Additional region-specific indicators of cattle operations were also used, such as characteristic CAFO infrastructure, manure lagoons, anaerobic digesters, hay storage, feeding troughs, open shade structures, building skylights, cattle pathways from pens to pasture, and especially the presence of dark, manure-rich soil surfaces.

All confirmed point locations were recorded as seed data in GeoJSON format and assigned high-confidence status in the asset-level inventory (Table 4). These points formed the foundational training dataset for subsequent automated detection. We acknowledge a key limitation: basemap imagery is often a composite of best-available scenes spanning multiple years. As a result, some seed locations may no longer be active cattle operations when processed by Earth Index or TDX models using more recent imagery. Nonetheless, downstream quality control and iterative validation consistently yielded high true-positive detection rates, supporting the reliability of the seed data approach.

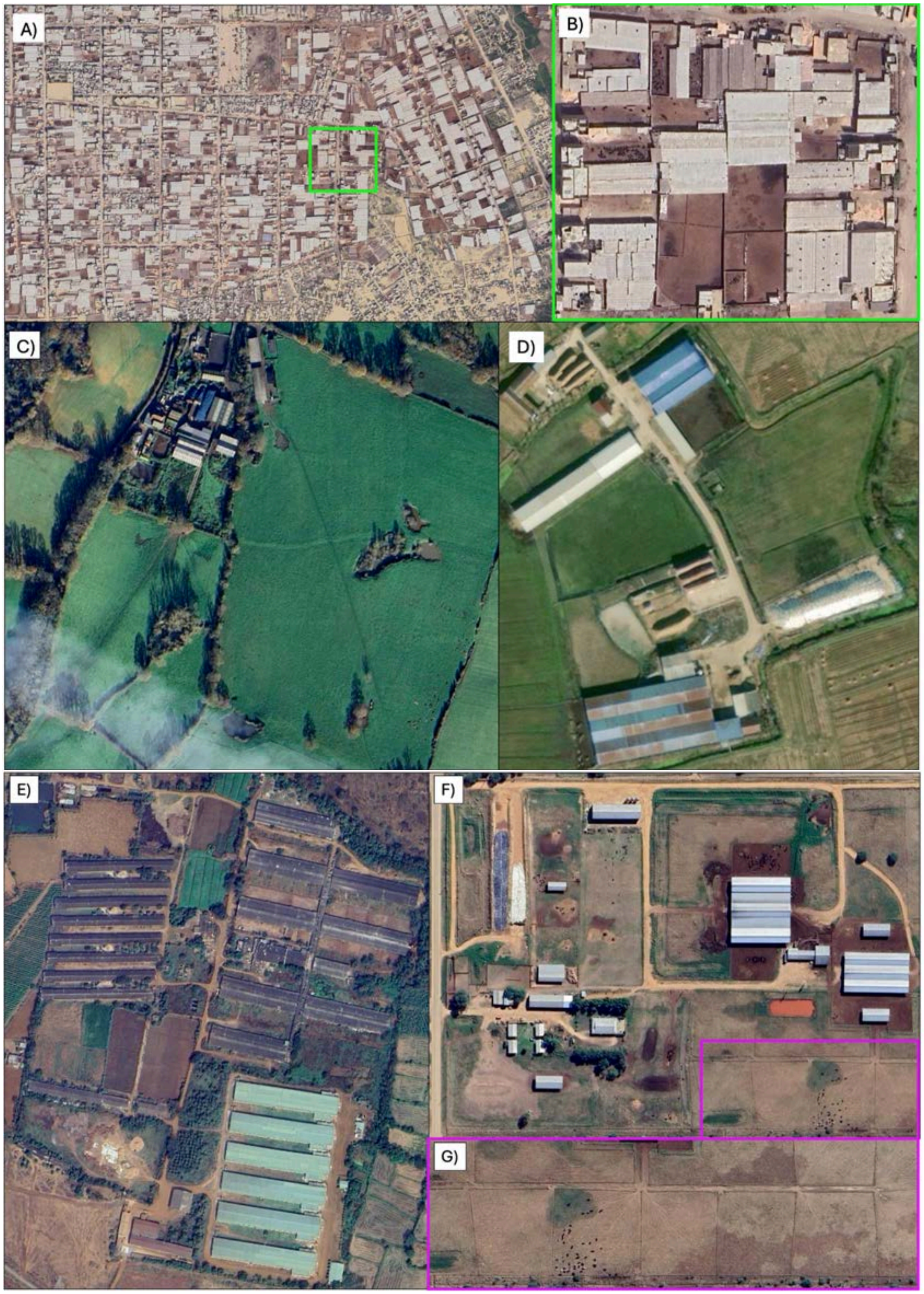

Figure 2 Cattle operations identified in A) Pakistan, a cattle colony with B) a close-up (green box) where the cattle are housed. Note, the cattle colony has mixed buffalo and cows in this area. C) An Irish dairy farm, where cattle can be seen in the lower right corner. D) A dairy farm in China and E) in India. F) A feedlot in Paraguay with G) a close-up of the pens (purple box) where the cattle occupy the lower left corner.

2.1.3 Country-level cattle data

2.1.3.1 Assigning dairy and beef types to operations

Cattle types - beef and dairy - needed to be assigned to identified cattle operations to match to IPCC "Mature Dairy Cattle" and "Other Cattle" (beef) EFs and equations (IPCC 2019b; IPCC 2019c). For countries with detailed cattle operation information, the detailed cattle type was used. In some cases, default assumptions were used based on literature. For Pakistan, Europe, the United Kingdom, and countries with no clear information, we defaulted all identified cattle operations "Mature Dairy Cattle" as beef production is the byproduct of their respective dairy systems (Steinfeld and Mäki-Hokkonen, 1995; Greenwood, 2021). For South American countries, the default assumption was "OtherBeefCattle" which is non-dairy cattle, other cattle and beef (Greenwood, 2021).

2.1.3.1 Assigning mean total head of cattle to operations and manure management systems

Total head of cattle is required to estimate total emissions. The majority of the AI identified cattle operations were point locations without a footprint area for regression modeling (see Figure 1, 5.1 box). As an alternative, country-specific mean total head by cattle type were applied to these operations (Table S2). For example, Ireland was assumed to be predominantly dairy operations, therefore the mean total head of dairy cows per Irish farm was applied to AI found cattle operations. In cases where country information could only be found for dairy or beef, then the other "beef" mean value was applied. If mean total head of cattle values for dairy and beef were not available for each year,then the missing years were forward or backfilled with the closest year found. Lastly, if cattle operations were found in a country but no mean value was available, then the nearest or representative country was used. For example, this was done for former Soviet states where Russian Federation or Kazakhstan values were used. For the U.S., USDA was used at the state-level for mean dairy and beef values (Table S2)

Similarly, manure management systems were researched to determine what was the general or common manure management system employed. For any cattle operations where the manure pond detection model was not run (see section 2.2.2) or no manure pond was determined, then the common manure management system employed by the country was assigned.

2.1.3.3 Assigning capacity factors

To estimate the *actual* total head of cattle held at an operation, utilization (hereafter, capacity factors) and death and loss rates were applied to Climate TRACE identified cattle operations.

Cattle operations are designed to hold a maximum number of animals. Generally, dairies maximize and maintain the number of dairy cows milked for production, with large dairies typically operating more efficiently in terms of labor and resources used. However, beef cattle operations, such as feedlots, have a number of factors that can limit the number of cattle occupying the feedlot space. This includes market demands, cost of feed, and the weight of the animal prior to feedlot placement (Turcios 2022). The last factor - weight of the animal prior to feedlot placement - reflects the fact that feedlots are “through systems" where beef cattle only spend a fraction of their time on feedlots where they are fattened for slaughter (Hayek and Garret 2018; USDA 2023). The fattening process can be influenced by market demands and the price of feed. As such, these factors influence the number of cattle, or capacity factor, at an operation generally resulting in less than 100% of the space utilized to house cattle.

To capture the difference between what a cattle operation can *potentially* house, the maximum number of cattle, versus what it can *actually* hold was estimated using capacity, and death and loss factors. See Supplementary S.1 and Table S3 for more information.

2.1.4 Remote sensing datasets

The following satellite datasets were ingested into the Earth Index and TerraDetect models to identify cattle operations in different countries shown in Table 1.

1. *Earth Index model*: the European Space Agency’s (ESA) Sentinel-2A (launched in 2015) and -B (launched in 2017) MultiSpectral Instrument (MSI) radiance measurements were employed to identify cattle operations in countries listed in Table 2. Together the Both satellites provide a ~5-day revisit rate for most land locations on Earth. Both collect 13 spectral band measurements, ranging from blue to shortwave infrared (SWIR) wavelengths (~442 nm to ~2,202 nm) and, depending on the band, vary from 10 meter to 60 meter spatial resolution. All bands were used as inputs in the Earth Index model. Sentinel-2A/-B L1C data were downloaded from Google Earth Engine (GEE) and combined to create cloud-free 2023 yearly median composite images per band for a given region that were employed in computing the embedding vectors. More information on Sentinel-2 can be found on the ESA’s website (https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2) and GEE (https://earthengine.google.com/).
2. *TerraDetect model*: Planet Lab’s PlanetScope visual basemaps created by their satellite constellation were accessed (Planet, 2022). Each basemap was generated from optimal PlanetScope imagery comprising blue, green, red visual imagery at approximately 3-5 meter resolution. Spring and summer basemaps from 2025 were accessed since TerraDetect worked best when the vegetation was greatest, making the cattle operations standout. More information on Planet basemaps can be found on The Planet website (https://www.planet.com/).

In Table 2, in the results section, some countries have an asterisk in the “Model” column. These regions have cattle operations detected using the Rapid Automatic Image Categorization (RAIC) tool developed by RAIC labs (formerly Synthetaic; https://raiclabs.com/). This model used PlanetScope basemap imagery from 2020 and 2024 to detect operations. See this sector's 2024 methodology in the Climate TRACE gitHub methodology repository for more information on the RAIC approach.

2.1.5 IPCC emission factors and equations

Emissions estimates were produced with IPCC 2019 equations and emission factors (EFs) from "Chapter 10: Emissions from Livestock and Manure Management" and "Chapter 11: N_2O Emissions from Managed Soils, and CO_2 Emissions from Lime and Urea Application" were applied (IPCC 2019a; IPCC 2019b).

Cattle emissions are produced by enteric fermentation, producing CH_4, and manure management, producing both CH_4 and N_2O (discussed further in *Cattle Operations- Country-level Enteric Fermentation and Manure Management Emissions* methodology section S.1 and S.2). To estimate enteric fermentation emissions, the tier 2 approach described in Chapter 10, section 10.3, was applied. Tier 2 allowed country-specific data and EFs to be applied, instead of defaults, to cattle operations identified in each country. To estimate manure CH_4 and N_2O emissions, both the Tier 1.5 approach from in Chapter 10, section 10.4, for methane, and section 10.5, for N_2O emissions.

2.1.6 Climate Zones - Climatic Research Unit Gridded Time Series

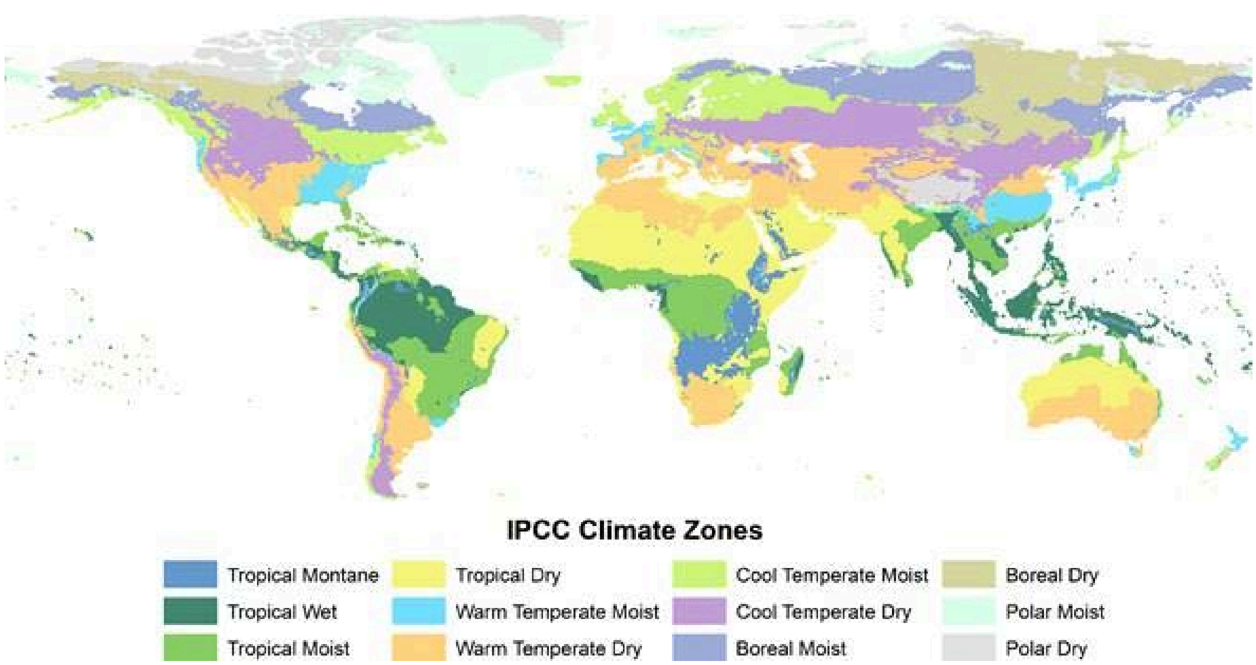

Figure 3 IPCC 2019 major climate zones identified (image taken from IPCC 2019 Chapter 3, volume 4; IPCC, 2019a).

The updated IPCC 2019 requires climate zones to estimate manure management methane emissions by manure management type, a change from IPCC 2006 which only used temperature-based EFs regardless of manure management type (Figure 3). To generate the climate zones to define the "methane emissions factors by animal category, manure management system and climate zone" in Table 10.14 employed the Climatic Research Unit gridded Time Series (CRU TS) v4.09, released March 19, 2025, taken from the Tropospheric Emission Monitoring Internet Service (TEMIS; https://crudata.uea.ac.uk/cru/data/hrg/; Harris et al., 2020). More detailed information on CRU TS can be found in the methodology, *Forestry and Land Use Change sector-Emissions from Reservoirs* hosted on the Climate Trace GitHub methodology repository.

Climate zones for each cattle operation identified and associated with the manure management system employed at each operation to identify the EF in Table 10.14 to apply. Additionally, climate zones were generated for ERS, described below.

2.1.7 Emission Reduction Solutions (ERS)

Enteric fermentation and manure management methane emissions are the primary focus for ERS. Both subsectors are approached separately with different strategies in order to achieve emission reductions.

A potentially effective emission reducing solution for enteric fermentation is introducing feed additives to dairy and beef diets. Feed additives are methane-inhibiting, meaning they discourage and reduce the bacteria that produce methane in the digestive system during the enteric fermentation process (see sections S.1 and S.2 in *Cattle Operations- Country-level Enteric Fermentation and Manure Management Emissions* methodology). For this ERS, studies have shown adding Agolin, Bovaer (also known as 3-NOP), or Monensin feed additives into cattle's diets can decrease emission factors by 10-45%, depending on the additive used, cattle type, and feeding situation. The following references were compiled by additive type to determine the percent decrease to apply to each cattle operation by cattle type:

1. Agolin - Castro-Montoya et al. (2015) and Batley et al. (2024);
2. Bovaer - Hristov et al. (2015); Alemu et al. (2021); and Kebreab et al. (2023);
3. Monesin - Vugt et al. (2005); Odongo et al. (2007); Place et al. (2013); Tomkins et al. (2015); Vyas et al. (2018); and Cooke et al. (2024).

Each feed additive ERS was applied to each cattle type at the country-level then averaged together to produce an overall mean ERS compared to the baseline emissions, the "business as usual", without ERS applied. We present this solution as a "best case scenario" since these feed additives may or may not be used in production in some cattle producing countries (IPCC 2019b).

Effective emission reducing solutions for dairy and beef manure management systems is to modify and/or retrofit a current manure system to generate less methane emissions, a potential 40% emissions decrease. This can involve shifting from an anaerobic to a more aerobic system or changing manure handling practice - shifting from dry lot to dairy spread. For the manure management ERS, we used “Chapter 10: Emissions from Livestock and Manure Management” Table 10.14 as a look-up table to understand different scenarios when shifting from a default, higher, manure system to a lower methane emitting manure system. This application is described in section 2.3.5.

“Burned for fuel” was not included since it falls under the sector “residential onsite fuel usage”. Lastly, while shifting manure systems from anaerobic to aerobic can reduce methane emissions, the shift may slightly increase N_2O emissions. However, the CH_4 emissions from manure systems are significantly larger in amount relative to N_2O.

2.2 Models employed

2.2.1 AI detection models

Detecting cattle operation proceeded with the two models- Earth Index and TerraDetect. Table 2 describes what countries received which model.

2.2.1.1 Earth Index

Earth Index is a digital platform developed by Earth Genome (https://www.earthgenome.org/earth-index) for detecting objects on Earth's surface using AI foundation models and satellite imagery. It supports an AI-powered “human-in-the-loop” workflow for constructing locally tuned models and datasets with an iterative approach.

The Earth Index computational systems process satellite imagery and run the resulting image composites through an AI foundation computer vision model, yielding *embedding vectors* that encode numerical representations of the topography on each small patch of Earth’s surface. These rich vector representations are then input to a target-specific classifier, trained by a user with successively larger labeled datasets. This secondary model yields comprehensive detections across a region with quantifiable accuracy metrics.

Cattle operations’ features vary from country to country along with the background topography. Accordingly, we decomposed the problem of detecting cattle operations globally into a series of loco-regional problems, on areas up to a few million square kilometers. Each region required its own labeled training dataset, constructed iteratively through Earth Index training, inference, and validation of model outputs (Figure 4).

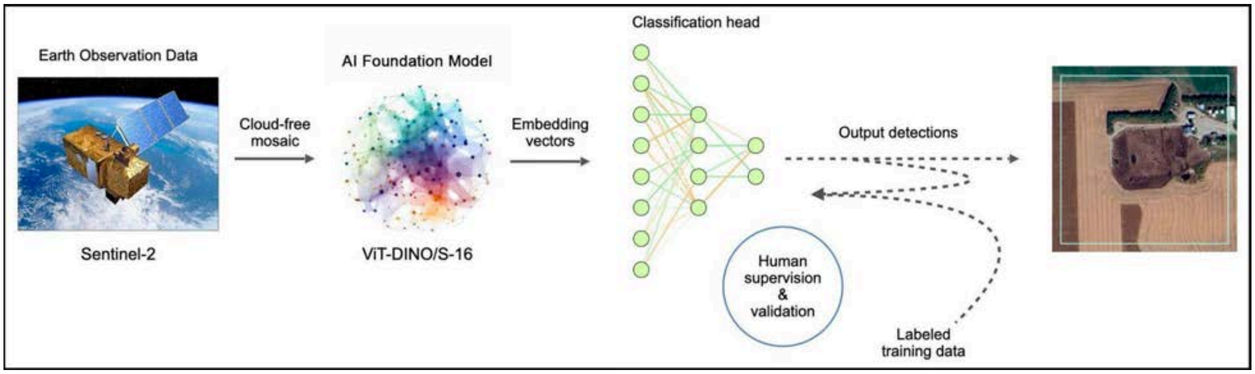

Figure 4 Schematic Earth Index workflow for cattle facility detection.

Details for key components of the Earth Index system are as follows:

- **AI Remote Sensing Foundation Model-** A remote sensing foundation model is a large neural network that has undergone extensive, self-supervised pre-training on satellite and other geospatial data. In this process, the model learns representations of objects on the Earth's surface, including buildings, vegetation, and terrain features, making it adaptable to many downstream tasks. We deployed an open-source foundation model trained on 500 GB of globally sampled Sentinel-2 imagery, specifically, a Vision Transformer (Wang et al., 2023) trained with a DINO objective (Caron, 2021). The foundation model was run on 32x32-pixel (~320 m x ~320 m) patches drawn from the cloud-free Sentinel-2 image composite, resized to the required model input shape. The model outputs a 384-dimensional embedding vector encoding the visible content for each patch of the Earth's surface. The patches cover the entire area of interest, overlapping by half a patch width.
- **Classification Head-** For final classifiers, we trained shallow, fully-connected neural networks, typically with two hidden layers, via the Scikit-learn Python programming package. The classification head ingests embedding vectors from the foundation model, and under training with labeled data, learns to discriminate cattle facilities from the background topography.

2.2.1.2 TerraDetect

TerraDetect is a proprietary AI model developed by Tulloch 2024 and is a fully developed pipeline that can be scaled globally, regionally adaptive framework for infrastructure detection using medium-resolution (3-5 m) satellite imagery. It combines an attention-based backbone, a multi-tiered inference cascade, and iterative domain adaptation to balance generalization and regional precision across heterogeneous geographies.

Overview

TerraDetect's AI object detection framework was designed for identifying and precisely locating global concentrated animal feeding operations (CAFOS) destined for beef and dairy production.

The data pipeline performs deep learning binary detection on several million machine learning-based imagery tiles. These georeferenced tiled images are created using a custom, geospatially parallelized process based on Planet Labs' PlanetScope monthly basemap imagery.

The AI processing pipeline leveraged a combination of flexible data preprocessing, multi-stage inference filtering, and geospatial clustering to balance sensitivity and precision at scale. A major focus of this work was resolving domain adaptation challenges through regionally aware training and iterative refinement.

Data Sources and Preprocessing

The input satellite data consisted of PlanetScope basemap RGB imagery from Planet Labs, offering monthly global coverage at ~3–5 meter resolution. Training and inference samples were generated via a flexible pipeline that performs multi-model, flexible window and stride-based processing.

Key Features:

- Flexible Windowing: Automatically adjusts patch size and stride;
- Positive Labels (seed data): Derived from curated target sites;
- Negative Labels: Pulled from OpenStreetMap, filtered by land use categories;
- Augmentation: Spatial and photometric transformations improve robustness;
- Oversampling: Maintains class balance by oversampling rare positives.

Domain Adaptation via Iterative Regional Training

A central challenge in applying global satellite models is domain shift — differences in landscape, architecture, and sensor artifacts between regions. To address this, the TerraDetect pipeline employed iterative, regionally focused training cycles. High-quality, manually validated datasets (seed data) were collected and used to train country-specific models. After initial detection, false positives were examined to identify underrepresented patterns. These were incorporated into retraining cycles, enabling the model to adapt to new regions.

Model Architecture and Tiered Model Cascade

The core classification backbone to identify cattle operations' features from PlanetScope basemap imagery used within TerraDetect's AI data pipeline was the Swin Transformer (Swin-Tiny), a hierarchical vision transformer that processes the basemap imagery and performing self-attention within non-overlapping shifted windows to determine what part of the features, or cattle operations, were related to each other. This makes it suitable for local-global reasoning in small satellite image patches. The Swin Transformer details include:

- Backbone: pretrained on various sources for visual feature extraction;
- Input size: varying satellite resolutions can be handled since PlanetScope basemap imagery can vary from ~3–5 meter resolution;

- Loss: weighted binary cross-entropy to classify if features (pixels) are related to a cattle operation and assign higher importance to those pixels relative to the background.

The TerraDetect framework uses a proprietary four-stage model cascade to progressively refine and improve detections.

2.2.2 Manure pond detection models

Once cattle operations were detected, two models were deployed to detect manure ponds at each location. For description on pond model deployments can be found in supplementary section S.2.

2.2.2.1 SLU manure pond detection model

The Dept. of Earth, Environmental and Geospatial Science, Saint Louis University (SLU) developed a convolutional neural network (CNN) approach for manure pond detection which used the Earth Index Model's Vision Transformer embeddings, which served as compact representations of Sentinel-2 multispectral satellite imagery (Figure 5).

The CNN architecture consisted of successive convolutional layers to extract increasingly complex spatial patterns. Each convolutional layer is followed with a max-pooling layer to progressively condense the information creating a convolutional block. The convolutional blocks provide a hierarchy of learned features, ranging from location textures to higher-level representations. After feature extraction, the network flattens the output of the convolutional blocks and passes them through fully connected layers, ultimately reaching a softmax classification layer providing a probability distribution of whether the cattle operation has a pond present in its premises or not. The CNN generated a binary output that classifies feedlots as either containing a pond or not. This output produced an interpretable, map-based product that can be applied across diverse geographies.

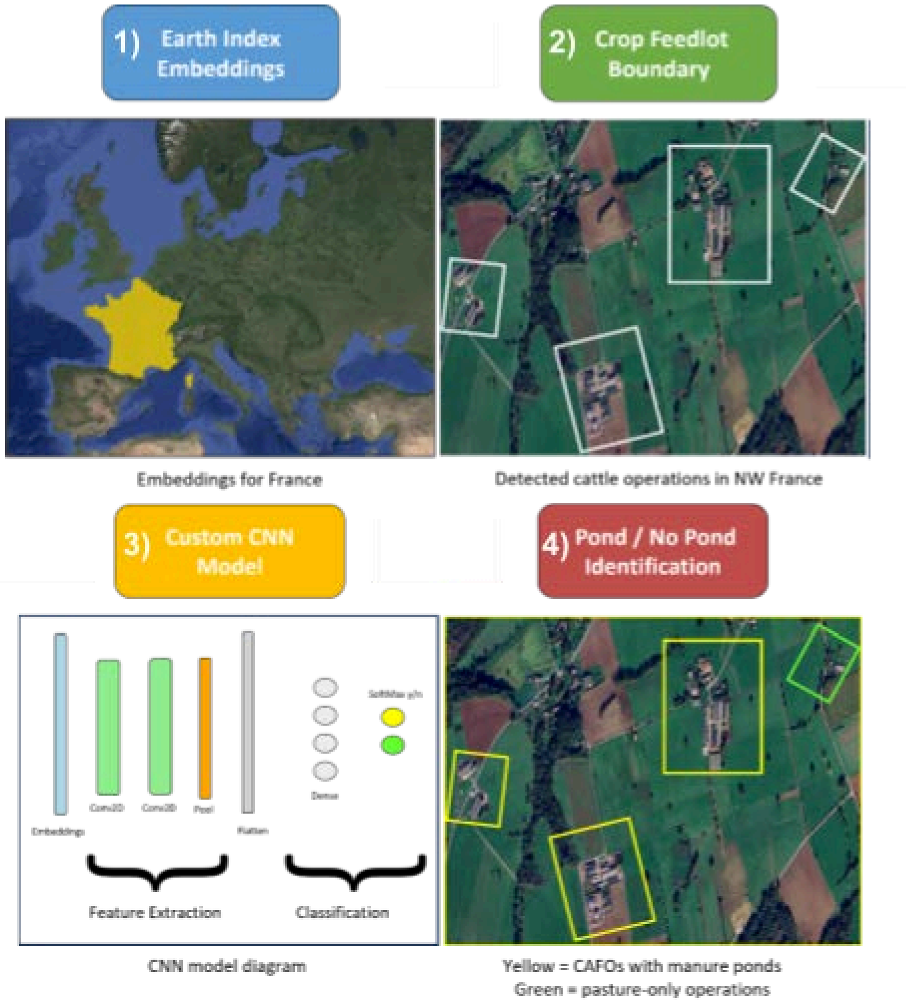

Figure 5 CNN-Based Manure Pond Detection Workflow. Convolutional Neural Networks (CNNs), trained on Earth Index multispectral and Vision Transformer (ViT) embeddings, classify cattle operations as pond-present or pond-absent, indicating the presence of a manure lagoon management system. The workflow consists of: 1) Embedding Acquisition: Retrieve Earth Index embedding vectors for the country or region of interest. 2) Training Sample Preparation: Crop embeddings to the cattle operation boundaries previously identified in the feedlot detection stage. 3) Model Training: Train a custom CNN classifier to distinguish operations with and without manure ponds. 4) Visualization: Map model outputs using class-specific symbology—yellow boundaries denote operations with ponds; green boundaries indicate no pond.

2.2.2.1 TerraDetect manure pond detection model

TerraDetect implements a deep learning–based segmentation pipeline for detecting manure ponds in satellite imagery. The system supports transformer backbones from the Hugging Face ecosystem—SegFormer (MiT encoder with lightweight decoders) and Mask2Former (query-driven segmentation over multi-scale features)—and extends them with dataset mechanics for native negative-image training, balanced sampling, and geospatially aware post-processing. The end-to-end pipeline spans data curation and augmentation, model construction, loss design, validation with positive and negative metrics, and georeferenced inference leading to vectorized pond polygons in GeoJSON**.**

Segmentation Backbones Applied to Identify Manure Ponds in Satellite Imagery

The following segmentation backbones were applied to each satellite imagery with a known cattle operation to identify the pixels associated with a manure pond feature.

- SegFormer (MiT-B0–B5): A hierarchical transformer encoder produces multi-scale token features that are fused through an multilayer perception (MLP)-based decoder into dense masks. For this work, the SegFormer was applied to satellite imagery to understand and categorize pixels belonging to a manure pond feature.
- Mask2Former (Swin): A transformer decoder with mask-classification queries predicts per-query class scores and mask logits. The classifier head is adapted for binary segmentation, and final per-pixel logits are reconstructed from the query-mask combination and upsampled.

Since manure ponds can vary at each cattle operation, both backbones captured long-range dependencies and multi-scale structure, enabling robust pattern detection of heterogeneous pond shapes and backgrounds globally.

Training Objective

Model optimization targets the foreground (pond) channel using a compound objective:

- Dice Loss to optimize overlap under severe class imbalance and sharpen boundaries.
- BCEWithLogits with configurable pos_weight to penalize false negatives where ponds are rare.

The models learn with a weighted sum of these losses to ensure balanced optimization. Gradients flow only through the pond channel to “learn” from the satellite image what pixels belong to a manure pond and the background channel, anything else that isn’t a manure pond, is implicitly modeled (Figure 6).

Figure 6 TerraDetect Pond Model Segmentation Outputs for various cattle operations globally. Red bounding boxes indicate what the model determined was a pond. Note that the red bounding boxes' extent are based on PlanetScope imagery, not the Google map imagery shown in this figure.

Negative-Image Strategy and Validation Metrics

Negative examples were incorporated into the sampling loop at a configurable negatives:positives (non-ponds:ponds) ratio. This unified strategy yields three benefits: (1) no need for separate loss functions, (2) calibrated confidence on true negatives, and (3) validation diagnostics including image-level false positive rate (FPR) and false-positive pixel area, which guide thresholding and augmentation tuning. This approach helps train the TerraDetect model to ignore non-pond areas, reduce mistakes, and improve overall performance.

Per-epoch evaluation reports intersection over union (IoU; threshold 0.5) on positive samples alongside FPR and FP area on negatives. Together, these metrics balance localization quality with suppression of spurious detections.

2.3 Methods

This section provides an overview of the model development and deployment which used feedlot and dairy area to predict total head of cattle which was converted to enteric fermentation and manure management emissions using IPCC EFs. Each colored box visualized in Figure 7 is described in detail below.

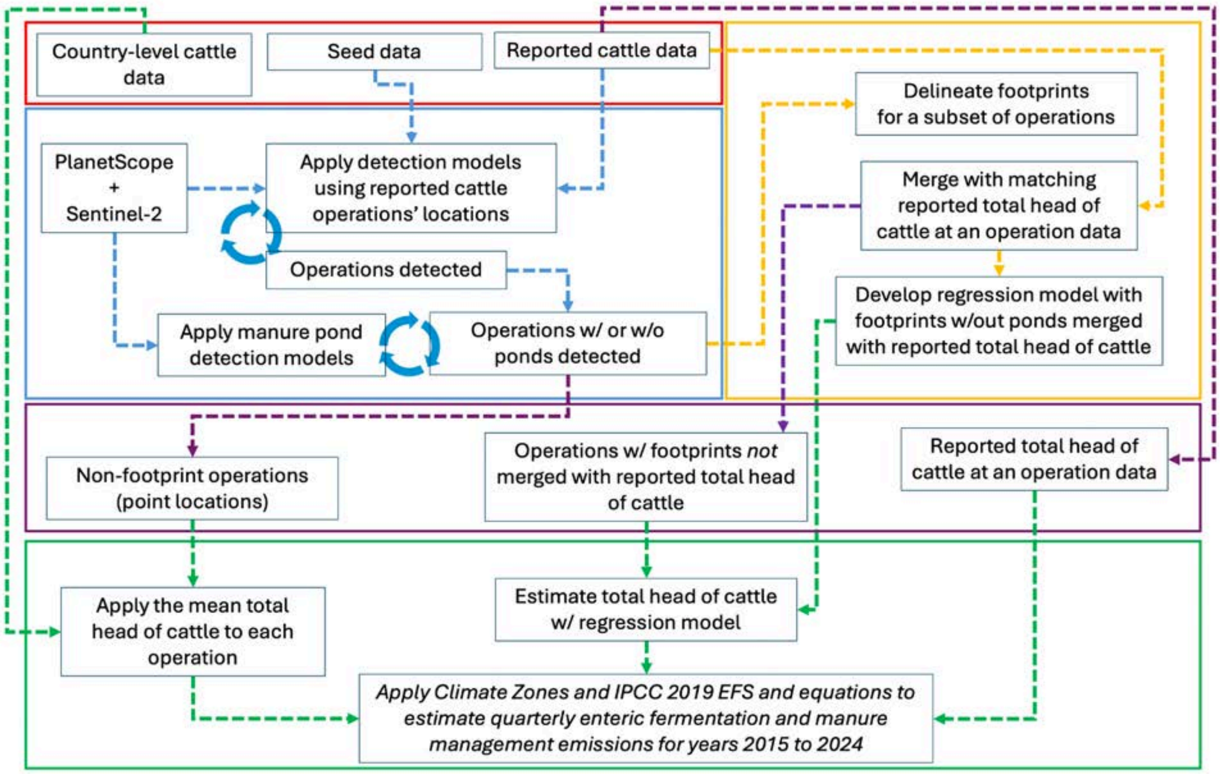

Figure 7 Flowchart summarizing the approach to identify and estimate cattle operation emissions. Each box indicates a specific step used in this methodology. Red box = cattle datasets employed. Blue box = AI identified cattle operations and ponds; Orange box = develop linear regression models; Purple box = cattle operation outputs for emissions estimates; Green box = estimate emissions with IPCC 2019 EFs and equations

2.3.1 Cattle datasets employed

All cattle data from sections 2.1.1 and 2.1.2 were filtered, cleaned, and deduplicated to contain only beef and dairy cattle information. For the U.S., this required using the Standard Industrial Classification (SIC) and North American Industrial Classification System (NAICS) codes, or by reported animal type (i.e., the number of milking cows at a location), or filtering for keywords in the ownership name - “feedlots”, “calves”, “beef” etc. For the Australian Farm Transparency Project dataset, similar keywords were used to filter for only cattle operations. Lastly, any cattle operations found using Google Map search were checked and verified by researching country specific features that define where cattle are held, such as the trampled path shown in Figure 2C and 2G.

Reported cattle data provided seed data for AI models to identify more operations in a country (blue box in Figure 7) and for regression model development (orange box in Figure 7).

2.3.2 AI identified cattle operations and ponds

Reported cattle operations, and ones identified through research, were used as seed data in the AI detection models (blue box in Figure 7). Once each AI detection model produced a set of cattle operations identified, pond detection models were applied, described further in the supplemental section S.2. The blue feedback loops indicate an iterative approach using AI outputs to feed back into the models to improve performance for detecting an operation and manure ponds.

A regression model was developed to estimate the total head of cattle by type (orange box in Figure 7). This was done by using a subset of cattle operations that had their area footprints delineated and spatially joined with reported total head of cattle to create the model. Any cattle operation with area footprints but not spatially joining with reported total head of cattle has the regression model applied to estimate total head of cattle.

2.3.3 Develop regression models

The linear regression models developed relied on the hypothesis that the cattle operation area (in ha) can be used as a predictor for the potential total head of cattle (see Results section, Table 2 and Figures 9 to 11). To generate regression models, the AI-identified cattle operations with area footprints were spatially joined with U.S. reported cattle operations (Table S1), Australia Farm Transparency Project map, and researched locations. Footprints spatially joined to locations with total head of cattle values were used to develop two linear regression models, with a third one:

1) *U.S.-AUS Beef*- this regression is based on spatially joined U.S. and Australia beef operations.
2) *U.S.-AUS Dairy*- this regression is based on spatially joined U.S. and Australia dairy operations. Note, while we did not have reported Australia dairy operation information, we include Australia in this model as they have similar dairy practices to the U.S.
3) *Dairy China Model*- this model was not developed through spatially joining but using data from Fan et al. (2018), which provided China dairy operation area estimates with total head of cattle without geolocation information. This model only used the reported milking cows from Fan et al. (2018) and was also applied to both Chinese dairy and beef operations with footprint areas.

All the models follow the general relationship in Eq. 1:

$$Potential\, Total\, Head\, of\, Cattle_{k,c} = (m_{k,c} * Area) + B_{k,c} \quad (Eq. 1)$$

Where, the *Potential Total Head of Cattle* at an individual beef or dairy operation, *k*, in a specific country, c*,* is the function of:

“*Area”*: the size of the beef or dairy operation footprint area, in hectares.

"m": the slope of the regression line based on how the total head of cattle changes relative to a change in footprint area size. This slope is region-specific to cattle operations type, beef or dairy, in a specific country
"B": the country-specific constant based on cattle operations type.

While the footprint area can be used to estimate the total head of cattle, some operations had their totals capped due to the regression models over predicting. When a beef operation or dairy operation was modeled with a total head of cattle greater than 40,000 or 4,000, respectively, then the total head of cattle was capped at 40,000 or 4,000, respectively. These values are based on the 75th percentile from statistical analysis of reported beef and dairy cattle numbers from Table S2.

2.3.4 Cattle operation outputs for emissions estimates

Three sets of outputs were generated for total head of cattle estimates (purple box in Figure 7):

A) Non-footprint cattle operations - represented as latitude and longitude point locations - with or without pond detections. Footprint cattle operations not spatially merged with reported total head of cattle with or without pond detections;
B) Footprint cattle operations spatially merged with reported total head of cattle with or without pond detections.
C) Reported cattle data - operations that contained total head of cattle with georeferenced coordinates.

The potential total head of cattle were estimated by:

1) Applying the mean total head of cattle to each operation to A) Non-footprint (point location) cattle operations with sources from Table S2.
2) Applying the regression models from section 2.3.3 to B) U.S., Australia, and China operations with footprints not merged with reported total head of cattle.
3) Using the reported total head of cattle directly from C).

This followed by applying a utilization factor, or capacity factor, to adjust the *potential* to *actual* total head of cattle at an operation capacity due to a number of factors that limit the amount of cattle that can be housed at an operation, discussed in 2.1.3.3. This adjusted the potential total head of cattle estimates from Eq.1 to the following:

$$Actual\,Total\,Head\,of\,Cattle_{k,c,q,yr} = Potential\,Total\,Head\,of\,Cattle_{i,c} * \; cf_{k,c,q,yr} \; (Eq.\;2)$$

Where, the *Actual Total Head of Cattle* for a feedlot or dairy operation in a country is the product of the *Potential Total Head of Cattle* from Eq.1 and the *cf*, or the capacity factor (including cattle death and loss plus environmental factors) for a beef or dairy operation in a country for a specific quarter, q, in a given year, *yr* (see section S.1). Once the *Actual Total Head of Cattle* per dairy and feedlot was generated, IPCC equations and default regional EFs were used to estimate enteric fermentation and manure management emissions.

2.3.4.1 Enteric fermentation and manure management emissions

To estimate enteric fermentation emissions, the Tier 2 approach from IPCC 2019 Chapter 10, section 10.3, was applied. Dry matter intake (DMI) for dairy and beef cattle used equations 1 and 4 in section 10B.4 “Feed intake estimates using a simplified Tier 2 method” in addition to the fat corrected milk yield described in this section.

To estimate manure CH_4 and N_2O emissions, both the Tier 1.5 approach from in Chapter 10, section 10.4, for methane, and section 10.5, for N_2O emissions. Manure management system emission factors from Table 10.14 were applied to each cattle operation with the following conditions:

1) If an operation reported a specific manure management system, they were mapped to IPCC equivalents in Table S4. Examples - cattle operations with identified wet manure management systems and some U.S. states’ reported data - Texas and Missouri - did describe manure management types at individual locations;
2) If the pond detection model detected a manure pond, this was set to “Uncovered anaerobic lagoon”;
3) If 1 or 2 not possible, then common manure management systems research from section 2.1.3.1 were applied to each operation.

It was assumed that only one manure management system was being used at each cattle operation to manage all the waste. Additionally to variables were ignored when estimating N2O emissions: the $AWMS_{(T,S,P)}$ or the “fraction of total annual nitrogen excretion for each livestock species/category T that is managed in manure management system S in the country, dimensionless; to consider productivity class P” and the $N_{cdg(s)}$ “annual nitrogen input via co-digestate in the country, kg N yr-1, where the system (s) refers exclusively to anaerobic digestion” were ignored.

To rescale IPCC variables from daily time steps to a quarterly timestep followed the example applied to Equation 10.22A, Annual Volatile solids (Vs) Excretion Rates (Tier 1). Instead of estimating the default one year, 365 days, of Vs, 30 days was substituted in to estimate total Vs in a quarter:

$$VS_{(T,P)} = \left(VS_{rate(T,P)} \bullet \frac{TAM_{T,P}}{1000} \right) \bullet 365$$

$$VS_{(T,P)} = \left(VS_{rate(T,P)} \bullet \frac{TAM_{T,P}}{1000} \right) \bullet 30$$

2.3.5 Applying Emission Reduction Solution (ERS) Strategies

Each feed additive ERS strategy was applied to each cattle operation by cattle type with a ranking applied based on the potential in employing such strategy. Table 6 provides more information on the potential emissions reduction per feed additive and we consider these "best case scenario" since these feed additives, and which ones, may or may not be used in meat and dairy production in some cattle producing countries (IPCC 2019b).

Methane reductions from enteric fermentation were applied after estimating total emissions for each cattle operation:

$$Total\ Methane\ Emissions\ Reduced_{k,c,q,yr} = Total\ Methane\ Emissions_{k,c,q,yr} \times (1 - \%Emissions\ Reduced_{fs}) \quad (Eq.\ 3)$$

Where the *Total Methane Emissions Reduced* is the product of *Total Methane Emissions* from enteric emissions for a given quarter, q, in a given year, yr, for an individual beef or dairy operation, k, in a specific country, c, and the *%Emissions Reduced* per ERS feed strategy, *fs,* applied. Table 6 displays the potential global mean "ch4_emissions_factor_new_to_old_ratio" for each feed additive strategy applied.

A potentially effective emission reducing solution for dairy and beef manure management systems is to modify and/or retrofit a current manure system to generate less methane emissions. For the manure management ERS, we used "Chapter 10: Emissions from Livestock and Manure Management" Table 10.14 as a look-up table to understand different scenarios when shifting from an assumed default, higher, manure system to a lower methane emitting manure system.

Table 10.14 (Updated) Methane Emission Factors by animal category, manure management system and climate zone (g CH_4 kg VS^{-1})[7]												
Livestock species	Productivity Class	Manure Storage System[4]	Cool				Temperate		Warm			
			Cool Temp. Moist	Cool Temp. Dry	Boreal Moist	Boreal Dry	Warm Temp. Moist	Warm Temp. Dry	Tropical Montane	Tropical Wet	Tropical Moist	Tropical Dry
Dairy Cattle	High Productivity	Uncovered anaerobic lagoon	96.5	[illegible]	[illegible]	78.8	117.4	122.2	122.2	128.6	128.6	128.6
		Liquid/Slurry, Pit storage > 1 month[5]	33.8	[illegible]	[illegible]	22.5	59.5	65.9	94.9	122.2	117.4	119.0
		Solid storage	3.2				6.4		8.0			
		Dry lot	1.6				2.4		3.2			
		Daily spread	0.2				0.8		1.6			
		Anaerobic Digestion -Biogas[8]	3.2				3.7		3.7			
		Burned for fuel	16.1									
	Low Productivity[1]	Uncovered anaerobic lagoon	52.3	58.4	43.6	42.7	63.6	66.2	66.2	69.7	69.7	69.7
		Liquid/Slurry, Pit storage > 1 month[5]	18.3	22.6	12.2	12.2	32.2	35.7	51.4	66.2	63.6	64.5
		Solid storage	1.7				3.5		4.4			
		Dry lot	0.9				1.3		1.7			
		Daily spread	0.1				0.4		0.9			
		Anaerobic Digestion -Biogas[8]	9.2				9.5		9.5			
		Burned for fuel	8.7									

Cattle Operation A

Cattle Operation B

Figure 8 IPCC 2019 Table 10.14 "Methane emissions factors by animal category, manure management and climate zone" g CH_4 kg VS^{-1} (grams of methane released per kilogram of volatile solid). This figure provides the look up table approach when applying ERS strategies: red boxes indicate the current manure management system cattle operation A and B and the green boxes indicate switching to a manure management system with lower EFs within the same columns of either operation.

For each methane emissions factor for a manure management system by climate zone, we assumed the "best case scenario" for what the emissions would be by shifting to the next lowest emission factor for a manure management system in Table 10.14, shown in Figure 8. For example, if cattle operation A currently has "Uncovered anaerobic lagoons", and is in a "Cool Temp. Moist" climate zone (left red box, Figure 8), then the EF is 96.5 g CH_4 kg VS^{-1} (grams of methane released per kilogram of volatile solid). Shifting to a liquid/slurry system (left green box, Figure 1) in the same "Cool Temp. Moist" column changes the EF to 33.8 g CH_4 kg VS^{-1}, a 65% reduction. For cattle operation B, an assumed current solid storage manure management system in "Warm Temp. Moist" or "Warm Temp. Dry" have an EF of 6.4 g CH_4 kg VS^{-1}. Shifting to daily spread changes the EF to 2.5 g CH_4 kg VS^{-1}, a 62.5% EF decrease. This is expressed with the equation:

$$Methane\ Emissions\ Reduced_{k,c,q,yr} = MMS\ EF\ Lower_{k,c,q,yr} \,/\, MMS\ EF\ Baseline_{k,c,q,yr} \qquad (Eq.\ 4)$$

Where, $Methane\ Emissions\ Reduced$ is the ratio of $MMS\ EF\ Lower,$ the lower emission factor by shifting to a lower emitting manure management system and $MMS\ EF\ Baseline$ is the original manure management system employed at an operation for a given quarter, q, in a given year, *yr*, for an individual beef or dairy operation, k, in a specific country, c.

Methane emissions reduced from switching to a lower emitting manure management system were estimated as if the cattle operation changed to that lower emitting system. Only one ERS strategy was assigned per cattle operation since it was assumed the whole cattle operation uses only one manure management system. Table 7 displays the potential global mean "ch4_emissions_factor_new_to_old_ratio" for each manure management change applied.

2.5 Climate TRACE emissions data produced

In total, 284,990 cattle operations across 33 countries had their enteric fermentation and manure management emissions estimated per quarter for years 2015 to 2024 (Table 2). Post-processing was performed to convert quarterly emissions to monthly, using the methodology "*Temporal Disaggregation of Emissions Data for the Climate TRACE Inventory*". For more information on how this was applied here and to all Climate TRACE sectors, refer to the document in the "Post Processing for Global Emissions and Metadata Completeness" directory on Climate TRACE GitHub methodology repository.

On the Climate TRACE website, enteric fermentation and manure management emissions were reported separately since the United Nations Framework Convention on Climate Change (UNFCCC) reports emissions as *Agriculture 3.A.1.a Enteric Fermentation - Cattle* and 3*.B.1.a Manure Management - Cattle*. Emissions values were reported as CH_4, N_2O, and CO_2 equivalent 20- and 100-year global warming potential (CO_2e 20yr and 100yr GWP) on the Climate TRACE website.

Section 5. Metadata information provides an overall description of the emissions data created in Table 3 and the confidence and uncertainty emission estimates in Table 4. Confidence and uncertainty values were included for different data fields. Confidence estimates were provided on a 5-point scale: very low, low, medium, high, and very high. This qualitatively indicates our confidence in the data used to estimate emissions. Additionally, uncertainty estimates were provided, either based on each regression model's standard deviation or the country's standard deviation of the mean total head of cattle and capacity factors for years' with values. For emissions, IPCC uncertainty percentages and ranges (i.e. +/-XX%) were used or the standard deviation of either. Note that uncertainty estimates were large and should not be interpreted as negative emissions.

Lastly, Table 5 provides a description for other column data provided with enteric fermentation and/or manure management asset-level files. This includes an estimate for Total water consumption for all cattle at the operation, in liters (L) in the enteric fermentation asset file (column 'other9'). The manure management other columns are more specific for estimating manure management emissions whereas the enteric fermentation other columns contain more general information related to the cattle operation.

2.5.1 Verification of approach

Cattle operation detection models and their outputs were QC'ed visually with a subset of detected locations and the subset quantity varied by country. Locations that were QC'ed are marked "high" in the location and livestock type columns (available upon request).

The following verifications were performed to evaluate the linear regression modeling approach to estimate total head of cattle at operations. To evaluate the relationship between cattle operation's area and reported total head of cattle a Spearman's rank correlation coefficient (Rs) was computed to assess the strength of the relationships between the two. Additionally, linear regression plots display the relationship between area to total head of cattle including the mean square error (MSE) and the goodness-of-fit measure (R^2), root mean square error (RMSE), and mean absolute error (MAE).

3. Results

3.1 The relationship between cattle operation footprint area to total head of cattle

To estimate total head of cattle using area footprints relies on the relationship between an operation's area to the total head of cattle. Our analysis found that the operation footprint area and the total head of cattle have a relationship. There is a direct relationship between operation size and the total head of cattle housed. For beef operations, the Rs value is 0.78 and 0.74 (both $p<.001$) for all operations in the U.S. and Australia, a strong relationship between the two (Table 1). For dairy operations, there was an overall moderate correlation, with an overall value of 0.54 and 0.60 (both $p<.001$; Table 1) for all operations in the U.S. and China. Within some regions and by cattle operation type, the correlations displayed a stronger relationship. Only beef operations in the eastern U.S. showed no statistically significant, which could be due to a lack of samples to compare since the eastern U.S. is not a significant beef producer.

Table 1 Spearman correlation coefficient between feedlot and dairy footprint area to total head of cattle for different regions. Included are the number of samples (*n*) compared. A "x" indicates there was no beef or dairy for comparison. The "***" represent statistically significant at *p<.001*.

<table>
<tr><th rowspan="2"></th><th rowspan="2">Region</th><th colspan="3">Total Head of Cattle</th></tr>
<tr><th>Overall</th><th>Beef</th><th>Dairy</th></tr>
<tr><th rowspan="5">Cattle Operation Area (ha)</th><td>U.S., all</td><td>0.61***
(n=1,327)</td><td>0.78***
(n=439)</td><td>0.54***
(n=888)</td></tr>
<tr><td>U.S., western</td><td>x</td><td>0.80***
(n=366)</td><td>0.61***
(n=299)</td></tr>
<tr><td>U.S., eastern</td><td>x</td><td>0.32
(n=24)</td><td>0.53***
(n=159)</td></tr>
<tr><td>Australia</td><td>x</td><td>0.74***
(n=41)</td><td>x</td></tr>
<tr><td>China</td><td>0.51***
(n=172)</td><td>x</td><td>0.6***
(n=86)</td></tr>
</table>

Figures 9 to 11 display the relationship between beef and dairy footprint area to total head of cattle. For all regions, as the total area increases, so does the total head of cattle. Beef operations have relatively higher R^2 values compared to dairy operations, ranging between 0.65 to 0.91 (p<.001; Figures 7 and 9). Additionally, beef operations tend to have larger cattle populations than dairies. In Figures 8 and 9, dairy R^2 values vary between 0.22 (not statistically significant) to 0.57 (p<.001). Dairy operations tend to have relatively smaller cattle populations compared to beef operations. The lower R^2 values for dairy operations also suggest there may be a density factor occurring. Based on literature describing dairy farm design, the stall width and length requirements allocate less space to dairy cows, ~2.8m^2 to ~3.2m^2, compared to beef, ~2.3m^2 to ~14m^2 (Euken et al., 2015; McFarland and Tyson 2016; Krekelberg 2020). Less area is allocated to dairy cows suggesting more cows are packed into an area, a density factor currently not captured here. However, based on the Spearman correlation analysis, and the scatter plots with R^2 values, does support our hypothesis that beef or dairy operation footprint area can be used as a useful predictor of the total head of cattle.

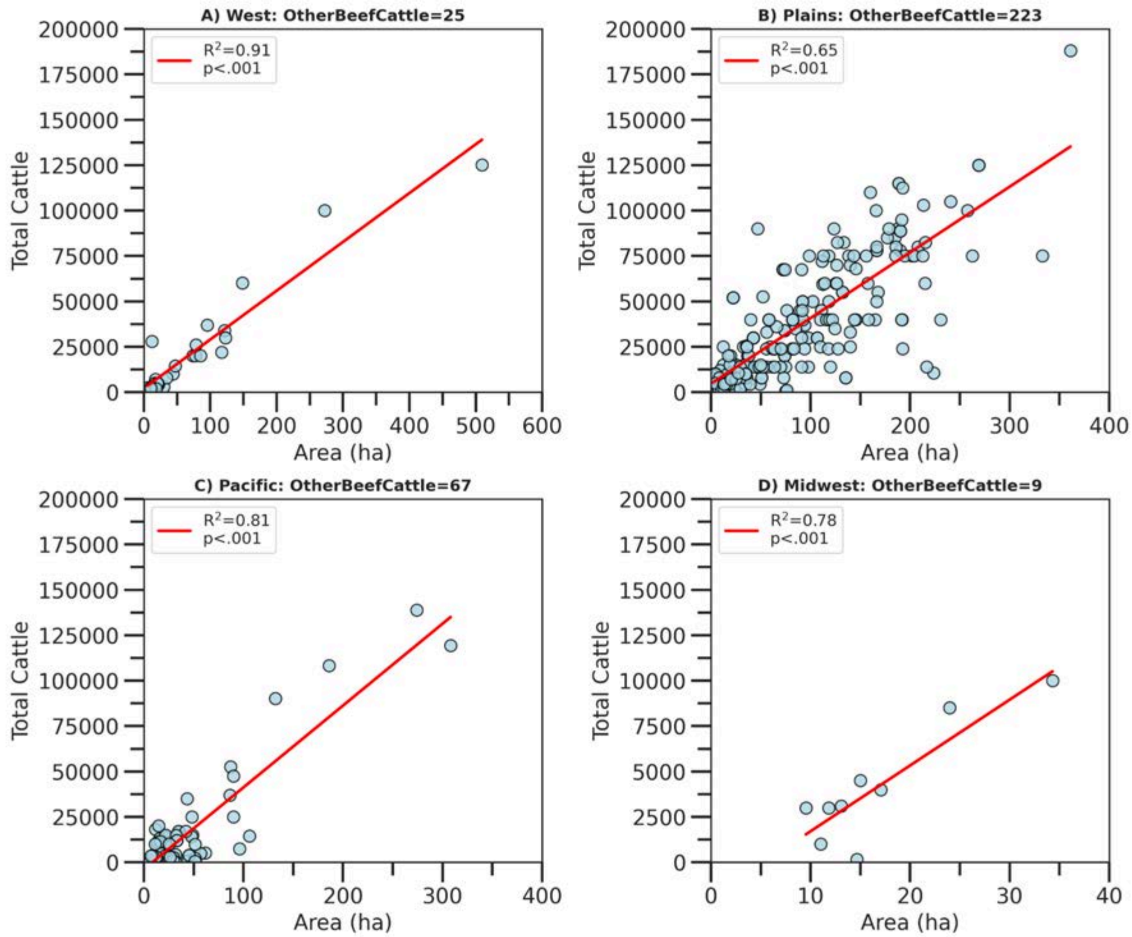

Figure 9 The relationship between U.S. beef operation footprint areas to total head of cattle for A) West, B) Plains, C) Pacific, and D) Midwest, Number of operations, R^2 values, and statistical significance are included for each U.S. region. Note, the x- and y-axis ranges differ for each plot.

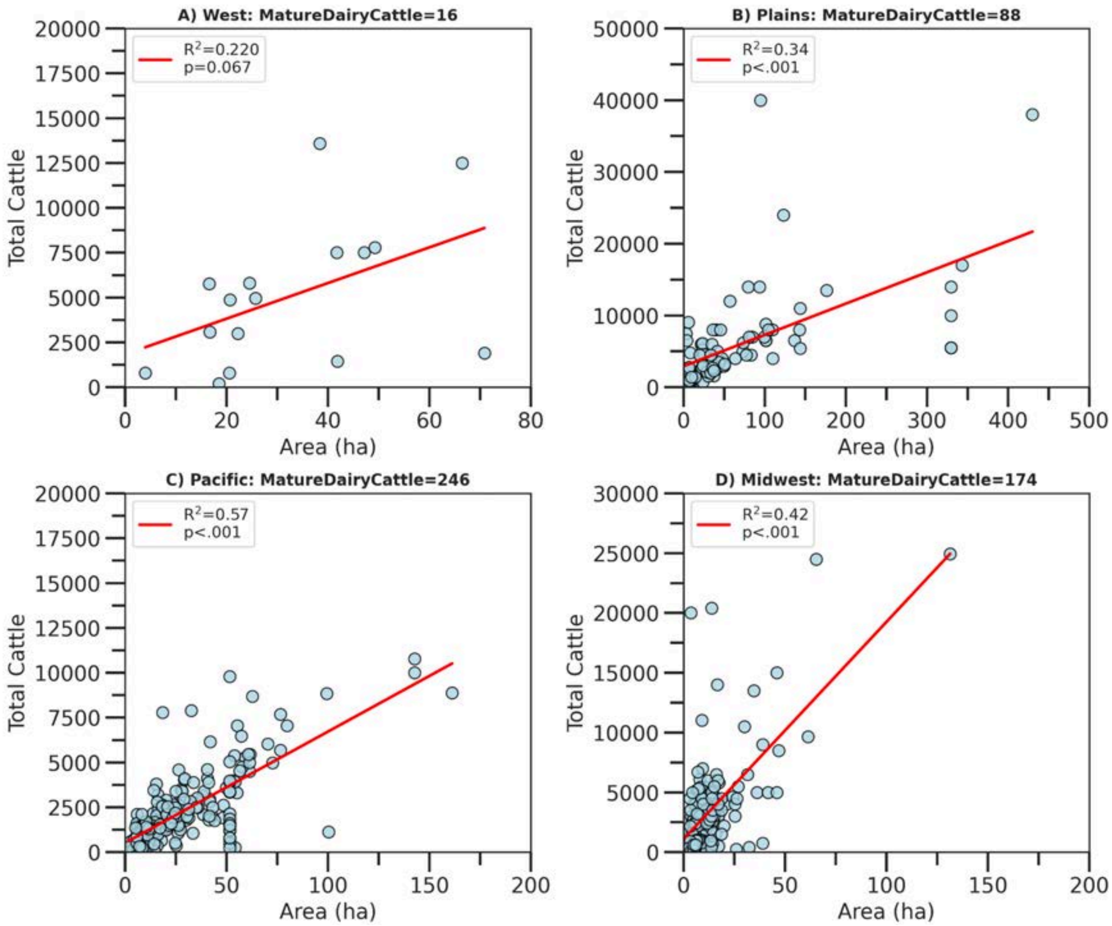

Figure 10 The relationship between U.S. dairy operation footprint areas to total head of cattle for A) West, B) Plains, C) Pacific, and D) Midwest, Number of operations, R^2 values, and statistical significance are included for each U.S. region. Note, the x- and y-axis ranges differ for each plot.

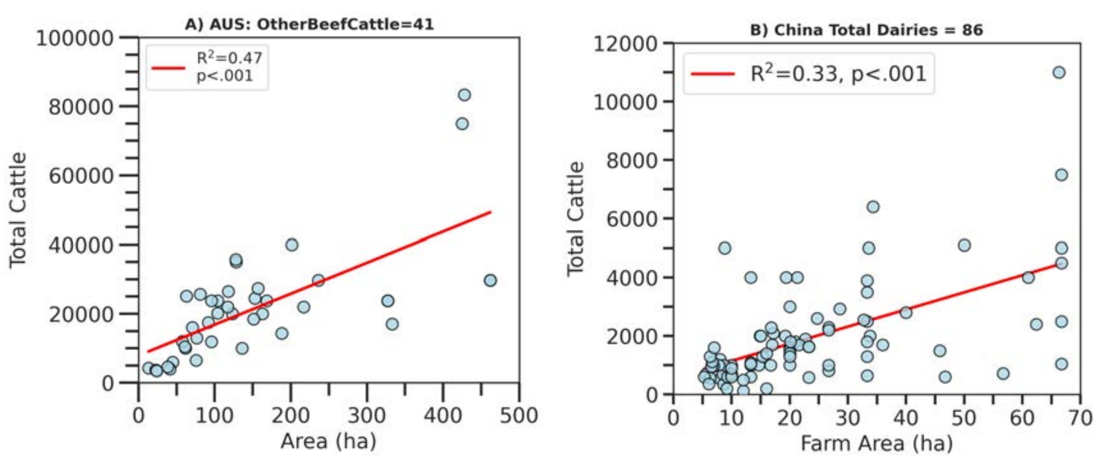

Figure 11 The relationship between A) Australia beef operation footprint areas and B) China dairy operation footprint areas to total head of cattle. Number of operations, R^2 values, and statistical significance are included for each country. Note, the x- and y-axis ranges differ for each plot.

3.2 Regression model results

Figure 12 displays each linear regression model's performance relative to estimate the total head of cattle. The *U.S.-AUS Beef* model has the largest RMSE at 22,590 followed by the *U.S.-AUS Dairy* at 3,605, and, lastly, *Dairy China at 1,467*. R^2 values range between 0.197 to 0.474 (p<.001). The *U.S.-AUS Beef* and *Dairy* tend to underpredict when the total head of cattle is 55,000 and 10,000, respectively. The *Dairy China model* tends to underpredict when the total head of cattle is ~2,000. This underprediction is due Climate TRACE seeking to identify the largest emitters in each sector. For this sector, we focused on the largest emitting cattle operations based on size. For the AI models discussed in section 2.2, it was easier to identify large cattle operations since they stand out relative to the background. Smaller operations, which could be a single barn and no other defining features, were harder to identify. As a result, our sample training data for the regression models are slightly biased. As a result, extremes in estimating total head of cattle can exist.

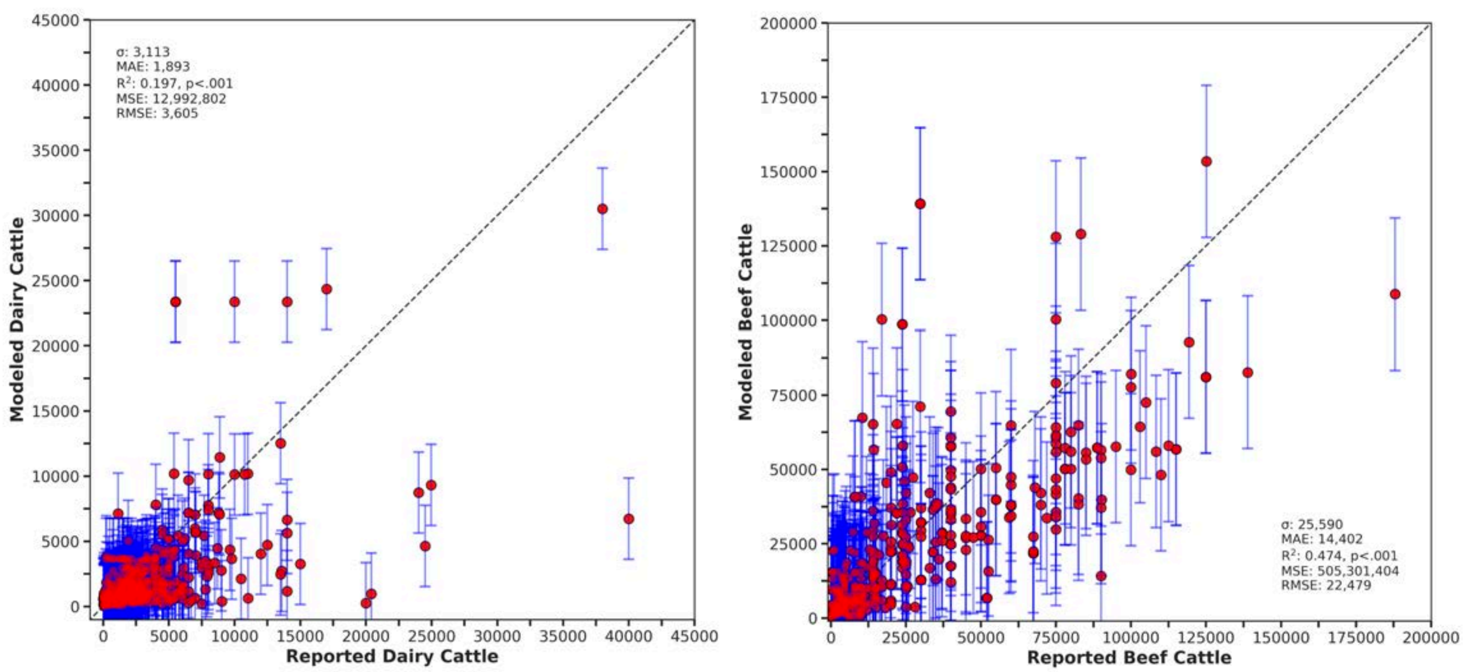

Figure 12 cont.

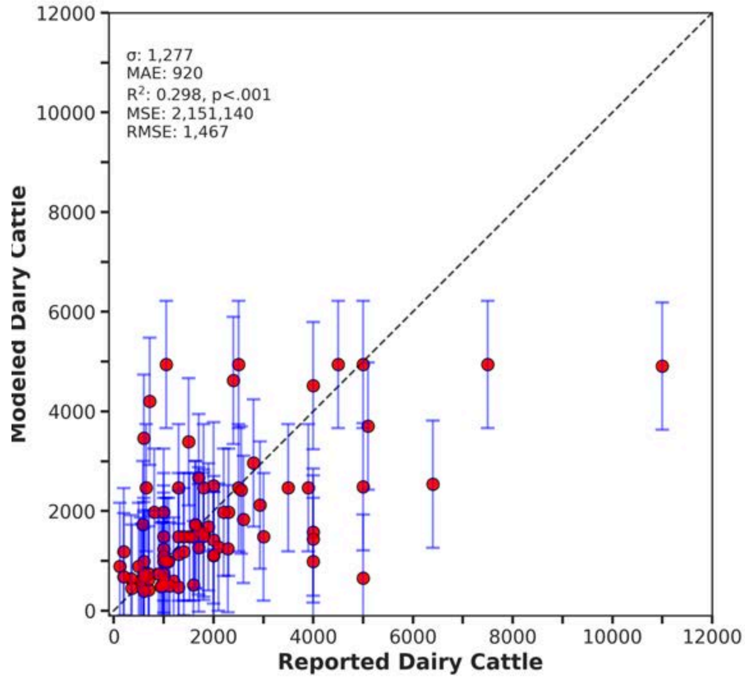

Figure 12 Scatter plots comparing reported total head of cattle (x-axis) to estimated (modeled) total head of cattle (y-axis). The models are as follows: Top left) U.S and Australia Beef Operations; Top right) U.S and Australia Dairy Operations; Bottom left) China Dairy Operations. Blue vertical lines are 95% confidence intervals.

3.3 Detections and spatially mapped emissions

Table 2 displays the countries with estimated cattle operations detected, totaling 284,990. The U.S. has the most coverage, 49,686, due to a combination of individual states reporting their concentrated animal feeding operations (CAFOs) and model detections. This is followed by Spain, Germany, France, then Poland with detections ranging between 26,000 to 31,000 estimated cattle operations detected.

Table 2 Number of cattle operations (count) per country and the percent of total global CH_4 (% of total global) manure management emissions based on FAOSTAT 2022 Emissions from livestock (version November 11, 2024). Included is the AI model deployed in each country: *ei* = earth index and *tdx* = TerraDetect. Model rows with an asterisk (*) indicate these countries include RAIC model detections from previous years, described in the supplement section. A country with a "†" indicates reported cattle data was used for additional coverage. Total estimated cattle operations identified, 284,990.

% of total global	Country	ISO	Count	Model
1.35	Argentina	ARG	7,036	*ei*
2.11	Australia†	AUS	1,232	*tdx*
0.48	Austria	AUT	139	*ei*
1.87	Bangladesh	BGD	78	*ei*
0.81	Belarus	BLR	1,145	*ei*
0.54	Belgium	BEL	6,414	*ei*
0.02	Botswana	BWA	1	*
5.81	Brazil	BRA	17,389	*ei*
1.43	Canada	CAN	4,616	*tdx*
3.97	China	CHN	11,311	*tdx*
0.43	Denmark	DNK	5,432	*ei*
4.01	France	FRA	26,329	*ei*
3.05	Germany	DEU	29,131	*ei*
13.74	India	IND	18,335	*ei*
1.54	Ireland	IRL	428	*ei*
1.93	Italy	ITA	12,388	*ei*
0.29	Japan	JPN	2,287	*ei*
0.05	Luxembourg	LUX	478	*ei*
0.9	Mexico	MEX	577	*tdx*
1.14	Netherlands	NLD	10,484	*ei*
2.87	New Zealand	NZL	1,044	*tdx*
3.82	Pakistan	PAK	891	*ei*
0.34	Paraguay	PRY	258	*ei*
1.21	Poland	POL	27,666	*
0.53	Portugal	PRT	7,933	*ei*
3.4	Russian Federation	RUS	3,165	*tdx*
0.3	South Africa	ZAF	108	*
1.67	Spain	ESP	30,703	*ei*
0.42	Switzerland	CHE	391	*ei*
0.58	Ukraine	UKR	310	*
2.12	United Kingdom	GBR	7,433	*ei*
13.22	United States†	USA	49,686	*ei+tdx**
0.29	Uruguay	URY	172	*ei*

The resulting mean annual enteric fermentation and manure CH_4 emissions (metric tonnes; mt) for years 2021 to 2024 are shown in Figures 13 and 14. These figures show spatial patterns with geographic distinctions in CH_4 from cattle operations. The variability largely reflects regional differences in operation size, beef/dairy production intensity, estimated total head of cattle by type, and manure management systems. The other top 10 countries with the highest CH_4 emissions are the following:

1. U.S. – 5.86 million mt: 53% of total CH_4 emissions from enteric fermentation;
2. India – 2.41 million mt: 95% of total CH_4 emissions from enteric fermentation;
3. Australia – 982k mt: 63% of total CH_4 emissions from enteric fermentation;

4. China – 971k mt: 53% of total CH_4 emissions from enteric fermentation;
5. Germany – 730k mt: 57% of total CH_4 emissions from manure management;
6. Spain – 612k mt: 51% of total CH_4 emissions from manure management;
7. France – 540k mt: 51% of total CH_4 emissions from manure management;
8. Brazil – 521k mt: 66% of total CH_4 emissions from enteric fermentation;
9. Denmark – 259k mt: 59% of total CH_4 emissions form enteric fermentation;
10. Netherlands – 248k mt: 57% of total CH_4 emissions from enteric fermentation.

Methane emissions are strongly concentrated in the top 2 countries, U.S. and India, which together account for the largest share of global CH_4 output, a combined mean of 8.27 million mt. For the U.S. and India, for years 2021 to 2024, the CH_4 emitted ranged between 5.73 to 5.93 million and 2.41 to 2.42 million mt, respectively. The higher methane range for the U.S. is the result of more detailed yearly USDA state-level data applied along with reported concentrated animal feeding operations (CAFOs) data folded into the U.S. model work whereas India used country-level mean values that are more constant year to year. For the U.S., the emissions reflect large-scale beef and dairy industries characterized by dense, clustered CAFOs. In India, the emissions are driven by its extensive cattle and, but not included, buffalo populations maintained under low-yield, high-enteric intensity systems.

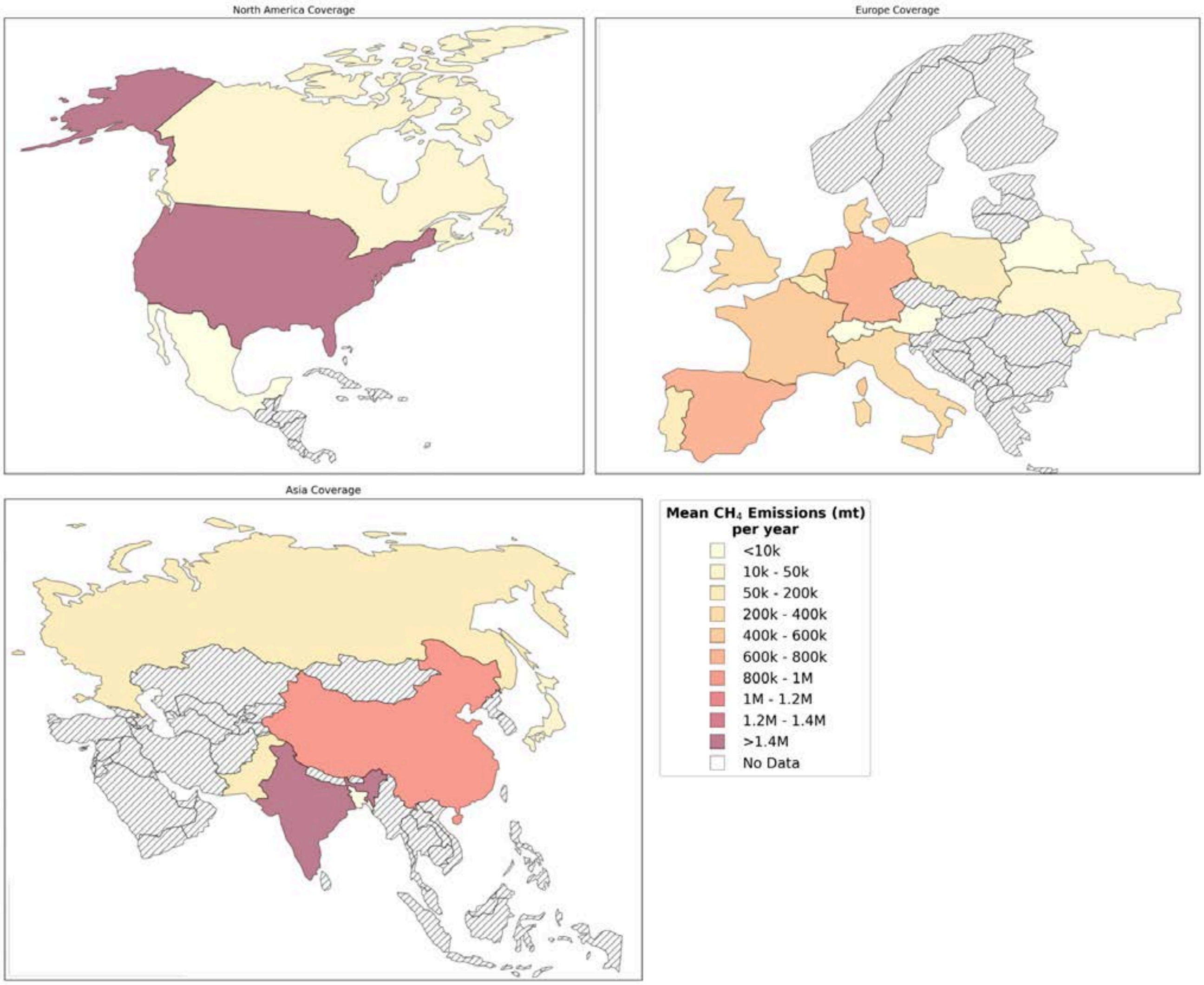

Figure 13 Mean annual enteric fermentation and manure CH_4 emissions (mt; 2021–2024) for countries in North America (top left), Europe (top right), and Asia (bottom left).

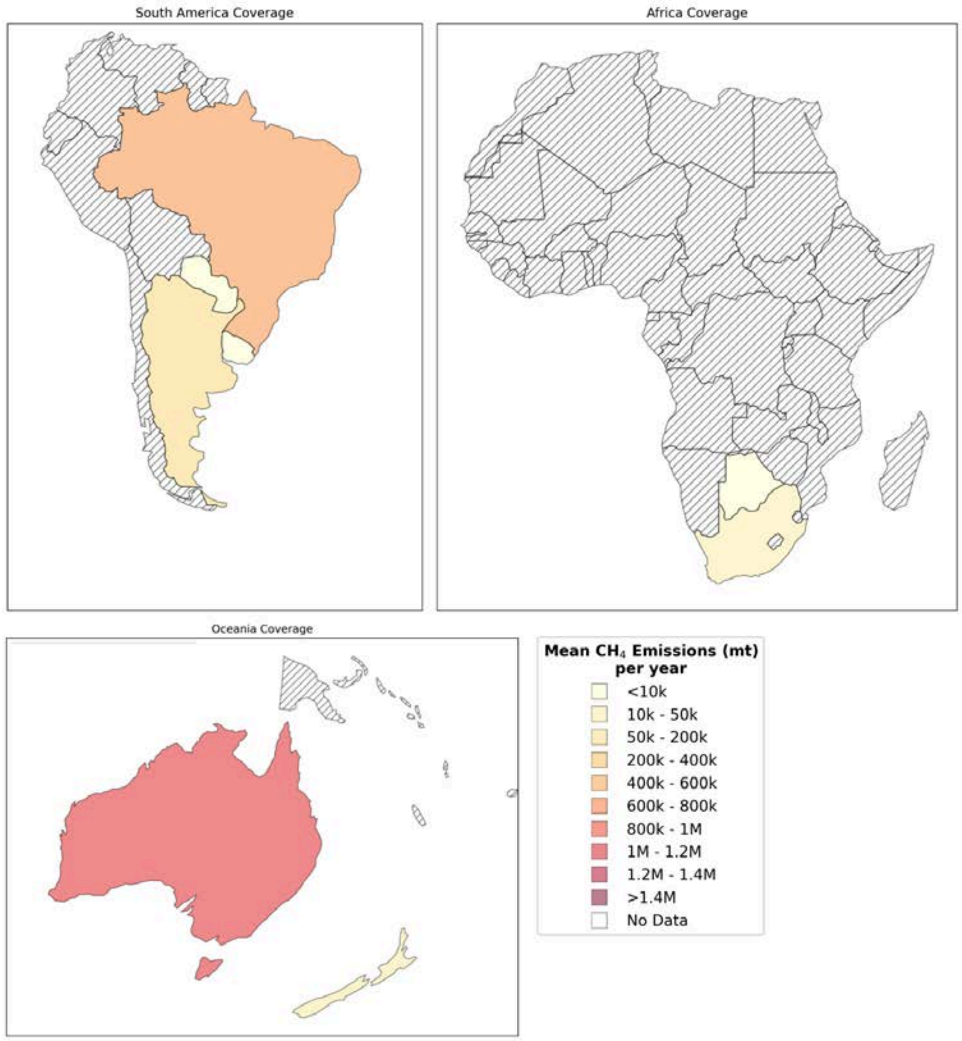

Figure 14 Mean annual enteric fermentation and manure CH_4 emissions (mt; 2021–2024) for countries in South America (top left), Africa (top right), and Oceania (bottom left).

A contrasting spatial representation is evident for manure management-derived N_2O emissions (Figures 15 and 16). Here, emissions are dominated by Australia (≈32,171 t N_2O yr^{-1}), followed by Germany (1,674 t N_2O yr^{-1}), Italy (1,597 t N_2O yr^{-1}), Denmark (1,415 t N_2O yr^{-1}), and the United Kingdom (1,361 t N_2O yr^{-1}). The high N_2O output in Australia likely reflects the identification of manure ponds by the TerraDetect model, which defaults to anaerobic lagoons. This combined with high mean total heads of cattle per operation (relative to other countries), and N_2O EFs associated with warm climates, which enhance nitrification and denitrification processes. In contrast, elevated values across Europe correspond to identified manure ponds using either the TerraDetect or SLU pond detection models (defaults to anaerobic lagoons) or assuming a liquid/slurry or pit storage manure management systems is employed at each cattle operation for locations without manure pond model detections.

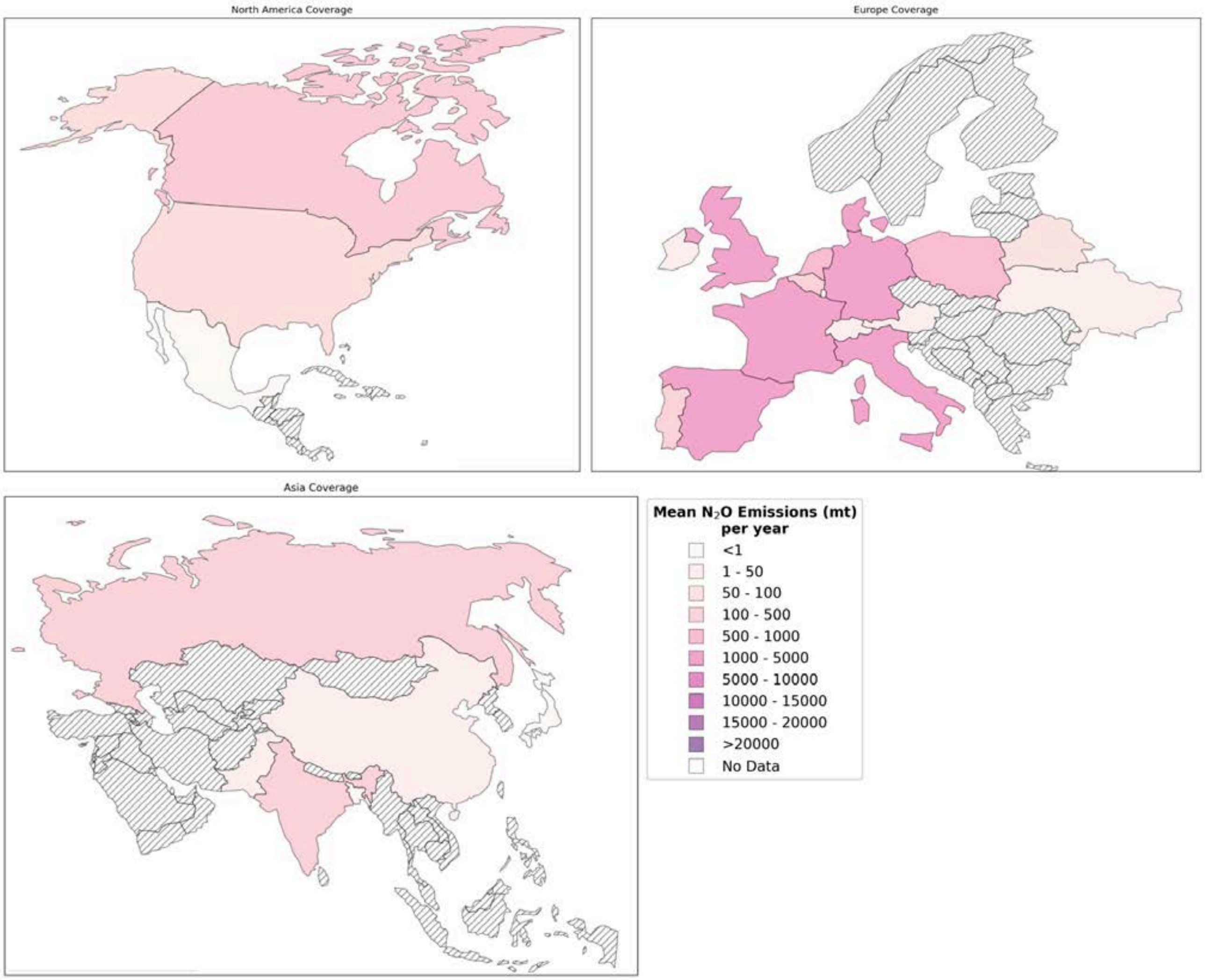

Figure 15 Mean annual manure N_2O emissions (mt; 2021–2024) for countries in North America (top left), Europe (top right), and Asia (bottom left).

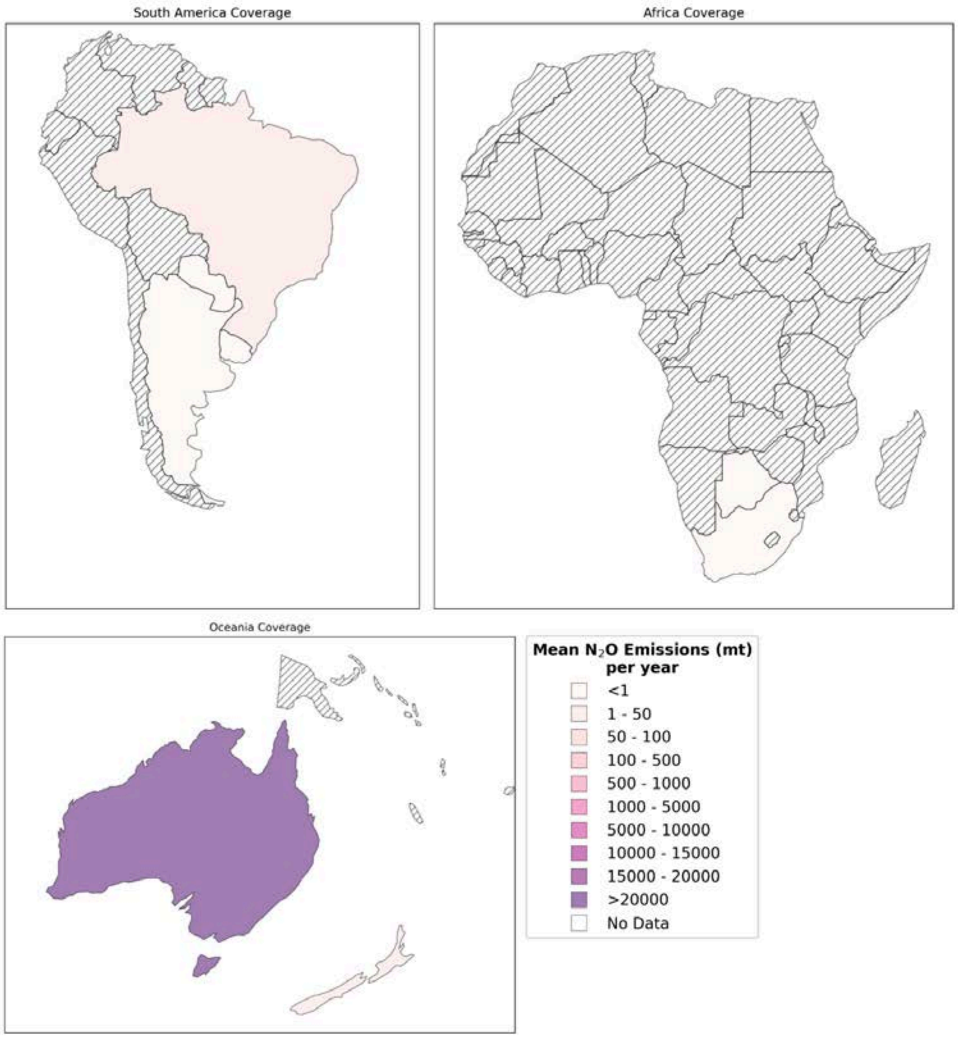

Figure 16 Mean annual manure N_2O emissions (mt; 2021–2024) for countries in South America (top left), Africa (top right), and Oceania (bottom left).

Taken together, these spatially resolved results demonstrate the geospatial differentiation of emission sources within the cattle sector. Enteric CH_4 remains highest in regions with large ruminant populations, while manure CH_4 and N_2O emissions are primarily governed by waste management infrastructure and climatic conditions. The GHG maps highlight the spatial heterogeneity of livestock emissions and the strong influence of production systems on the partitioning of CH_4 and N_2O fluxes across national and regional scales.

4. Discussion and Conclusion

Climate TRACE's identification of cattle operations and their enteric fermentation and manure management emissions estimates provides insights into where and how much emissions are being generated at the operation to country-level. The deployment of AI tools provided a scalable approach for spatially mapping and estimating individual cattle operation emissions.

This approach leverages available reported data to estimate total head of cattle at individual cattle operations without publicly available population data. In cases where no footprints were available, a country mean value by cattle type was applied. These paired approaches alongside the application of relevant emissions factors represents one of the first attempts to downscale emissions modeling to the individual operations across an entire state or province.

There are conditions where this modeling approach works well for individual cattle operations. Both AI tools were best at identifying cattle operations in contexts where they were sufficiently large and could be differentiated from nearby land uses. As a rule, the TerraDetect is only capable of correctly labeling cattle operations in contexts where the human eye can successfully differentiate a feedlot from nearby land uses. Countries with intensive cattle production, such as Australia, South Africa, and the U.S., are more easily detected by the models, resulting in higher confidence than in less industrialized agricultural countries. Because of this, the reported operations identified in Table 1 have higher confidences. Thus, small operations can blend into the landscape, or areas with low resolution imagery or high levels of haze that obscure aerial photography, extensive grazing lands that look similar to crop lands, or indoor facilities near adjacent enclosed buildings may be missed when utilizing the TerraDetect tools. This can be the case in former Soviet countries - Belarus, Poland, and Ukraine - and Russia, which have a combination of some large-industrial scale operations (as seen in the U.S.) and smaller rural farms. This can create issues with identifying a farm with cattle versus a crop producing farm. However, both models offered marked improvement compared to previous years by identifying smaller operations via human input, which did improve and increase the number of cattle operations identified.

Previously, in 2024, we stated it was currently infeasible to label the manure management practices at every cattle operation in the Climate TRACE dataset. In this phase, we have developed preliminary models to detect manure ponds. This is a critical first step that will see refinement over time. While this model can provide up-to-date information on the management system currently in use at an operation, false-positives can occur. In some cases, a manure pond appears dark in visual satellite imagery. When a model is trained on this aspect, other dark features - a naturally occurring pond or a large dark tree - at an operation can be misclassified as a pond. Because of this, false-positives can occur where the manure detection model marks a facility with a manure pond where in fact it is not.

Furthermore, the shift to IPCC 2019 approach helps create an emissions database that accounts for global changes in commercial cattle breeding and production practices which can impact enteric fermentation and manure management emissions. Updating to IPCC 2019 allowed for emission reducing solutions (ERS) to be applied to understand how changing and adjusting certain practices, by adding feed additives and changing manure management systems, can reduce enteric fermentation and manure management methane emissions.

Future modeling will attempt to address the limitations of this process. Remote sensing approaches that detect features like manure lagoons, slurry pits, or anaerobic digesters, and label sites with the feature's accompanying manure management emissions factor may improve the model's performance in regions with more heterogeneous production systems. Feature identification will also improve the beef and dairy footprint area estimates.

Total head of cattle adjustment factors may be incorporated should the estimates overestimate annual production. In areas where livestock spend less time on confined feedlots relative to open pasture, the current approach will fail to capture livestock emissions that originate upstream of feedlots in the supply chain. Countries with predominantly pasture-based systems, tend to still finish beef cattle on concentrated rations in feedlots even if cattle spend less time on those facilities, thus it may still be possible to reverse engineer emissions estimates from grazing operations by integrating the region's total feedlot capacity, the utilization rates of those facilities, the prevailing practices for the number of days cattle are on pasture before a feedlot, and the appropriate emissions factor for grazing in that area. Mass balance or survey approaches may be the most appropriate available methods in those contexts.

The next step with this research will continue to expand AI model deployment globally. Future work will include refining the detected cattle operations and increasing coverage in Africa. Climate TRACE will, in parallel, collect in situ, operation-level population data to help tune the model to local practices, and test whether other variables may impact cattle density and warrant incorporation into the model. Future work may also integrate practice identification with remote sensing or even top down methane measurements, from providers such as AVIRIS and GHGSat, to help improve emissions modeling at identified facilities, or apply revised emission factors from Wolf et al. (2017) that account for breed and practice changes.

Acknowledgements
We would like to thank Jennifer Bockhahn (https://www.concordagriculturepartners.com/) for providing information on dairy farms; the RAIC Lab team (https://raiclabs.com/) for their contribution to this work in previous years; lastly, all who contributed to QC'ing individual cattle operations: Jackie Vandermel, Allan Mendoza, and Clay Smalley.

5. Metadata information

Enteric fermentation and manure management emissions from individual cattle operations provides the following data on the Climate TRACE website:

- Cattle operations (ranging from CAFOs to farms) enteric fermentation CH_4, and 20yr and 100yr GWPs emissions.
- Cattle operations (ranging from CAFOs to farms) manure management CH_4 and N_2O emissions, and 20yr and 100yr GWPs emissions.

Emissions estimates were generated quarterly for years 2015 to 2024 with the Climate TRACE websites providing only 2021 - 2024 years. The cattle emissions described here overlap with: "*Cattle Operations- Country-level Enteric Fermentation and Manure Management Emissions-AgricultureSector*". Meaning the country-level emissions encompass the subset of emissions contained at individual cattle operations' emissions estimates. For some countries, when individual cattle operations emissions were summed, these summed values were greater than what FAOSTAT reports. For example, the N_2O emissions from manure management due to more detailed manure management information Climate TRACE was able to identify. In these cases, the aggregated sum replaced the FAOSTAT reported country value for years where this occurred. This sector does not include cattle on pasture emissions. All data is freely available on the Climate TRACE website (https://climatetrace.org/). A detailed description of what is available is described in Tables 3 to 5.

Table 3 Metadata for this sector. For agricultural users, the following terms translate to the following: Capacity = potential (max) total head of cattle at an operation; Capacity factor = utilization capacity (specific to beef feedlots), which represents the number of cattle on feed; Activity = the actual total head of cattle at the operation. Note, Capacity *x* Capacity factor = Activity.

General Description	**Definition**
Sector definition	*Cattle operations' emissions*
UNFCCC sector equivalent	*3.A.1 Cattle*
Temporal Coverage	*2015 – 2024. Climate TRACE websites provide 2021 - 2024 years only.*
Temporal Resolution	*Quarterly (original); Monthly on website; see Temporal Disaggregation of Emissions Data for the Climate TRACE Inventory*
Data format	*CSV*
Coordinate Reference System	*None. ISO3 country code provided*
Number of emitters available for download	*284,990 cattle operations in 33 countries (iso3 codes): ''ARG', 'AUS', 'AUT', 'BEL', 'BGD', 'BLR', 'BRA', 'BWA', 'CAN', 'CHE', 'CHN', 'DEU', 'DNK', 'ESP', 'FRA', 'GBR', 'IND', 'IRL', 'ITA', 'JPN', 'LUX', 'MEX', 'NLD', 'NZL', 'PAK', 'POL', 'PRT', 'PRY', 'RUS', 'UKR', 'URY', 'USA', and 'ZAF'.*
Ownership	*All operations include country-level ownership. Only AUS and USA have country-level and territory or state-level ownership information.*
What emission factors were used?	*IPCC 2019 CH. 10 and 11*
What is the difference between a "0" versus "NULL/none/nan" data field?	*"0" values are for non-existent emissions. If the sector has emissions for that specific gas, but the gas was not modeled, this is represented by "NULL" or blanks. Note, cattle operations with 0 GHG emissions that*

General Description	Definition
	precede years with years that have GHG emissions indicate the operation was not active in the "0" years.
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	*Climate TRACE uses IPCC AR6 CO_2e GWPs. CO_2e conversion guidelines are here: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FullReport_small.pdf*

Table 4 Beef and dairy cattle operation metadata description for confidence and uncertainty for enteric fermentation and manure management emissions. The standard deviation is represented by σ.

Data attributes	Confidence Definitions	Uncertainty Definitions
location	*Low:* either the operations' location wasn't QC'ed or reported locations where greater than >1km away from actual location; *Medium:* a subset of locations in a country or U.S. state were QC'ed and found to be with 1km of the actual operations location; *High:* if an operations' location was visually confirmed in a GIS program	
type	*Low*: if operation has features similar to a cattle operation but no additional information to confirm; *Medium*: if operation has visible features are available to confirm operation type; *High*: if type is reported or researched and confirmed	Not used; N/A
capacity_description	*Low*: if the estimated type was "*fill*" (mean value used based on country-level information), "*floor*", or "*ceiling*"; *Medium*: capacity derived by "*lnr_model*", capacity based on an operation's ha size by livestock type; *High*: if estimate type was from "*reported*"	In the asset-level emissions csv, the "other2" column describes the asset's capacity derived by: *'mean*: the σ normalized to the mean value based on each country's mean total head of cattle reported. mean value reported for the country'; "*lnr_model*", "*floor*", or "*ceiling*": the σ is model-based; "*reported_capacity*": no σ estimated and set to 0
capacity_factor_ description	<u>*Low*</u> *Beef operations:* if capacity factor is a fixed value, fill-in, or an average for all years <u>*Medium*</u> *Beef operations:* if capacity utilization rate derived from USDA or FAS based on country or regional-level information; *Dairy operations:* assumed 100% or capacity factor =1.0	Assumed ±10% for all operations

Data attributes	Confidence Definitions	Uncertainty Definitions
	High All operations- farm-level specific capacity factor	
activity_description	*Low*: if activity value was filled-in (mean value), or a floor (min) or ceiling (max) value was used based on reported data; *Medium*: activity derived with linear model; *High:* permit/reported total head of cattle for that operation	Use "capacity" and "capacity factor" uncertainty values to generate activity uncertainty
CO2_emissions_ factor	Not estimated based on IPCC definition	
CH4_emissions_ factor	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* Tier 2 default is ± 20%; *Manure Mgmt:* Tier 1 default is ± 30%
N2O_emissions_ factor	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* N/A; *Manure Mgmt:* A derived factor from: $\frac{N2O\ emissions\ uncertainty}{activity}$
other_gas_emissions _factor	Not used; N/A	
CO2_emissions	Not estimated based on IPCC definition	
CH4_emissions	*Medium*: based on IPCC emissions factors	Uncertainty is the cumulative of each variables' uncertainty applied to the original emissions value
N2O_emissions	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* N/A; *Manure Mgmt*: Uncertainty is the cumulative of each variables' uncertainty applied to the original emissions value
other_gas_emissions	Not used; N/A	
total_CO2e_ 100yrGWP	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* the CH4_emissions uncertainty value *x* 100yr GWP; *Manure Mgmt:* the CH4_emissions uncertainty value *x* 100yr GW; N2O_emissions_uncertainty *x* 100yr GWP
total_CO2e_ 20yrGWP	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* the CH4_emissions uncertainty value *x* 20yr GWP;

Data attributes	Confidence Definitions	Uncertainty Definitions
		Manure Mgmt: the CH4_emissions uncertainty value *x* 20yr GW; N2O_emissions_uncertainty *x* 20yr GWP

Table 5 Other columns metadata provided in the enteric fermentation and/or manure management asset-level file.

column	description
other1	Estimated year active. If year active was before 2015 then it was set to 2015
other2	How activity was estimated
other3	Data source
other4	*Enteric fermentation:* Cattle operation footprint area (ha) or or null/blank if no value; *Manure Mgmt*: Table 10.14-Methane EF by animal category, manure mgmt system, and climate zone
other5	*Enteric fermentation:* Dry matter intake converted to mt; *Manure Mgmt*: 10.13A-Default values for volatile solid excretion rate converted to mt
other6	*Enteric fermentation:* Methane yield (My) converted to mt; *Manure Mgmt*: Nitrogen excretion rates converted to mt
other7	*Enteric fermentation:* Feeding Situation for Methane yield (My); *Manure Mgmt*: EF4
other8	*Enteric fermentation:* Fat corrected milk (dairy only) converted to mt; *Manure Mgmt*: Nitrogen loss fractions due to volatisation
other9	*Enteric fermentation:* Total water consumption for all cattle at the operation, in liters (L); *Manure Mgmt*: Nitrogen loss fractions due to leaching
other10	*Enteric fermentation:* Assumed productivity class *Manure Mgmt*: Estimated manure mgmt system

Table 6 Enteric Fermentation ERS strategies include the feed additives Agolin, Bovaer, and Monensin. The values in the "ch4_emissions_factor_new_to_old_ratio" column represent the ratio of the updated ERS methane emission factor to the default (baseline) methane emission factor for all operations that applied each specific feed additive strategy.

native_strategy_id	strategy_name	strategy_description	mechanism	ch4_emissions_factor_new_to_old_ratio
1a	include agolin feed additive to the dairy cattle diet	adding agolin, a planet-based additive, can alter the cattle rumen's microbiome which can reduce methane gas production, leading to reduced emissions.	retrofit	0.894
1b	include bovaer feed additive to the dairy cattle diet	adding bovaer, also known as 3-Nitrooxypropanol (abbr. 3-NOP), can alter the cattle rumen's microbiome which can reduce methane gas production, leading to reduced emissions.	retrofit	0.640

native_strategy_id	strategy_name	strategy_description	mechanism	ch4_emissions_factor_new_to_old_ratio
1c	include monensin feed additive to the dairy cattle diet	adding monensin, an ionophore, can alter the cattle rumen's microbiome which can reduce methane gas production, leading to reduced emissions.	retrofit	0.847
2a	include agolin feed additive to the beef or other cattle diet	adding agolin, a planet-based additive, can alter the cattle rumen's microbiome which can reduce methane gas production, leading to reduced emissions.	retrofit	0.844
2b	include bovaer feed additive to the beef or other cattle diet	adding bovaer, also known as 3-Nitrooxypropanol (abbr. 3-NOP), can alter the cattle rumen's microbiome which can reduce methane gas production, leading to reduced emissions.	retrofit	0.307
2c	include monensin feed additive to the beef or other cattle diet	adding monensin, an ionophore, can alter the cattle rumen's microbiome which can reduce methane gas production, leading to reduced emissions.	retrofit	0.862

Table 7 Manure Management ERS strategies. The values in the "ch4_emissions_factor_new_to_old_ratio" column represent the global average ratio of methane emission factors between the lower-emitting and higher-emitting manure management systems for all cattle operations that implemented a retrofitted system.

native_strategy_id	strategy_name	strategy_description	mechanism	ch4_emissions_factor_new_to_old_ratio
0	cattle on pasture	For all cattle identified at these operations, the manure is left on pasture and not in a manure management system. The ERS solution for these operations are reported in the 'manure-left-on-pasture-cattle' sector.	retrofit	0
2a	shift to liquid/slurry and/or pit storage management	For dairy cattle high productivity, retrofit equipment for 1) Liquid/slurry - manure is stored in steel/concrete cylinders; and/or 2) Pit storage - manure is collected and stored below a slatted floor for less than a year.	retrofit	0.608
2b	shift to liquid/slurry and/or pit storage management	For dairy cattle low productivity, change manure handling to solid storage: where manure is stored, typically for several months, in unconfined piles or stacks.	retrofit	0.550
2c	shift to liquid/slurry and/or pit storage management	For non-dairy cattle high productivity, retrofit equipment for 1) Liquid/slurry - manure is stored in steel/concrete cylinders; and/or 2) Pit storage - manure is collected and stored below a slatted floor for less than a year.	retrofit	0.605
3a	shift to solid storage management	For dairy cattle high productivity, change manure handling to solid storage: where manure is stored, typically for several months, in unconfined piles or stacks.	retrofit	0.086
3b	shift to solid	For dairy cattle low productivity, change manure handling to	retrofit	0.079

native_strategy_id	strategy_name	strategy_description	mechanism	ch4_emissions_factor_new_to_old_ratio
	storage management	solid storage: where manure is stored, typically for several months, in unconfined piles or stacks.		
3c	shift to solid storage management	For non-dairy cattle high productivity, change manure handling to solid storage: where manure is stored, typically for several months, in unconfined piles or stacks.	retrofit	0.090
4a	shift to dry lot management	For dairy cattle high productivity, modify the existing system and change manure handling to dry lot, where the manure is periodically removed from the paved or unpaved confined area and can be spread onto fields.	retrofit	0.423
4b	shift to dry lot management	For dairy cattle low productivity, modify the existing system and change manure handling to dry lot, where the manure is periodically removed from the paved or unpaved confined area and can be spread onto fields.	retrofit	0.435
4c	shift to dry lot management	For non-dairy cattle high productivity, modify the existing system and change manure handling to dry lot, where the manure is periodically removed from the paved or unpaved confined area and can be spread onto fields.	retrofit	0.423
5a	shift to daily spread management	For dairy cattle high productivity, change manure handling to daily spread: the manure is removed within 24hrs of excretion from confined area and applied directly to fields and/or pasture.	retrofit	0.364
5b	shift to daily spread management	For dairy cattle low productivity, change manure handling to daily spread: the manure is removed within 24hrs of excretion from confined area and applied directly to fields and/or pasture.	retrofit	0.466
5c	shift to daily spread management	For non-dairy cattle high productivity, change manure handling to daily spread: the manure is removed within 24hrs of excretion from confined area and applied directly to fields and/or pasture.	retrofit	0.369
5d	shift to daily spread management	For non-dairy cattle low productivity, change manure handling to daily spread: the manure is removed within 24hrs of excretion from confined area and applied directly to fields and/or pasture.	retrofit	0.477

Citation format: Davitt, A., Tesser, D., Boyda, E., Pawar, A., Al Akkad, O., Tulloch, P., Tulloch, P., Schiller, S., Sridhar, L., Betz, L., and Sagan, V.. (2025). *Agriculture sector- Enteric Fermentation and Manure Management Emissions from Cattle Operations*. WattTime, USA, Climate TRACE Emissions Inventory. https://climatetrace.org [Accessed date]

Geographic boundaries and names (iso3_country data attribute): The depiction and use of boundaries, geographic names and related data shown on maps and included in lists, tables, documents, and databases on Climate TRACE are generated from the Global Administrative

Areas (GADM) project (Version 4.1 released on 16 July 2022) along with their corresponding ISO3 codes, and with the following adaptations:

- HKG (China, Hong Kong Special Administrative Region) and MAC (China, Macao Special Administrative Region) are reported at GADM level 0 (country/national);
- Kosovo has been assigned the ISO3 code 'XKX';
- XCA (Caspian Sea) has been removed from GADM level 0 and the area assigned to countries based on the extent of their territorial waters;
- XAD (Akrotiri and Dhekelia), XCL (Clipperton Island), XPI (Paracel Islands) and XSP (Spratly Islands) are not included in the Climate TRACE dataset;
- ZNC name changed to 'Turkish Republic of Northern Cyprus' at GADM level 0;
- The borders between India, Pakistan and China have been assigned to these countries based on GADM codes Z01 to Z09.

The above usage is not warranted to be error free and does not imply the expression of any opinion whatsoever on the part of Climate TRACE Coalition and its partners concerning the legal status of any country, area or territory or of its authorities, or concerning the delimitation of its borders.

Disclaimer: The emissions provided for this sector are our current best estimates of emissions, and we are committed to continually increasing the accuracy of the models on all levels. Please review our terms of use and the sector-specific methodology documentation before using the data. If you identify an error or would like to participate in our data validation process, please contact us.

Supplementary information

Table S1 U.S. state CAFO data used to estimate cattle operations' emissions for Climate TRACE 2025 data release.

State	Link to state CAFO data or where to request data
California	https://ciwqs.waterboards.ca.gov/ciwqs/readOnly/CiwqsReportServlet?inCommand=reset&reportName=RegulatedFacility
Colorado	https://cdphe.colorado.gov/environmental-agriculture-program/general-information-for-animal-feeding-operations
Delaware	Denied access; non-Delaware citizens cannot access data
Idaho	Emailed state government for access
Iowa	https://geodata.iowa.gov/documents/abfbd972640d4e87b6c48dc669775767/about
Kansas	https://agriculture.ks.gov/docs/default-source/dah---forms/2015-annual-feedlot-report.pdf
Kentucky	https://cdn.arcgis.com/home/item.html?id=ecc3f0b1bfb946ba940fd3add6fb1839&view=list&sortOrder=desc&sortField=defaultFSOrder#data
Missouri	https://data-msdis.opendata.arcgis.com/datasets/MSDIS::mo-npdes-animal-feeding-operations/explore?location=37.433226%2C-90.840151%2C6.36 https://modnr.maps.arcgis.com/apps/webappviewer/index.html?id=cf630b020a17452fb30994cb4b36f003

State	Link to state CAFO data or where to request data
	https://info.mo.gov/dnr/DNR_GIS/metadata/WASTE.NPDES_AFO.xml
Nebraska	Nebraska feeders directory https://deqmaps.nebraska.gov/deqmapportal/nebraskaMapPortal.html
New Mexico	https://www.env.nm.gov/gwqb/permits/
New York	https://data.gis.ny.gov/datasets/8f81795a3d1745ab9867d0af872e87a1/explore
North Dakota	https://deq.nd.gov/OpenRecords.aspx
Ohio	https://oepa.maps.arcgis.com/apps/webappviewer/index.html?id=a3f7dbe293ed4c9a8218ed8c013dfb68
Oklahoma	https://gis.deq.ok.gov/maps/?page=page_0&views=view_97%2Cview_88%2Cview_91%2Cview_83
Pennsylvania	Emailed state government for access
South Dakota	https://danr.sd.gov/Press/DataAndMapping.aspx
Texas	https://www2.tceq.texas.gov/wq_dpa/index.cfm
Washington	https://www.arcgis.com/apps/dashboards/095a77415ea947278ecc394b0c47b845
West Virginia	Freedom of Information Act
Wisconsin	https://dnr.wisconsin.gov/topic/CAFO/StatsMap.html

Table S2 Referenced country specific mean dairy and beef total head of cattle sizes per farm.

ISO3 Code	Source	ISO3 Code	Source
ARG	Modernel et al. (2018); Lopez-Villalobos (2019); van Heerden, B. (2019)	IRL	Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.
AUS	Australian Bureau of Agricultural and Resource Economics and Sciences (n.d.)	ITA	Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.
BLR	Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.	JPN	Ministry of Agriculture, Forestry and Fisheries (n.d.).
BRA	Modernel et al. (2018);	KAZ	Petrick, M. and Götz, L. (2019)
BWA	UNEP Copenhagen Climate Centre (2023).	MEX	USDA Report Dairy and Products Annual Mexico; Peel, D.S. (2010); Ibarrola-Rivas, M.J. et al. (2023).
CAN	Government of Canada. (2021).	PAK	Zia (2009)
CHN	DuBois, T. and Gao, A., 2017. Big meat: The rise and impact of mega-farming in China's beef, sheep and dairy industries. *Asia-Pacific Journal, Japan Focus*, *15*(17).	RUS	Korobkov et al. (2021).

ISO3 Code	Source	ISO3 Code	Source
DEU	Gieseke, D. et al. (2018); Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.	UKR	Tulush, L et al. (2023)
FRA	Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.	URY	Modernel et al. (2018)
GBR	Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.	USA	United States. U.S. National Agricultural Statistics Service NASS. Version 2025-06-07
		ZAF	Scholtz et al. (2008); van Heerden, B. (2019)

S.1 Actual versus potential total head of cattle

To capture the difference between what a cattle operation can *potentially* house, the maximum number of cattle, versus what it can *actually* hold was estimated using capacity, and death and loss factors. This was done for the following cattle types:

Dairy

1. It was assumed that the total head of cattle at dairy operations were maximized for milk production. Therefore, the total dairy cattle population capacity factor was set to “1” in the model input to represent the dairy was operating at 100% full capacity per quarter or housing the maximum number of dairy cows possible at that operation per quarter. Meaning, the potential total head equals the actual total head of cattle.
2. The death and loss rate of a dairy cow herd at a dairy farm was set to a mean of 1.5% per year (Bagley et al. 1999). For quarterly estimates, this value was divided by 4 to produce a death and loss rate of ~0.4% per quarter.
3. Values 1 and 2 were subtracted to generate an overall “dairy capacity-death and loss value” of 99.6% per quarter (100% - 0.40%). This combined factor was applied to all identified dairy operations globally (see section 2.4.3 for more information on how these factors were applied).

Beef

1. For beef cattle operations, literature research was performed to identify country-level capacity utilization factors for different countries (Table S8). Beef operations’ utilization values range between 0%, no beef cattle present, to 100% utilization, maximum number of cattle housed. These capacity factors were applied to beef cattle operations in their respective regions, shown in Table 3. Australia, Canada, and the USA reported capacity

factors, represented as the "number of cattle on feed". For countries that provided slaughter and slaughter and beginning beef stocks (Beef Cows Beg. Stocks) data to the U.S. Department of Agriculture Foreign Agricultural Service (USDA FAS), we used these values to generate a rough estimate of cattle on feed. USDA FAS provides these cattle stocks in their Livestock and Poultry production, supply and distribution (PSD) reports (USDA 2024; PSD accessed August 2024). For regions where country-level capacity factors and have no USDA FAS beef cattle data (i.e., Russia and Argentina), then the mean value per quarter from all identified sources in Table 3 was applied.

2. The death and loss rate for beef cattle herds was taken from the "Death Loss %" in Table 3 from Stehle (2016). Monthly mean values were added together per quarter with the mean quarterly values created- Q1 = 1.9%; Q2 = 2.6%; Q3 = 1.5%; and Q4 = 1.4% for each year. These values were applied to all beef operations identified in the Climate TRACE database.
3. Values 1 and 2 were subtracted to generate an "overall beef capacity-death and loss value" that varied each quarter in each country. For example, if Q1 capacity factor was 0.80 and the Q1 death and loss was 1.9%, then the value 78.1% was applied to determine the number of actual beef cattle held at a beef operation (see section 2.4.3 for more information on how these factors were applied).

Table S3 Beef operation capacity factors by country.

Country	Source	Comments
Australia	Meat & Livestock Australia Lot Briefing Reports	Provided quarterly "Utilisation %" per year. Includes Feedlot capacity and Numbers on feed
Canada	CanFax cattle on feed reports	Provided "Placed on Feed" for each month per year
U.S.	USDA NASS	For each quarter per year, the capacity factors were determined by: $\frac{\text{'CATTLE, ON FEED} - \text{INVENTORY, CAPACITY: (1,000 OR MORE HEAD)'}}{\text{'CATTLE, ON FEED} - \text{INVENTORY, TOTAL'}}$
ROW	USDA FAS PS&D	If country data reported data, then the following was used to generate capacity factors per quarter per year: $\frac{\text{'Cow Slaughter'} + \text{'Total Slaughter'}}{\text{'Beef Cows Beg. Stocks'}}$
	If no capacity values were not available, the mean values from the above sources were generated on a quarterly per year basis	

Table S4 Reported or identified manure management systems at cattle operations and the IPCC equivalent used in emissions modeling. Included is the IPCC description of the manure management system, taken from IPCC (2006a). In some cases, cattle operations have digesters identified (i.e., anaerobic digester or digestor) but digester emissions were not estimated.

Manure management system identified	IPCC manure management system equivalent	IPCC description
● Aerobic treatment ● Lagoon - aerobic ● Treatment & Storage pond ● Treatment pond ● Vegetative Infiltration Basin ● Wetland	Aerobic treatment	The biological oxidation of manure collected as a liquid with either forced or natural aeration. Natural aeration is limited to aerobic and facultative ponds and wetland systems and is due primarily to photosynthesis. Hence, these systems typically become anoxic during periods without sunlight.
● Dry lot	Dry lot	A paved or unpaved open confinement area without any significant vegetative cover where accumulating manure may be removed periodically. Dry lots are most typically found in dry climates but also are used in humid climates.
● Effluent Basin ● Evaporation pond ● Lagoon - anaerobic ● Liquid slurry ● Outside Concrete - uncovered ● Outside Formed Concrete ● Pond* ● Retention pond ● Retention pond present ● Runoff Control ● Sand Settling Lanes ● Settled Open Feedlot ● Settling basin ● Settling pond ● Slurry Store ● Solids Settling ● Storage pond ● Storage Lagoon ● Transfer pond ● *Pit storage* ● *Pit storage - Deep*	Liquid/slurry *Pit storage below animal confinements*	Manure is stored as excreted or with some minimal addition of water in either tanks or earthen ponds outside the animal housing, usually for periods less than one year. *Collection and storage of manure usually with little or no added water typically below a slatted floor in an enclosed animal confinement facility, usually for periods less than one year.*
● Concrete Pad ● Impervious Soil Pad ● Roofed Storage Shed ● Solid storage ● Stockpiling Structure (covered or uncovered)	Solid storage	The storage of manure, typically for a period of several months, in unconfined piles or stacks. Manure is able to be stacked due to the presence of a sufficient amount of bedding material or loss of moisture by evaporation.

S.2 Pond detections models

S.1.1 SLU CNN pond detection

Sentinel-2 embeddings were cropped to the cattle operation boundaries in order to remove the agricultural land-use from the classification workflow to emphasize the features that are highly related to manure ponds. By removing landcover types such as buildings or lakes or grasslands adjacent to cattle operations, the cropped embeddings reduced noise and improved classification accuracy. The cropped cattle operation embeddings were fed into a custom CNN designed to distinguish between cattle operations with and without manure ponds that captured both spectral and spatial information, making the CNN well-suited for identifying subtle environmental features such as manure ponds. After feature extraction, a softmax classification layer provided a probability distribution of whether the cattle operation has a pond present in its premises or not.

To convert the probability distribution into an actionable output, we established a decision threshold of 0.5. This value was chosen because it represents a balanced trade-off between detecting true ponds and avoiding false detections, ensuring the classifier assigns a "has pond" label only when it's more than 50% sure the cattle operation has a pond, and aligning with standard practices in binary classification. In practice, the threshold can be tuned in future iterations depending on the geographical location. For example, lowering it captures more ponds in locations where ponds are scarce, or raising it to ensure high certainty for confirmed detections in locations where manure ponds are visually similar to lakes or water ponds.

By highlighting only cattle operations with detected ponds, it streamlined analysis and reduced manual effort. Instead of checking every cattle operation individually, QC was performed on a targeted subset of locations most likely to have a pond on their premises.

For easier interpretability, final model outputs were inserted into a GeoJSONs containing information about the detected cattle operations. Each feature in the GeoJSON represented a single cattle operation and included attributes such as location (EPSG 4326), confidence level of the location being a cattle operation, livestock type, manure management type and their number if present, and the CNN generated pond detection confidence values. The confidence level ranges from low to high depending on if the location was detected through the AI detection models or manually detected and the livestock type explains what type of livestock is present in the operation. The manure management type explains whether the manure is being managed using digesters or rectangular or circular shaped ponds and their count as countries use different types of manure management systems. The file also included a column derived from the threshold set for the pond detection confidence values, where the column's value would be 'yes' as in the operation having a pond present if the value is greater than the threshold set, or 'no' if it is not.

S.1.2 TerraDetect pond detection

Since manure ponds can vary at each cattle operation, both SegFormer and Mask2Former backbones enabled a robust pattern detection of heterogeneous pond shapes and backgrounds globally.

Data Pipeline

PlanetScope monthly basemaps provided the training imagery. Candidate cattle operations within each country were sampled, and an autoencoder was used to characterize variance across image patches. Clustering of the learned feature manifold guided selection of training samples. These training samples were manually inspected by subject matter experts and target ponds were outlined to produce masks (stored as raster masks or rasterized from GeoJSON). A curated negative dataset from Open Street Maps provided imagery without ponds; in these cases, the dataset deterministically assigns all-zero masks so the same segmentation loss applies consistently. Data augmentation was used to provide more robust training through Albumentations (flips, rotations, color jitter, RandomResizedCrop) with ImageNet-style normalization; validation applies padding and resizing to maintain consistency.

Inference & Vectorization

During inference (manure pond detection), logits were passed through sigmoid to convert the probability that a pixel is a manure pond to between 0 and 1 and thresholded the probability a pixel is a pond to greater than 0.50. This produced a binary pond mask in each satellite imagery where a cattle operation was identified. The pipeline then (1) computes per-polygon confidence by averaging probabilities inside each rasterized polygon and (2) Measures geodesic area (m^2) on WGS84 for filtering and reporting.

Outputs include per-pond and per-image GeoJSONs containing pond count, total area and mean confidence—enabling downstream spatial analysis. For this work, only the pond detected was used and future work will include per-pond and total area identified for future emissions estimates.

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