Agriculture sector:
Enteric Fermentation and Manure Management Emissions from Cattle Operations

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Update Fall 2024: This sector was previously known as "Enteric Fermentation and Manure Management Emissions from Individual Cattle Feedlots and Dairies". Climate TRACE updated the emitting source (asset) definition to "Cattle Operations" to reflect the broader coverage this sector represents- from smaller cattle farms to animal feed operations (AFOs).

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.

The current de facto beef and dairy cattle emissions estimates are from the FAOSTAT and are based on country-level official, implicit, or estimated activity data and an indication of global cattle emissions in each country. While an indication 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).

In order to understand individual beef and dairy milk 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 (AI) in remote sensing imagery. 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 emissions estimates for cattle operations in specific countries that were identified during different research phases of this project, starting in 2021. Once individual operations were identified, total head of cattle was estimated two ways- 1) with a regression modeling using the operation's footprint area, or 2) mean total head of cattle (by cattle type) that is reported at an operation in each country. Once each operation's total head of cattle was estimated, the Intergovernmental Panel on Climate Change (IPCC) emissions factors (EFs) were applied based on the regional characteristics, temperature, cattle type, and manure management system to generate quarterly emissions for years 2015 to 2023. The approach employed here has generated a first of its kind database of global cattle operation emissions estimates globally.

2. Materials and Methods

A combination of reported total head of cattle by type, AI models, remote sensing imagery, modeling, and EFs were used to estimate cattle operation emissions four times per year (quarterly) for years 2015 to 2023 (Figure 1). The quarters per year are: Q1 = January/February/March; Q2 = April/May/June; Q3 = July/August/September; and Q4 = October/November/December. These trimesters were selected based on quarterly cattle reports generated by the U.S., Canada, and Australia.

The overall approach is the following:

1) Identify reported information, i.e. U.S. state and federal CAFO permit data.
    a) In regions or countries that lacked reported cattle operations data, perform research to find "Seed data" for AI models.
2) Apply the AI models to find unreported locations in countries that lack reported information.
3) Clean and homogenize datasets from 1 and 2 into a comprehensive and consistent database.
4) Estimate the total head of cattle with a regression model or used country-level mean cattle values.
5) Use IPCC EFs to estimate CH_4 from enteric fermentation and CH_4 and N_2O from manure management emissions at each cattle operation identified.

For step 4, the linear regression approach relied on the hypothesis that the cattle operation footprint area (in hectares or ha) can be used as an estimator for the total head of cattle (see Results section, Table 6 and Figures 7 to 9). This can be translated into estimated enteric fermentation and manure management emissions. Previous studies and here have shown that number of animals per farm, or the total head of cattle, has a direct relationship to total GHG and non-GHG emissions (Harper et al., 2009; Vechi et al., 2022). This basis was applied to a subset of cattle operations that had their footprints known, discussed further in section 2.2.1.

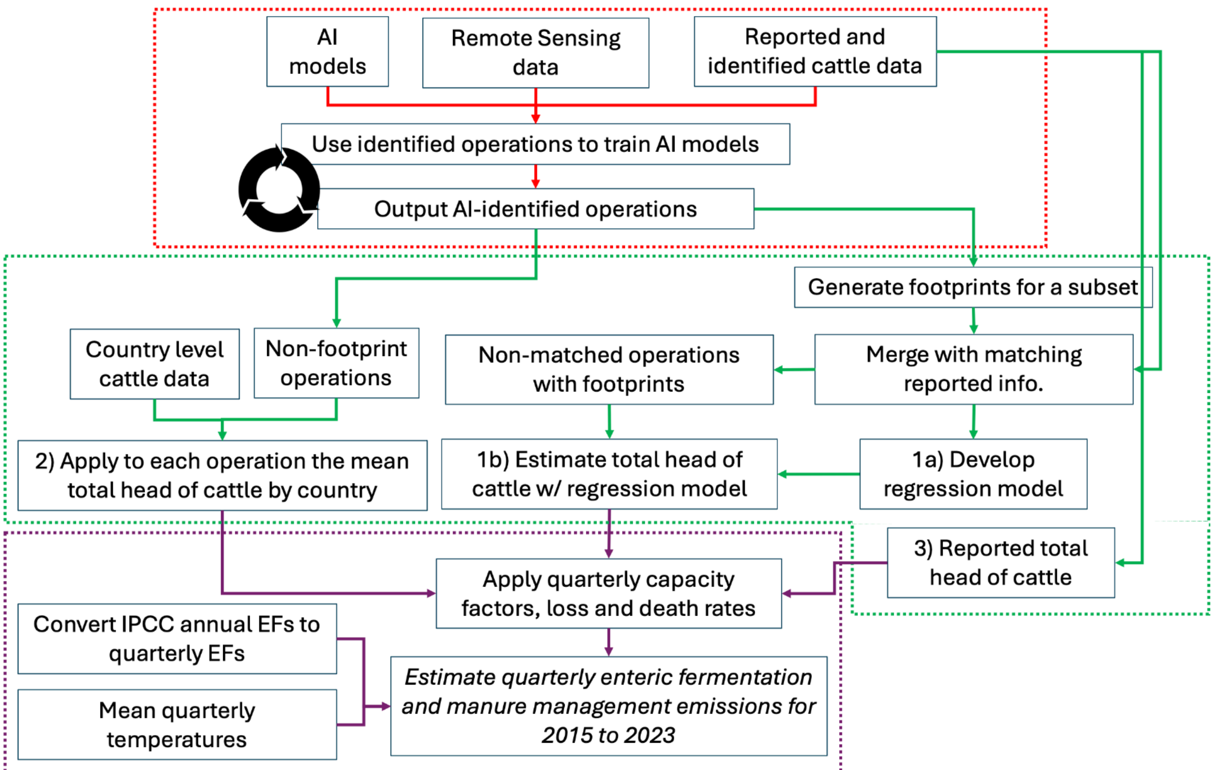


Figure 1 Flowchart summarizing the approach to identify and estimate cattle operation emissions. Red box: The approach to identify cattle operations in different countries. Seed data from reported sources were fed into the AI models to identify more operations in a country. The black feedback loop indicates an iterative approach using AI outputs to feed back into the models to identify more operations. Green box: Using the AI-identified cattle operations, a subset had their footprint areas drawn and spatially joined to reported data to develop a 1a) regression model that was used to estimate total head of cattle for 1b). Operations with no footprint used the mean total head of cattle per year. For 3) reported information used in model development was used directly to estimate emissions. Purple box: IPCC EFs, quarterly mean temperatures, and capacity factors (including death and loss) were applied to each operation to estimate quarterly enteric fermentation and manure management emissions.

This approach was applied to 18 countries, which have high cattle emissions based on each countries' percent of total global manure management CH_4 emissions (Table 1; Figure 7). Additionally, the AI and remote sensing approach resulted in a "spillover" when imagery tiles crossed national boundaries and identified additional operations in adjacent countries.

Table 1 Number of cattle operations per country and the percent of total global CH_4 manure management emissions based on FAOSTAT 2021 data (version November 9, 2023). Spillover countries are marked with an asterisk.

Country (% of total global)	Number of Cattle Operations	Country	Number of Cattle Operations
Argentina (1.27)	896	Kazakhstan (0.69)*	16
Australia (2.04)	1,099	Mexico (0.85)	998
Belarus (0.78)*	70	Pakistan (3.52)	194
Brazil (5.32)	1,094	Russia (3.32)	3,347
Botswana (0.02)*	1	South Africa (0.29)	108
Canada (1.36)	3,710	Ukraine (0.31)*	2,750
China (3.77)	601	Uruguay (0.28)*	1
France (3.91)	12,238	U.S. (12.74)	46,804
Great Britain (2.03)	5,814	Total Cattle Operations = 77,728	
Ireland (1.48)	428		

2.1 Materials

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 Remote sensing datasets

The following satellite imagery datasets were ingested into AI models (see section 2.2) to identify cattle operations. Table 2 highlights each phase which used AI models and remote sensing datasets to identify cattle operations.

1. RAIC model, USA locations: To identify U.S. operations, The National Agricultural Imagery Program (NAIP) aerial imagery distributed by The U.S. Geological Survey (USGS). NAIP acquires aerial imagery in the red, blue, green and near infrared wavelengths at a 1 meter spatial resolution, or finer, as part of an agricultural census conducted in the U.S. Imagery is available every three years beginning in 2009. NAIP

imagery acquired in 2020 to 2022 (year image varying by the state) were used to identify cattle operations listed in Table 2 (described further in section 2.2 and 2.3.1). More information on NAIP imagery can be found at the USGS NAIP imagery program page (U.S. Geological Survey, 2018).

2. RAIC model, worldwide: 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 meter resolution. To account for seasonality that can lead to increased cloud cover and hazy conditions, the summer months' basemap were accessed and used within RAIC (described in section 2.2 and 2.3.1). For the purposes here, mosaiced basemap imagery from 2020 and 2024 were used. More information on Planet basemaps can be found on The Planet website (https://www.planet.com/).

3. Earth Index models, worldwide: 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. 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/).

Table 2 Remote sensing datasets in specific countries. Included are the models the datasets were employed in and the phases of this work.

Remote Sensing Dataset	Country	Comments
NAIP	USA *(California, Colorado, Idaho, Iowa Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, New Mexico, New York, North Dakota, Ohio, Oklahoma, Pennsylvania, South Dakota, Texas, Washington, Wisconsin)*	Employed by RAIC from Phase 1 to 3 (2021 to 2024)
PlanetScope	Argentina, Australia, Brazil, Canada, China, Mexico, Pakistan, Russia, South Africa	Employed by RAIC from Phase 1 to 3 (2021 to 2024)
Sentinel-2A/-B	China, France, Ireland, United Kingdom	Employed by Earth Index model for Phase 3 (2024)

2.1.2 Identifying site-specific cattle information

2.1.2.1 Publicly accessible cattle operation information

To assess the cattle operation area footprint relationship to total head of cattle at an operation, various public and published sources were accessed, shown in Table 3. In addition to total head of cattle, some of these databases reported additional information of various types- latitude and longitude, cattle types, facility area size, and/or manure management types. All databases were filtered and cleaned to contain only beef and dairy cattle information only. 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 dataset Farm Transparency Project, similar keywords were used to filter out cattle only locations. Lastly, to develop a China model, Fan et al. was used and provided information on operation area size, and the number of dairy cows and non-dairy cows.

Table 3 Reported cattle databases with information related to model development and emissions estimates listed in the columns. All datasets, except Fan *et al.* (2018), have latitude and longitude information. Links to sources are in the references section.

Country	Source	Location	Total head of cattle	Cattle type	Footprint area	Manure management systems	Other info	Accessed
Australia	Farm Transparency Project: https://www.farmtransparency.org/map	yes	no	yes	no	no	Milking vs non-milking	Sept. 2023
China	Fan *et al.* (2018)	no	yes	yes	yes	no	Milking vs non-milking	Feb. 2023
U.S.	*See supplementary information in Table S1 for a list of states and federal sources. Note each state contains varying levels of detailed information based on individual U.S. state reporting requirements.*							

2.1.2.2 Geosearch tool

For cattle operations identified by RAIC in Phase 2: regions and countries that do not have publicly available cattle databases, Climate TRACE developed a tool called "Geosearch" to query other search engines and datasets. Geosearch ingests identified cattle facilities and then queries multiple data sources based on the latitude and longitude information, and presents results in a unified user interface. The core data integrations included are shown in Table 4.

Table 4 Geosearch core data integrations to enable cattle operation identification.

Source	Information
Google Maps; Google Places; Google Translate	Imagery (present-day); Location Metadata; Location metadata for ownership information and total head of cattle (if available); Language translation for location metadata and web pages, such as Chinese and Russian web pages
Planet Labs	Imagery (historical) to identify when a facility was active
Bing Search	Web pages (based on Location name, coordinates) for ownership information and total head of cattle (if available)

Using a multimodal, single-search interface allowed comparing data sources side-by-side, as well as joining data from one source to another – e.g. combining a list of Google Places with a sub-list of Bing Search results for each place – without leaving the interface. Human annotators used the tool to search the web for additional data, and visually inspected historical remote sensing imagery, in order to manually annotate the identified cattle operations by feedlot or dairy and additional metadata - total head of cattle, ownership, the year facility was built (year active), and the presence of pollution control technologies such as anaerobic digesters.

2.1.2.3 Desk research

In some cases, through quality control work or to generate an initial seed data for both RAIC and Earth Index models, Google search was employed to generate site-specific information. In certain regions, a combination of publicly available high resolution satellite basemaps (Mapbox, Google maps, Bing maps, etc.) and search tools were used to perform a visual appraisal of cattle operation sites identified in the AI models. Often cattle were directly visible via satellite, and at sub-meter resolution cattle are generally distinguishable from other livestock, including horses, sheep, and poultry. Additional characteristics indicative of cattle operations may include, depending on jurisdiction, general farm infrastructure, manure holding ponds, manure digesting tanks, hay bales, feeding troughs, shade structures, skylights in buildings, cattle tracks, and especially, a characteristic dark brown soil mixed of manure and bare earth.

2.1.3 Identifying country-to-region cattle information

2.1.3.1 Cattle types

For countries with detailed cattle operation information, the cattle type was used. To match IPCC definitions, any operation identified as “dairy” or “beef” was assumed to be “Mature Dairy Cattle” or “Other Cattle” (IPCC 2006a; IPCC 2006b). In some cases, a default assumption was used based on literature. For Pakistan, and Europe and the United Kingdom, we assumed all identified operations were “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 and for countries with no clear information, the “Other Cattle”, or beef, were assumed as the default choice (Greenwood, 2021).

2.1.3.2 Mean total head of cattle per farm

Many cattle operations identified by the AI models did not have a footprint area to use for modeling total head of cattle (Figure 1, green box section). As an alternative, country-specific mean total head of cattle per operation was used (Table S2). For example, Ireland was assumed to be predominantly dairy operations, therefore the mean total head of dairy cows per farm was identified and applied to AI found cattle operations. In cases where country information could only be found for dairy or beef, then the other mean value was applied to the missing type. If mean values for all years in 2015 to 2023 could not be found, 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 country was used. For example, this was done for former Soviet states.

2.1.3.3 Operation capacity factors, and death and loss rates by cattle type

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. 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 5). 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 5 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

Country	Source	Comments
U.S.	[USDA NASS](#)	For each quarter per year, the capacity factors were determined by: $\frac{\text{'CATTLE, ON FEED − INVENTORY, CAPACITY: (1,000 OR MORE HEAD)'}}{\text{'CATTLE, ON FEED − INVENTORY, TOTAL'}}$
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	

2.1.4 IPCC emission factors

EFs from The IPCC "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" (IPCC 2006a; IPCC 2006b) were used to translate cattle populations into emissions estimates. Cattle emissions are produced by enteric fermentation, producing CH_4, and manure management, producing both CH_4 and N_2O. To estimate CH_4 and N_2O emissions, the IPCC Tier 1 approach was applied with a Tier 2 approach included for Indirect N_2O emissions due to leaching from manure management only. For dairies and feedlots that lacked detailed manure management systems, assumptions were applied, discussed further in section 2.3.2.

Default IPCC EFs based on region, temperature, and manure management systems were applied to the total head of cattle at individual feedlots and dairies. Additionally, the uncertainty estimates, were expressed as a percentage above or below the mean estimate (i.e. +/-XX%), or as an interval with an upper and lower bound of values. For example, Table 10.14 "Manure management methane emission factors by temperature" states these EFs have an uncertainty of ±30 % (IPCC 2006a). For the uncertainty range for leaching from manure management systems, a lower, 1%, and upper, 20%, range was used from the typical reported range of 1 - 20% (IPCC 2006a). See Table S2 for more information on the IPCC uncertainty estimates.

2.1.5 Temperature data

Appropriate application of IPCC EFs to estimate manure methane emissions required temperature data for each modeled facility per quarter. The average annual temperature for each individual feedlot and dairy was produced by ERA5-Land Daily Aggregated from the European Centre for Medium-Range Weather Forecasts (ECMWF) Climate Reanalysis via Google Earth Engine (Muñoz Sabater, J., 2019). The specific image collection accessed was "ECMWF/ERA5_LAND/DAILY_RAW", which provided temperature data up to 2023 data, needed for this work (ERA5-Land Daily Aggregated data was accessed February 2023). The "temperature_2m" band was used to derive the mean quarterly temperatures per year for years 2015 to 2023 for each cattle operation. The quarterly temperature values were used to determine the IPCC "Manure management methane emission factors by temperature" in Table 10.14 (IPCC 2006a).

2.2 AI modeling and deployment

From 2021-2024, cattle facility detection proceeded with the Rapid Automated Image Characterization (RAIC) tool from RAIC Labs. In mid-2024 detection work transitioned to the Earth Index platform from the U.S. non-profit Earth Genome. Both tools use AI to analyze satellite imagery for the presence of cattle operations, with human analysts involved in data labeling, model refinement, and validation. However, they operate with different source data and model architectures.

2.2.1 Rapid Automatic Image Categorization (RAIC) tool

Identification of cattle operations was performed in partnership with RAIC labs (formerly Synthetaic; https://raiclabs.com/) using their RAIC proprietary artificial intelligence tool. By providing RAIC with raw, unlabeled imagery, this tool can be applied to large volumes of data to automatically find objects of interest. Additionally, using a human nudge tool, users can further refine the AI to better identify areas that contain a user-defined object of interest. For the work here, using a set of images of pre-validated cattle operations facilities in each region, RAIC searched millions of square kilometers of remote sensing imagery and identified operations with similar features relative to the seed data, such as color, shape, and orientation. Once identified, a human-review process followed to validate the results. Figure 2 provides an overview of the RAIC process. See section 5.1 for more information on the RAIC model identification and aggregating of detections to detect cattle operations.

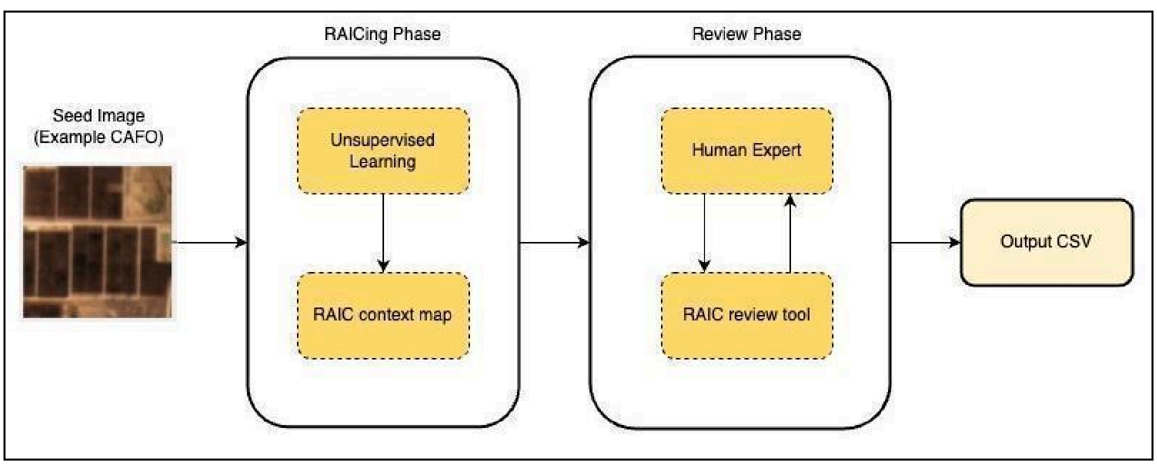


Figure 2 An example of the RAIC process to identify feedlots and dairies. Further description in text below.

The components of the RAIC steps are as follows and shown in Figure 3:

1) **Imagery preparation**- NAIP or PlanetScope basemap imagery was downloaded and tiled (mosaiced) for the region of interest for RAIC.
2) **RAICing**- In each region, either permit/reported data or research was conducted, discussed in section 2.1.2. If a cattle operation was identified, the latitude and longitude coordinates were input into RAIC to produce a seed point. Using this initial seed point, the RAIC process was continued to identify similar visualizations to generate more seed points that can be used. Some countries - China and Russia - required a number of significant seed points because of the diverse cattle operations identified (Figure 4).
   Utilizing the seed points generated, the RAIC tool proposed other NAIP and PlanetScope imagery tiles which had a high probability of containing cattle operations (Figure 4). Human reviewers, within the RAIC tool, filtered what was and was not a feedlot or dairy to further refine the proposed tiles.
3) **Area calculation**- Once the RAICing process was completed, the cattle operations boundary was generated using GIS polygon tools (Figure 5). Polygons could then be translated into area footprint estimates, in hectares (ha), that were used as a predictor to estimate the total cattle headcount at an individual operation. The boundary drawing was performed two ways based on specific regions:
   a) RAIC tool drew a convex hull heat map to calculate the boundary area (Figure 5A and B). This was done by calculating the land mass inside each convex hull to generate an area estimate for each identified cattle operation. As a result, some operations had their boundaries over and underestimated the size of the cattle operation, leading to larger or small area sizes. This is due to the challenges of separating the cattle operation features from physical features of the surrounding land.
   b) To improve the representation of a cattle operation's area, manual drawing was performed to better represent a feedlot or dairy. Only a subset of cattle operations in California and Texas, U.S., and for Mexico, Brazil, South Africa, Australia, China, and Russia were completed. Non-U.S. locations had ~200 operations drawn.

   Additionally, for 3b) wet manure management systems (i.e. retention ponds) were identified and were manually drawn to provide an indication of manure management systems employed at these operations.

Component 3b, along with seed data generated for component 2, also allowed for validation of RAIC identified cattle operations. Any false positives from the manual drawing of cattle operations were removed from the final dataset.

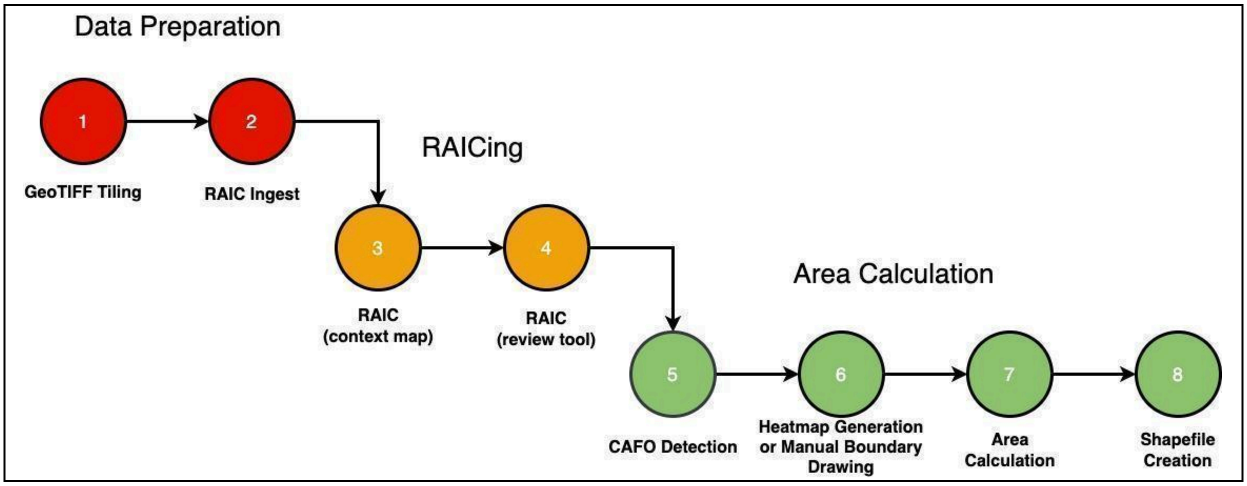


Figure 3 RAIC utilization to identify cattle operations.

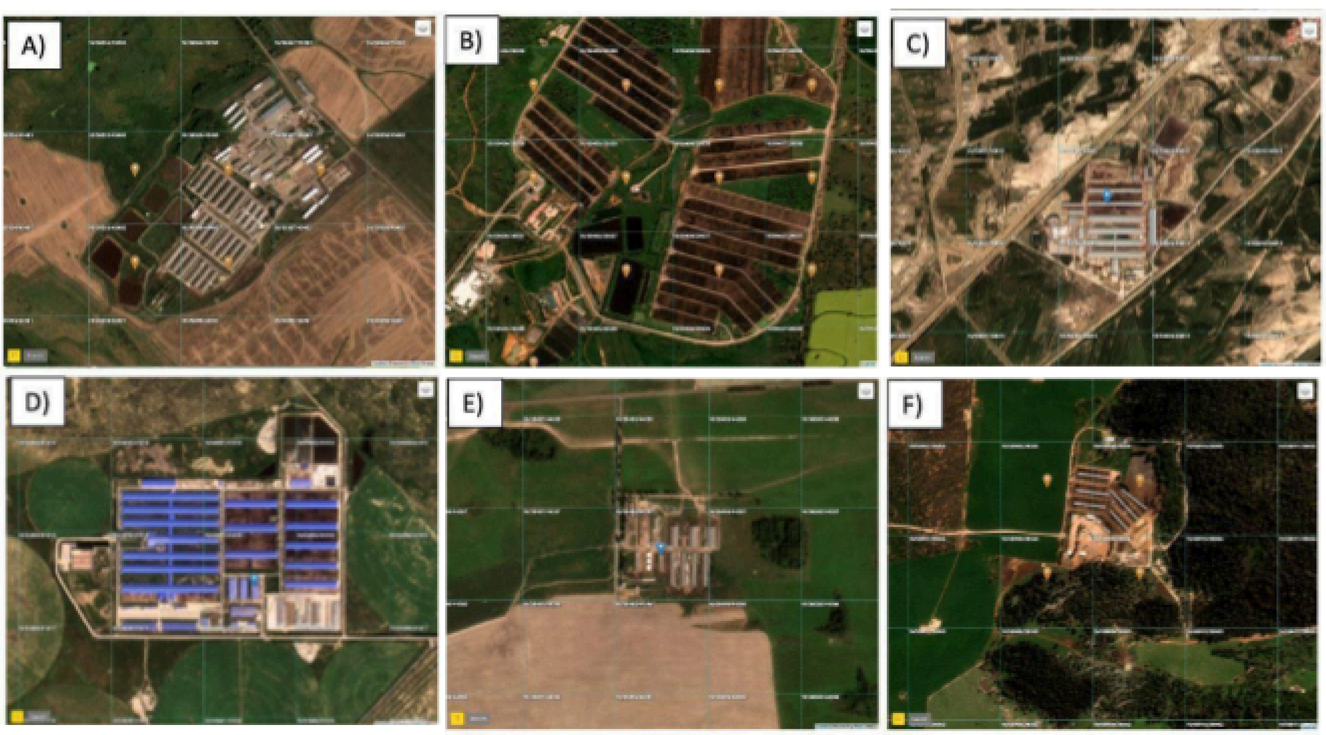


Figure 4 Examples of the diverse cattle operations in Australia, China, and Russia. A) A small (~7 tiles) and B) large (~17 tiles) feedlots in Australia, respectively. C) A small (~4 tiles) feedlot relative and D) large (~9 tiles) dairy in China. E) A small (~2 tiles) and F) large (~4 tiles) feedlot in Russia. Cattle operation features that extend over more than one tile were grouped together to represent a single feedlot or dairy.

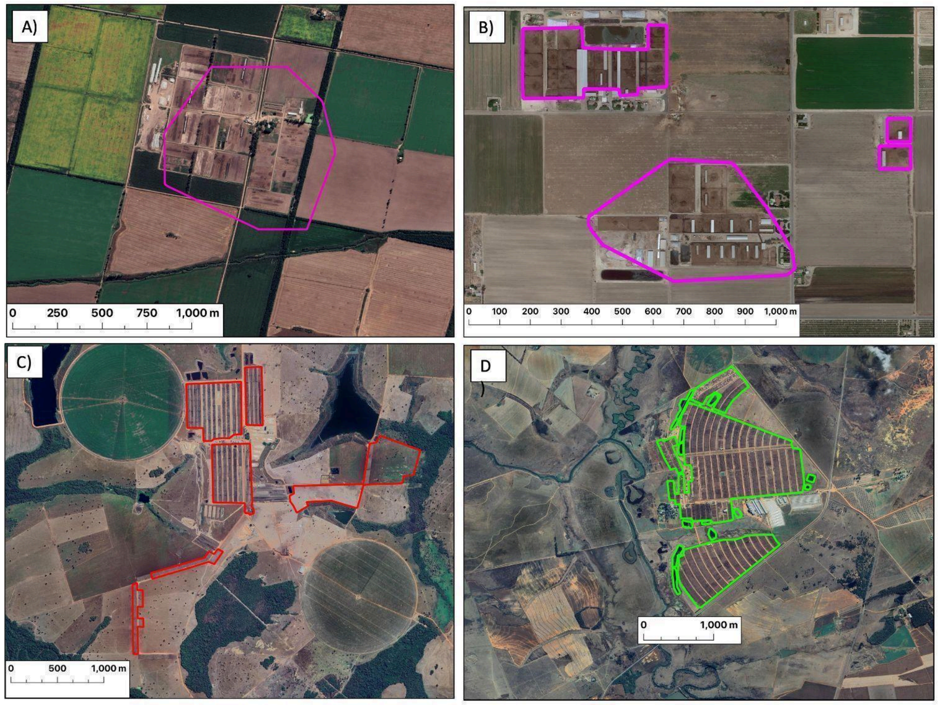


Figure 5 Examples of boundary areas shapefile creation in Phase 1: A) Argentina, B) California, and Phase 2: C) Brazil, and D) South Africa. Argentina and California cattle operation area footprints were drawn using the "convex hull" process, leading to over and underestimating of area size. An example of a fixed boundary is shown in the California image (boundary top left). Brazil and South Africa cattle operation area footprints were drawn manually.

2.2.2 Earth Index

Earth Index is a digital platform developed by Earth Genome for search and detection of objects on Earth's surface using 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, run open-source AI computer vision models (Large Earth Models) on the imagery, and reprocess model outputs, called *embedding vectors*, in one of two modes:

1) Search: In a web-map user interface, a human user clicks on one or more instances of an object of interest, and fast search of the embedding vectors retrieves other similar objects.
2) Classification: With additional labeled training datasets, indicating where sample beef and dairy operations are or are not present, a user can train a small machine learning model to distinguish the two cases, using the embedding vectors as inputs. This secondary model, or classification head, can then be run to yield comprehensive detections across a region with quantifiable accuracy metrics.

The visual characteristics of beef and dairy operations vary considerably from country to country, as do the background topography and the built environment. Accordingly, we decompose the problem of detecting cattle operations globally into a series of loco-regional problems, working on areas from one hundred thousand up to a few hundred thousand square kilometers, about the size of the U.S. state of Nebraska (~200,000 km^2).

As shown in Figure 6 and described here, each region needs its own labeled training dataset. When no such dataset exists, we iteratively construct it through use of Earth Index search and classification capabilities, beginning with a few seed locations and saving validated locations of cattle operations as we proceed. At each stage, the machine model proposes candidate sites, and a human reviewer evaluates them with respect to visual characteristics and, when needed, to external map data and internet search. Then a new model is trained on a larger dataset. As the final detections are automated, this can be considered a human-in-the-loop process of iterative model training. The feedback loop repeats until output detections reach a required level of precision and comprehensive coverage.

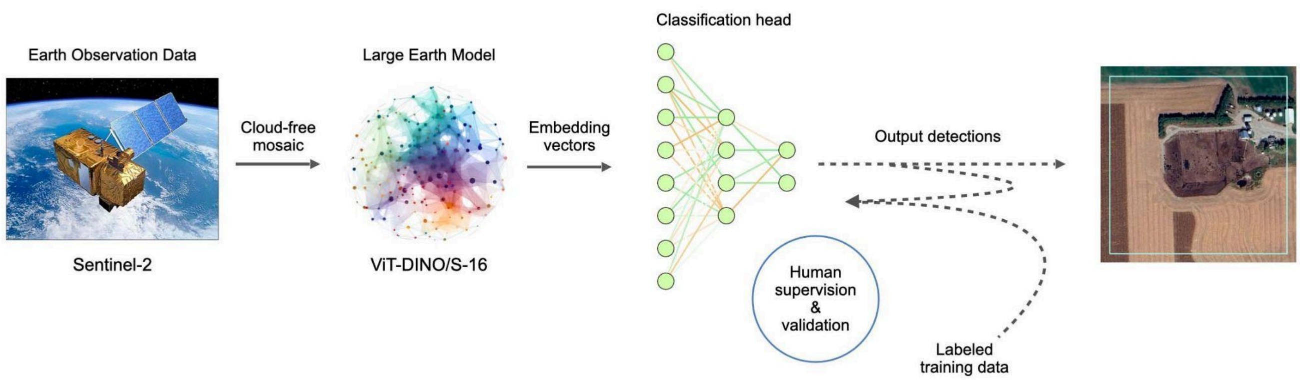


Figure 6 Schematic Earth Index workflow for cattle facility detection.

In more detail, the components of the Earth Index system are as follows:

1) **Imagery**- Satellite image data comes from the Sentinel-2 program of the European Space Agency. Using the L1C data product, cloud-free yearly median composite images are computed on GEE for 2023, with filtering based on the cloud probability score from the S2Cloudless algorithm (Zupanc, 2017). The resulting composite images are input to the machine learning models.
2) **Large Earth Model-** In analogy with Large Language Models (LLMs), Large Earth Models are large neural network models trained with self-supervised learning objectives, with satellite and other geospatial data as inputs.
For cattle operation detection, we applied a model trained on 500 GB of globally sampled Sentinel-2 imagery, specifically, a Vision Transformer model (Wang et al., 2023) trained with a DINO objective (Caron, 2021). Through pre-training, the model learns semantic

representations of objects on the Earth's surface, including buildings, vegetation, and terrain features, rich enough that it can perform few-shot learning for object detection tasks.

We ran the Large Earth Model 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 vector, called an embedding vector, encoding the visible content of that patch of the Earth's surface. The patches cover the entire area of interest, overlapping by half a patch width. Roughly 8 million embeddings covering a 200,000 km^2 region.

3) **Earth Index Search-** Business addresses cannot generally and consistently be mapped to actual cattle holding pens or barns. However, some sites can usually be identified through business addresses and internet map search.

   Often a single cattle operation example is sufficient for Earth Index search to return additional useful candidate sites. A latitude and longitude or a point clicked on a web map denotes an image patch and its corresponding embedding vector. Earth Index performs a similarity search on this vector, returning other close vectors and their corresponding patches for appraisal by the human analyst. The action of the Large Earth Model makes this useful: If the vectors are mathematically similar, then the corresponding image patches should *look* similar to human eyes as well. More technically, Earth Index performs a top-N approximate nearest-neighbor (ANN) vector search of the embedding vector space, with a cosine distance metric. Typically we set N in the range 200-500.

   We use a combination of publicly available high resolution satellite basemaps (Mapbox, Google maps, Bing maps, etc.) and search tools to perform a visual check of candidate sites, discussed in section 2.1.2. The search can be refined by flagging additional positive or negative sites. For a typical region, roughly a hundred validated sites are sufficient to proceed to model training.

4) **Trained Classifiers**- A classification head is a linear classifier or a small, fully-connected neural network (a Multilayer Perceptron (MLP)) implemented atop a much larger pre-trained neural network, which in this context is the Large Earth Model. The embedding vector outputs of the Large Earth Model become inputs to the classification head, which is trained to a specific task with an additional labeled dataset. Splitting the model in this way allows for flexibility and economy of effort, as a single foundation model can be tuned to many downstream tasks.

   For this work, we trained MLPs using the Scikit-learn Python programming package. Generally, we achieved satisfactory performance with models trained on about 1,000 positively labeled image patches (those with cattle operations) and 10,000 negative patches (those without cattle operations). The latter are selected randomly to ensure even sampling of terrain across a broad geographic area. Even in regions with thousands of cattle operations, they are sparse on the landscape, and a random selection of negative samples yields a tolerable level of noise in the data. During validation, we also negatively sample specific locations that tend to raise false positive detections.

Through several rounds of model training, inference, and validation, we grow the labeled dataset and, as needed, the capacity of the model, monitoring performance on a withheld validation dataset.

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 step is described in further detail below.

2.3.1 Combine reported data with AI models

To identify cattle operations in different countries, reported cattle operations and ones identified through research were used as seed data in the AI models, described in section 2.2 and shown in Figure 1. A feedback system was applied where model outputs were quality controlled to confirm positively identified locations and were fed back into the AI models to improve their detection ability to find more cattle operations.

2.3.1 Estimating total head of cattle

The linear regressions developed here relied on the hypothesis that the cattle operation footprint area (in ha) can be used as a predictor for the total head of cattle (see Results section, Table 6 and Figures 7 to 9). To generate regression models for this approach the AI-identified cattle operations were split into two groups: footprint and non-footprint groups. Operations with area footprints were spatially joined with reported cattle operations, containing information shown in Table 3 and other researched locations. Locations joined with information were used to develop a linear regression model to predict the total head of cattle at each operation identified that were not spatially joined with reported information (Figure 1). Three regression models were created using information from Table 3:

- *U.S.-AUS Beef*- this model was based on the U.S. and Australia operations identified as beef and the relationship between their footprint area and the reported total head of beef cattle at each operation.
- *U.S.-AUS Dairy*- this model was based on the U.S. operations identified as dairy and the relationship between their footprint area and the reported total head of dairy cattle at each operation. 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.
- *Dairy China Model*- this model was based on the China operations identified as dairy and the relationship between their footprint area and the reported total head of dairy cattle at each operation. Note, this model only used the reported milking cows from Fan et al. (2018) and this model was applied to beef operations identified in China.

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

$$Total\ Head\ of\ Cattle_{i,r} = (m_{t,r} * Area_i) + B_{t,r}\ (Eq. 1)$$

Where, the *Total Head of Cattle* at an individual beef or dairy operation, "i", in a region of interest - China or U.S. and Australia - "r", 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, "t", beef or dairy.
"B": the region-specific constant based on cattle operations type.

While the footprint area can be used to estimate the total head of cattle, some operations have their totals capped due to the regression models over predicting some locations. 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 3.

For cattle operations with no footprint, a latitude and longitude centroid only, the country specific mean dairy and beef total head of cattle sizes per farm from Table S2 were applied to each location using assumptions from section 2.1.3. In total, three sets of total head of cattle were generated (Figure 1, green box):

1) Estimated total head of cattle with regression model;
2) Estimated with the mean total head of cattle by country;
3) Reported total head of cattle

All three sets represent the *potential* capacity for each beef and dairy cattle operation, described further in section 2.1.3.3.

2.4 Estimating actual total head of cattle and emissions

2.4.3 Applying capacity factors

The actual total head of cattle can differ from the potential operational capacity due to a number of factors, discussed in 2.1.3.3. As such, beef and dairy capacity factors were applied based on country information (Table 5). This adjusted the total head of cattle estimates in Eq.1 to the following:

$$Actual\ Total\ Head\ of\ Cattle_{i,r,qyr} = Total\ Head\ of\ Cattle_{i,r} *\ cf_{t,r,qyr}\ (Eq.\ 2)$$

Where, the *Actual Total Head of Cattle* for a feedlot or dairy operation in a country is the product of the *Total Head of Cattle* from Eq.1 and the *cf*, the capacity factor (including death and loss) for a beef or dairy operation in a country for a specific quarter in a given year, *qyr*.

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.

2.4.3.1 Enteric fermentation and manure management emissions

To estimate emissions per quarter for each year in 2015 to 2024, IPCC annual EFs were modified into quarterly EFs. This was done by the general equation:

$$EF\ Frac_{i,r,qyr} = EF_{i,r} *\ Qtr\ Frac_{qyr}\ (Eq.\ 3)$$

Where, the $EF\ Frac$ is the product of the IPCC annual EF for a country by cattle type, $EF_{i,r}$, multiplied by the numbers of days in the quarter relative to the total days in a year (accounting for leap years) .

To generate quarterly enteric fermentation CH_4 and manure management CH_4 and N_2O emissions, the general approach in Eq. 4 was applied:

$$Total\ GHG_s\ Emissions_{i,r,qyr,x} = Actual\ Total\ Head\ of\ Cattle_{i,r,qyr}\ x\ EF\ Frac_{i,r,qyr}\ \ (Eq. 4\ )$$

Where, $Total\ GHG_s\ Emissions_{i,r,qyr,es}$ is the total GHG emissions by cattle type in a country for a specific quarter in a given year from either enteric fermentation or manure management, *x*.

For methane from enteric fermentation, Table 10.11 EFs were applied (IPCC 2006a). The "Other cattle" EF was applied to beef operations and equation 10.19 was used to estimate the total feedlot CH_4 emissions (IPCC 2006a). For dairy operations the "Dairy" EF was applied. Both enteric fermentation emission estimates were estimated using equation 10.19 and summed to estimate total dairy CH_4 emissions (IPCC 2006a).

For manure management, two pathways were used to estimate CH_4 and N_2O emissions. CH_4 emissions from manure handling are affected by temperature. The 2015 to 2023 ERA5 mean quarterly temperatures generated for each cattle operation were used to find the nearest temperature-based EF in Table 10.14 (IPCC 2006a). The "Other Cattle" and "Dairy Cows" EF was applied to beef and dairy corporations, respectively, then equation 10.22 was applied to estimate the total CH_4 emissions for that quarter.

As described in section 2.2.1, 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. These were translated into IPCC equivalents to estimate N_2O emissions, shown in Table S3. However, some assumptions had to be made. For example, it was assumed if a system is liquid-based, it was assigned to "liquid/slurry"; anything related to aerobic treatment was assigned to "aerobic treatment". Additionally, any location with an anaerobic system, which IPCC assigns a 0 EF, was assigned as liquid/slurry since previous work indicates that this type of system may underestimate emissions (Owen and Silver, 2011; Petersen 2018). If the manure management system was unknown, it was assumed some manure handling was performed and assigned as liquid/slurry if it was a known dairy operation and "dry lot" for beef operations.

N_2O emissions from manure management can be produced directly and indirectly - volatilization and leaching - from the systems employed at a feedlot or dairy (IPCC 2006a). To estimate direct and indirect emissions, first, using each feedlot or dairy's location, the default regional dairy or other cattle nitrogen excretion rates (N_{ex}) from IPCC Table 10.19 was applied to estimate total Nex (IPCC 2006a).

To estimate direct N_2O emissions, IPCC equation 10.25 was used; indirect emissions due to volatilization used equations 10.26 and 10.27; and indirect emissions due to leaching used equations 10.28 and 10.29. The manure managements system(s) at each operation was used to select the manure management EFs from Table 10.21 and 11.3, along with nitrogen loss due to the volatilization of NH_3 and NO_x from the manure management system ($Frac_{GasMS}$; Table 10.22) and the percent of managed manure nitrogen losses for livestock category T due to runoff and leaching ($Frac_{LeachMS}$) were applied to the equation where required (IPCC 2006a and 2006b). The $Frac_{LeachMS}$ value was set to a fixed value of 10.5% based on the reported typical range of 1-20% (IPCC 2006a). Once each direct and indirect emissions estimate was derived, then each one was multiplied by the number of cattle.

To represent on-site manure management emissions, modifications were made to the IPCC approach to reflect more detailed information available. First, 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" or $MS_{(T,S)}$ was set to 1 since the emissions from the manure management itself was estimated. Second, there were beef operations with a liquid/slurry system but no IPCC "Other Cattle" $Frac_{GasMS}$ for liquid/slurry. Instead, any feedlot with a liquid/slurry system used the "Dairy Cow" $Frac_{GasMS}$ for liquid/slurry.

Once the direct and indirect N_2O emissions were derived, the total N_2O emissions were produced by summing the two.

2.5 Climate TRACE emissions data produced

In total, 77,728 cattle operations across 18 countries had their enteric fermentation and manure management emissions estimated per quarter for years 2015 to 2023 (Figure 7). Note that the Climate TRACE website provides emissions estimates for this sector for 2024. This was done with the Climate TRACE 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.

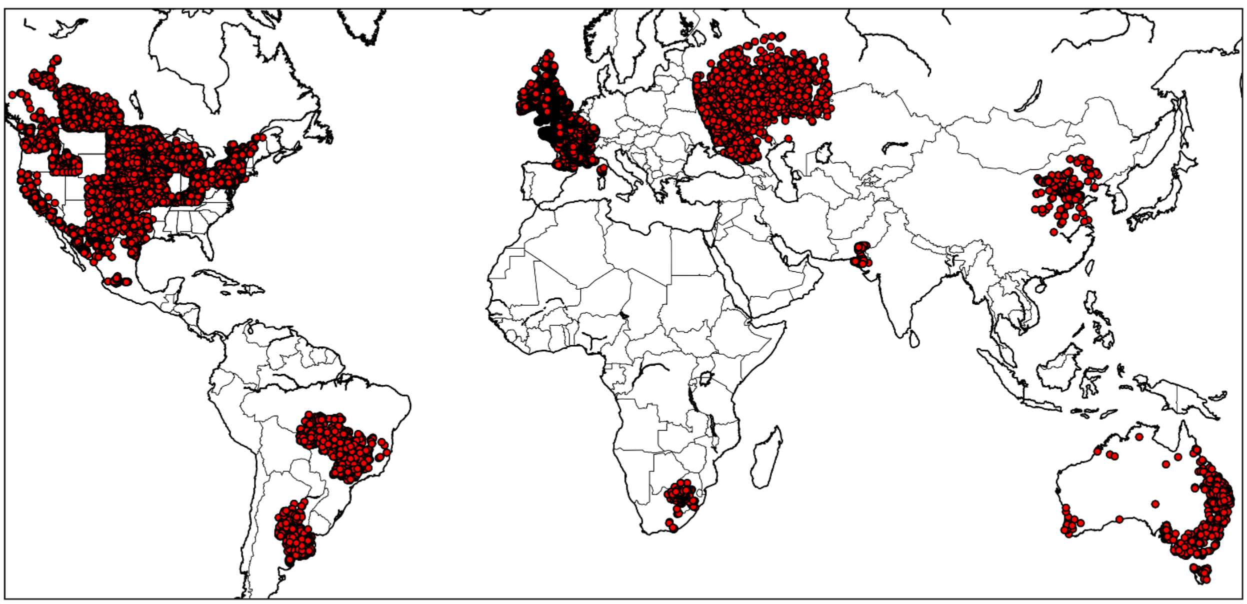


Figure 7 Countries where cattle operations were identified for the Climate TRACE 2024 release.

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.

Lastly, 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 is to indicate how certain we are of a data field used to generate emissions. Additionally, uncertainty estimates were provided, either based on each model's standard deviation or the country's standard deviation of the mean total head of cattle and capacity factors for years' that have values. For emissions, IPCC uncertainty percentages and ranges were used or the standard deviation of either. Note that uncertainty estimates were large and should not be interpreted as negative emissions. Section 5.2, Metadata information, provides an overall description of the emissions data created in Table S2 and the confidence and uncertainty emission estimates in Table S3.

2.6 Verification of approach

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

The model development relies on the relationship between cattle operations area to the total head of cattle at each location. Our analysis found that the operation footprint area and the total head of cattle have a relationship. As the operation size increases, the total head of cattle increases. 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 5). For dairy operations, there was an overall moderate correlation, with an overall value of 0.54 and 0.60 (both $p<.001$) for all operations in the U.S. and China. Within some regions and by cattle operation type, the correlations displayed a stronger relationship (Table 6). 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 6 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 $p < .001$.

		Total Head of Cattle		
	Region	***Overall***	***Beef***	***Dairy***
Cattle Operation Area (ha)	U.S., all	0.61*** (*n=1,327*)	0.78*** (*n=439*)	0.54*** (*n=888*)
	U.S., western	x	0.80*** (*n=366*)	0.61*** (*n=299*)
	U.S., eastern	x	0.32 (*n=24*)	0.53*** (*n=159*)
	Australia	x	0.74*** (*n=41*)	x
	China	0.51*** (*n=172*)	x	0.6*** (*n=86*)

Figures 8 to 10 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.

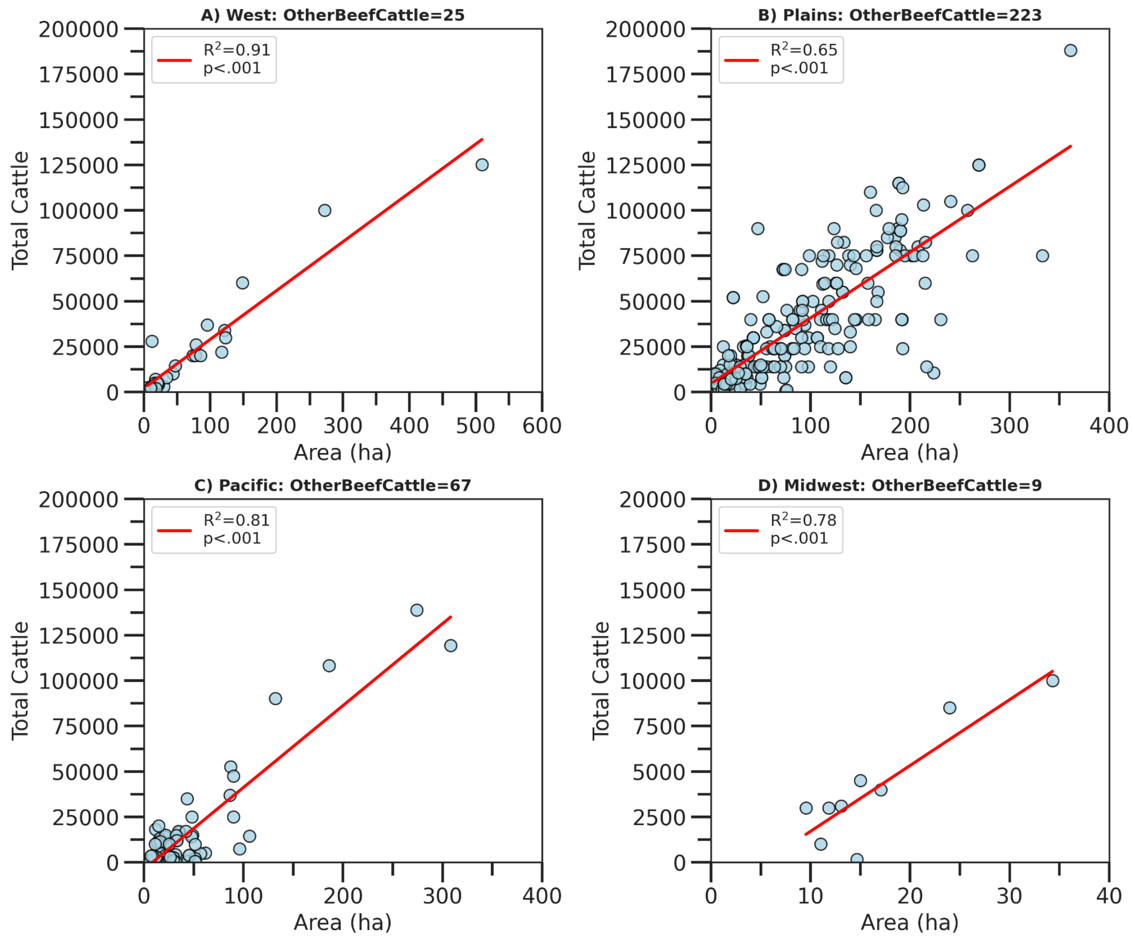


Figure 8 The relationship between U.S. beef operation footprint areas to total head of cattle for A) West, B) Plains, C) Pacific, and D) Midwest, Number of operations, R^2 values, and statistical significance are included for each U.S. region. Note, the x- and y-axis ranges differ for each plot.

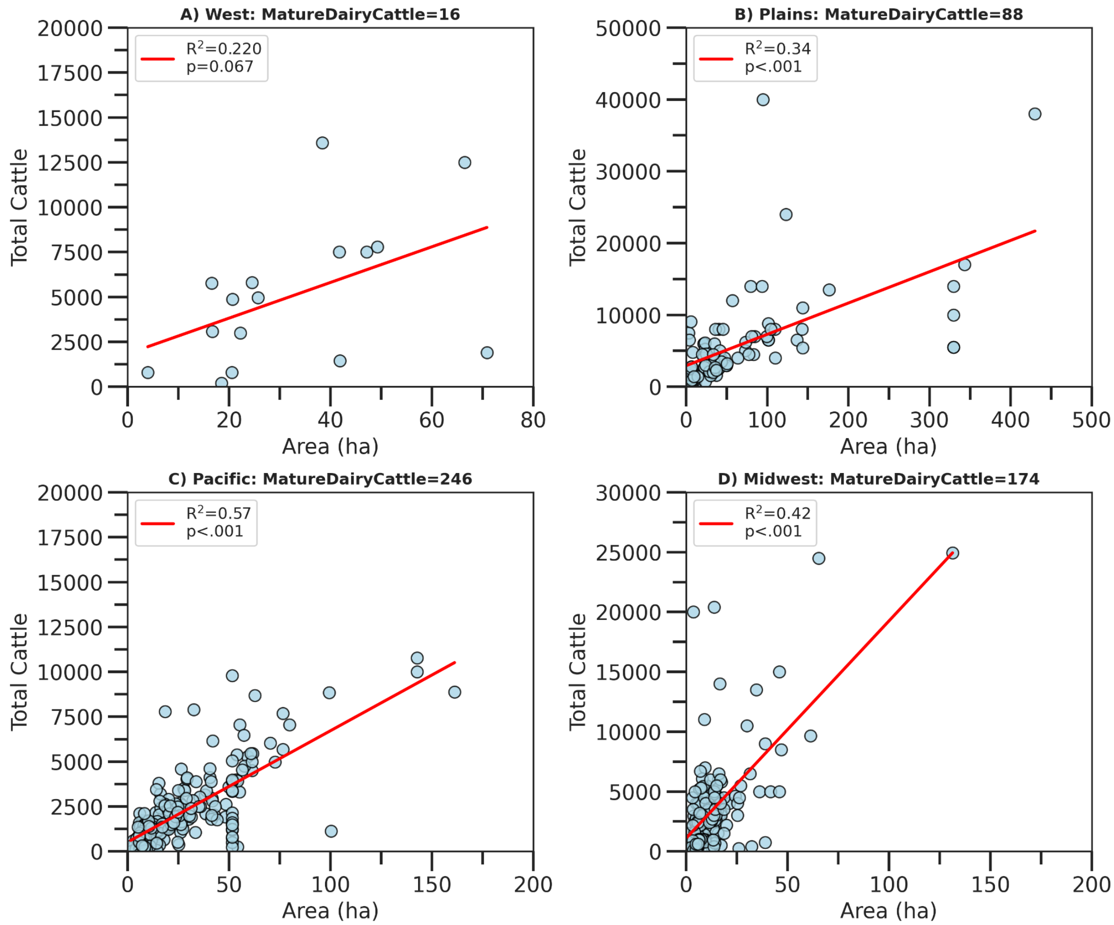


Figure 9 The relationship between U.S. dairy operation footprint areas to total head of cattle for A) West, B) Plains, C) Pacific, and D) Midwest, Number of operations, R^2 values, and statistical significance are included for each U.S. region. Note, the x- and y-axis ranges differ for each plot.

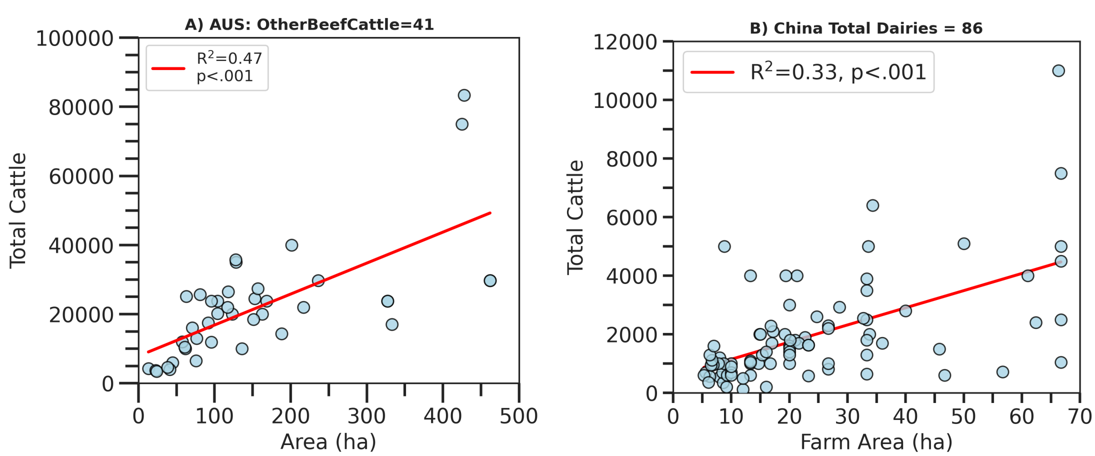
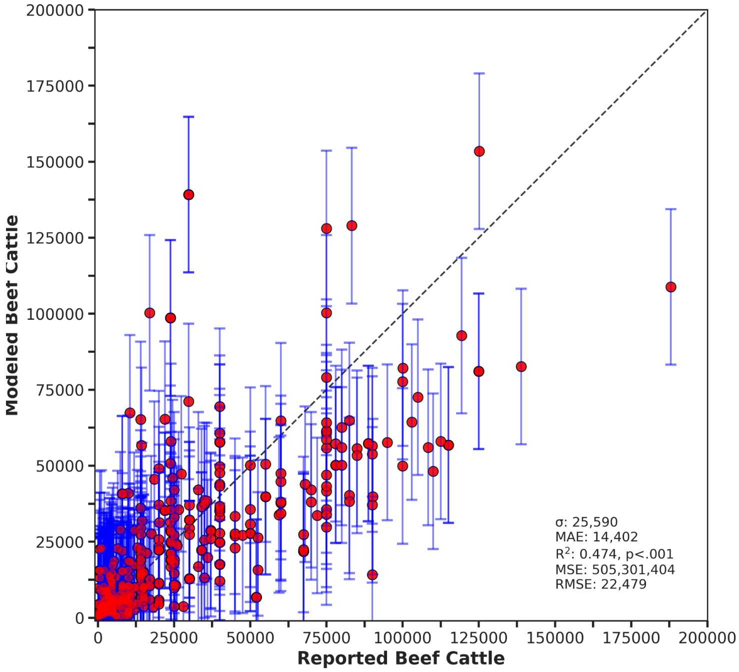
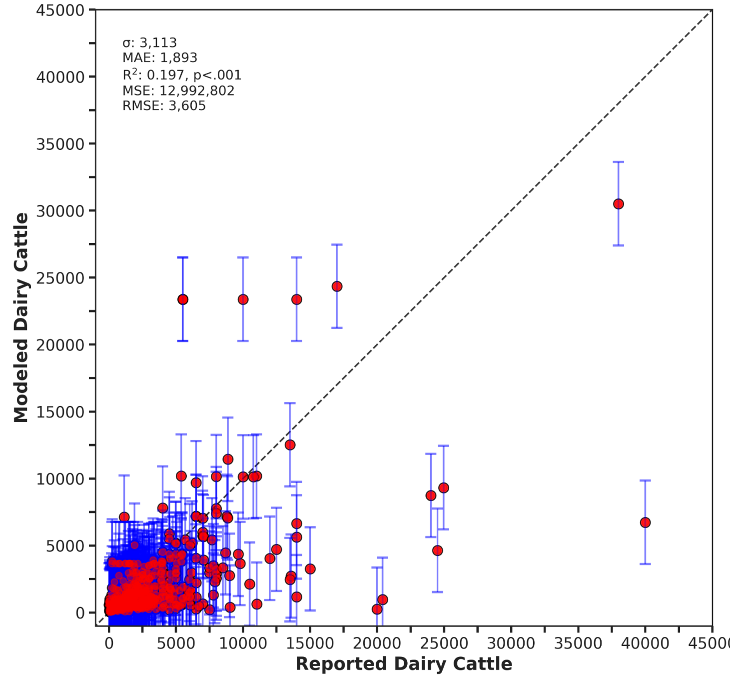


Figure 10 The relationship between A) Australia beef operation footprint areas and B) China dairy operation footprint areas to total head of cattle. Number of operations, R^2 values, and statistical significance are included for each country. Note, the x- and y-axis ranges differ for each plot.

3.2 Regression model results

Figure 11 reports each 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.





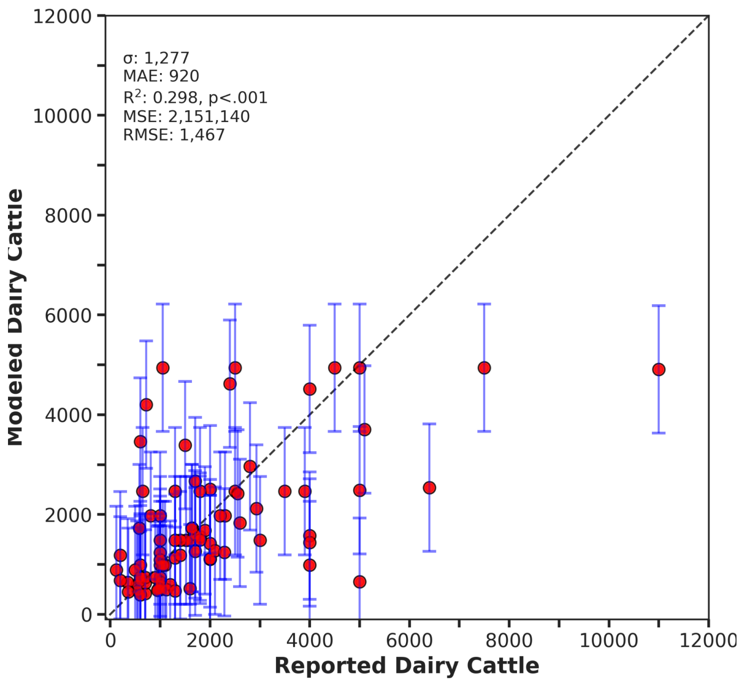


Figure 11 Scatter plots comparing reported total head of cattle (x-axis) to estimated (modeled) total head of cattle (y-axis). The models are as follows: Top left) U.S and Australia Beef Operations; Top right) U.S and Australia Dairy Operations; Bottom left) China Dairy Operations. Blue vertical lines are 95% confidence intervals.

3.3 Largest emitters - U.S. and Australia case study

Here we focus on the top 10 largest emitters in the U.S. and Australia as these countries have the best coverage for cattle operations identified by Climate TRACE. Table 7 shows the largest emitters ranked by CH_4 enteric fermentation emissions. The largest Australia and U.S. emitters are beef operations, 962.1 and 2,032.6 metric tonnes (mt) of methane. The mean total head of cattle are 64,142.1 and 153,374.1 for years 2015 to 2023. These totals represent the 9-year means of cattle that live at these locations, influenced by capacity factors and death and loss rate. Eight of the Australian beef operations have the same methane and total head of cattle values. This is due to capping modeled cattle numbers at 40,000 to prevent overprediction (see section 2.3.1). For the U.S. operations, the methane and total cattle are from reported data in Table S1.

Table 7 Top 10 U.S. and Australia cattle operations based on mean enteric fermentation CH_4 emissions from 2015 to 2023. Included are the mean total head of cattle for the same time period.

Rank	Asset Identifier	CH_4 (mt)	Mean Total Head of Cattle	Asset Identifier	CH_4 (mt)	Mean Total Head of Cattle
1	AUS_QLD_OtherBeefCattle_17	962.1	64,142.1	USA_Texas_OtherBeefCattle_21266	2032.6	153,374.1
2	AUS_QLD_OtherBeefCattle_37	865.9	57,728.1	USA_California_OtherBeefCattle_4	1501.6	113,310.0
3	AUS_NSW_OtherBeefCattle_48	461.8	30,788.3	USA_Colorado_OtherBeefCattle_664	1353.1	102,099.8
4	AUS_NSW_OtherBeefCattle_56	461.8	30,788.3	USA_Texas_OtherBeefCattle_21307	1351.4	101,977.4
5	AUS_NSW_OtherBeefCattle_7	461.8	30,788.3	USA_Kansas_MatureDairyCattle_5203	1274.9	39,840.0
6	AUS_NSW_OtherBeefCattle_70	461.8	30,788.3	USA_Texas_OtherBeefCattle_21264	1243.3	93,819.2
7	AUS_QLD_OtherBeefCattle_129	461.8	30,788.3	USA_Texas_OtherBeefCattle_21315	1216.3	91,779.7
8	AUS_QLD_OtherBeefCattle_151	461.8	30,788.3	USA_Texas_MatureDairyCattle_21435	1211.1	37,848.0
9	AUS_QLD_OtherBeefCattle_183	461.8	30,788.3	USA_Texas_OtherBeefCattle_21308	1200.3	90,569.4
10	AUS_QLD_OtherBeefCattle_207	461.8	30,788.3	USA_Texas_OtherBeefCattle_21372	1189.3	89,740.1

Figures 12 and 13 display quarterly enteric fermentation and manure management emissions for operations in Table 7. In Figure 11, Australia beef cattle operations "AUS_QLD_OtherBeefCattle_17" and "AUS_QLD_OtherBeefCattle_37" are the two largest emitters, whereas the other eight are the lowest and have emission values that overlap each other since they have the same modeled value. The enteric fermentation emissions variation mirrors change in the actual total head of cattle (activity) at the operation, after the capacity (utilization) factor is multiplied by the potential total head of cattle (capacity) for each quarter. Enteric fermentation methane emissions for these two large emitters are generally greater than 800 mt. This is the same for manure management N_2O emissions, where emissions vary between 0.20 and 0.35 mt, and mirrors changes in the total head of cattle at each operation. However, manure management CH_4 emissions decrease rapidly in quarters 2 (April/May/June) and 3 (July/August/September) as this is wintertime in the southern hemisphere. Lower temperatures lead to lower emissions based on the IPCC methane manure management EFs employed.

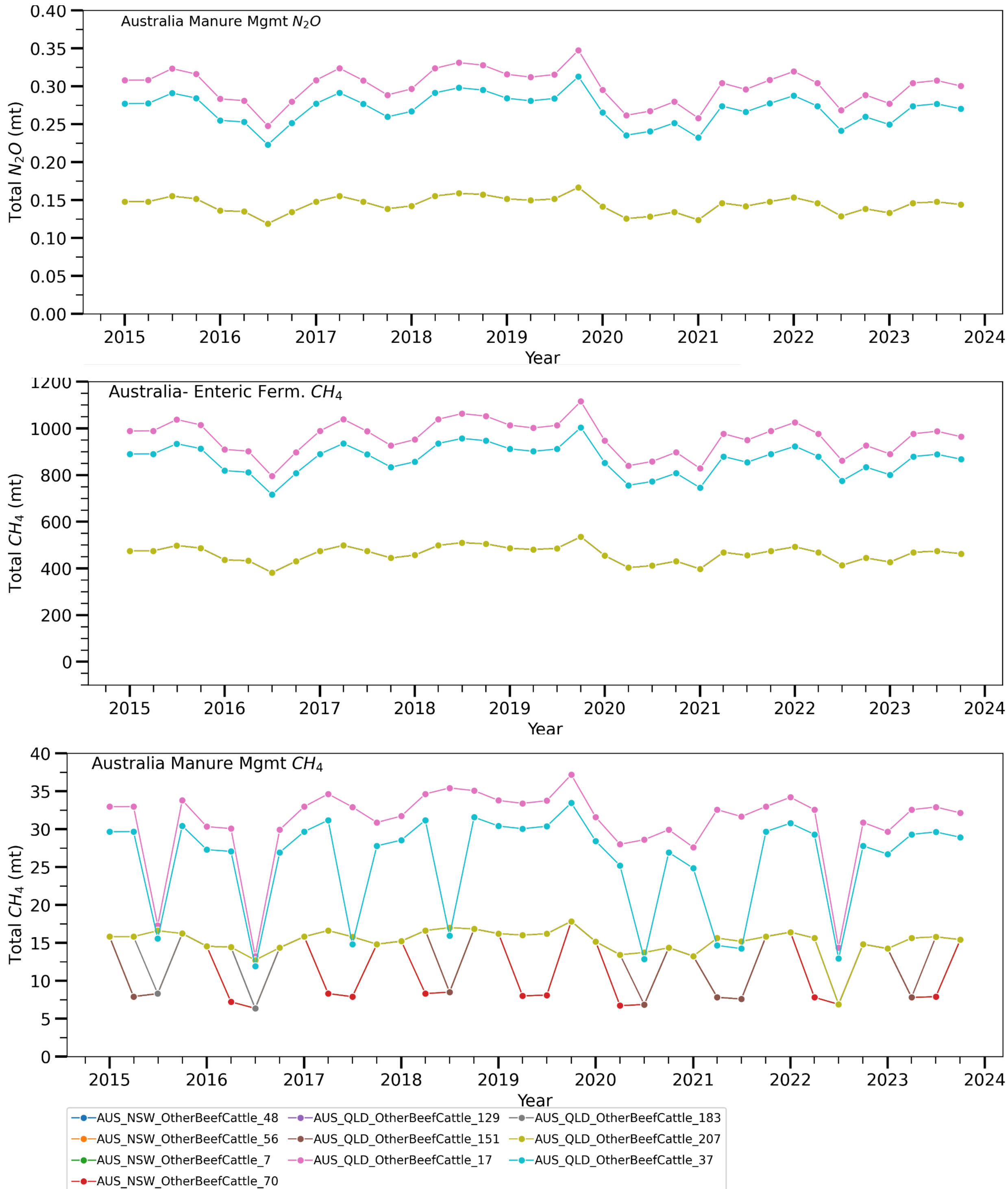


Figure 12 Top 10 Australia cattle operations' quarterly emissions estimates for years 2015 to 2023. Top image: CH_4 from enteric fermentation; middle image: N_2O from manure management; button image: CH_4 from manure management. For enteric fermentation and manure management N_2O plots, all cattle operations, except for AUS_QLD_OtherBeefCattle_17 and AUS_QLD_OtherBeefCattle_37, have the same emission values. Note, y-axis ranges differ for each image and units are in metric tonnes (mt).

A similar pattern is observed for the largest emitters identified in the U.S. Beef operation "USA_Texas_OtherBeefCattle_21266" is the largest enteric fermentation methane and N_2O emitting source, with methane emissions ranging between 1,900 and 2,300 mt and N_2O emissions varying between 0.40 and 0.50 mt. GHG variation reflects changing activity at this cattle operation, along with all the other cattle operations shown in Figure 12. However, for methane manure management emissions, the largest emitting sources are "USA_Kansas_Mature_DairyCattle_5203" and "USA_Texas_MatureDairyCattle_21435", which emit CH_4 emissions greater than 400 mt from 2015 to 2023, ~400 mt more compared to the other operations identified. The larger CH_4 manure management emissions is due to "USA_Texas_MatureDAityCattle_21435" and "USA_Kansas_Mature_DairyCattle_5203" having liquid slurry manure management system, which generates higher emissions than beef operations which are assumed to be dry lot manure management system.

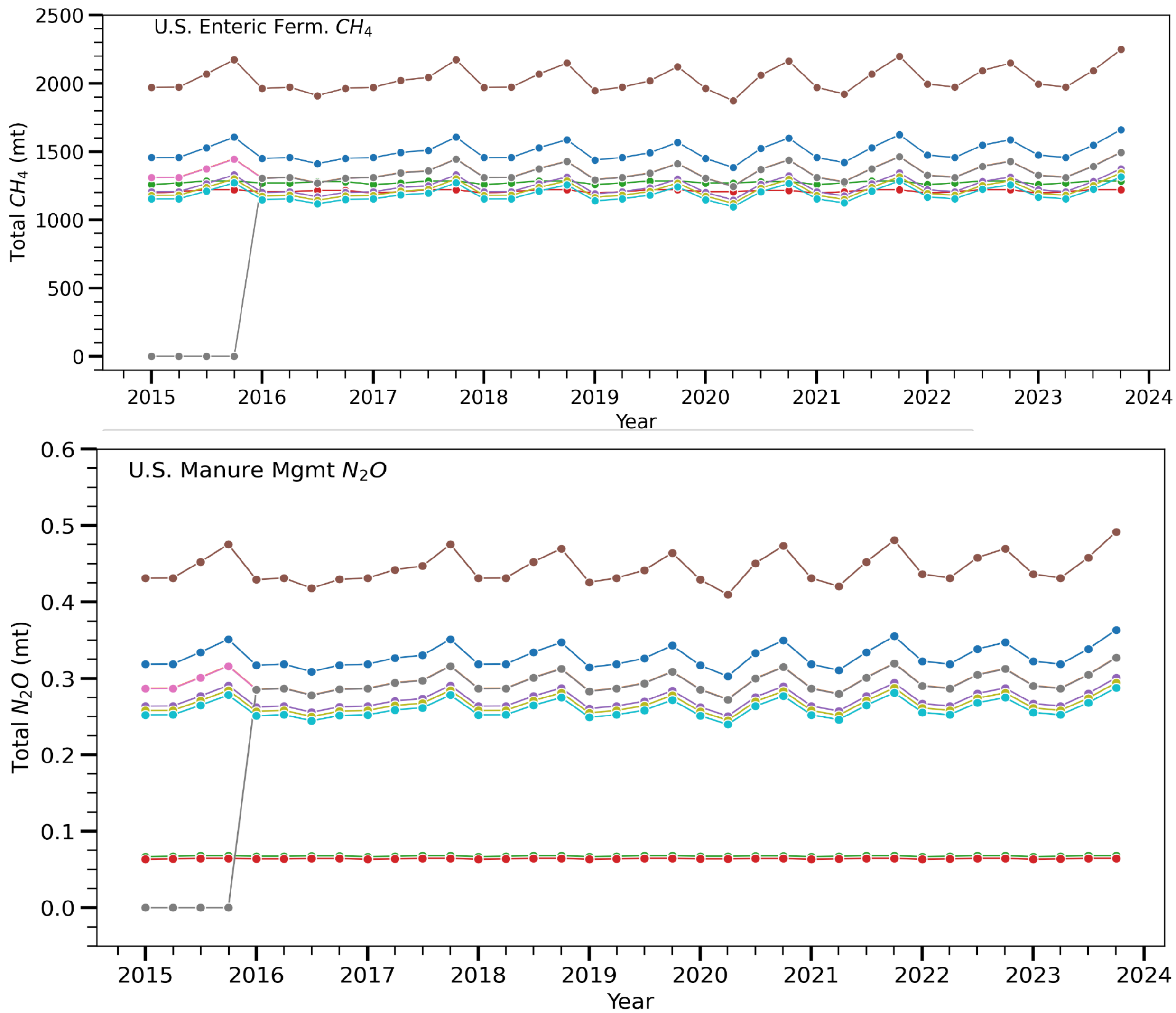


Figure 12 cont.

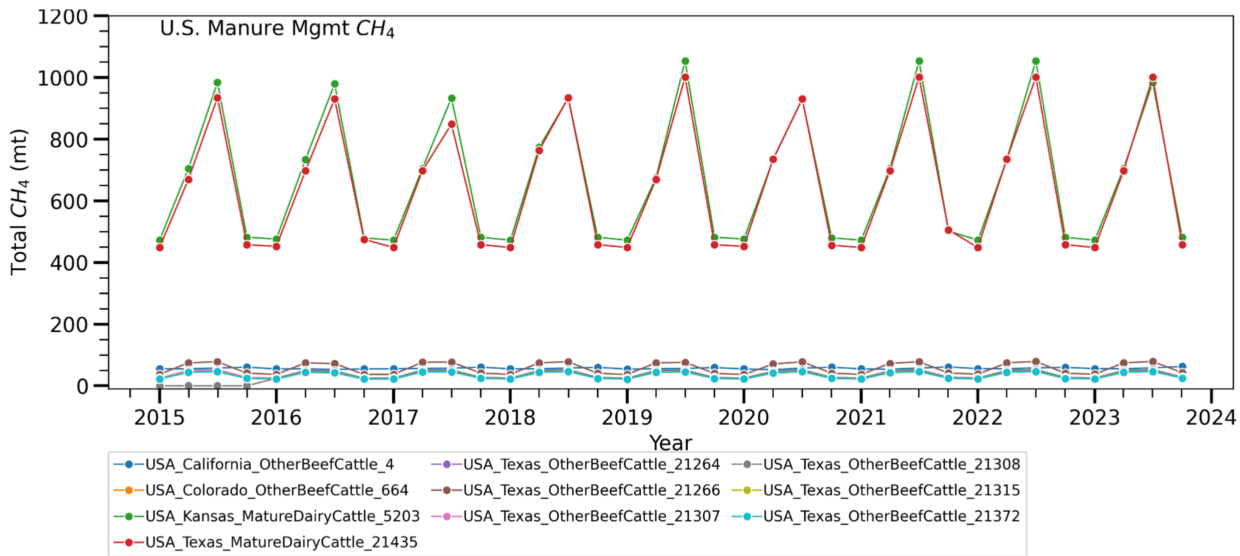
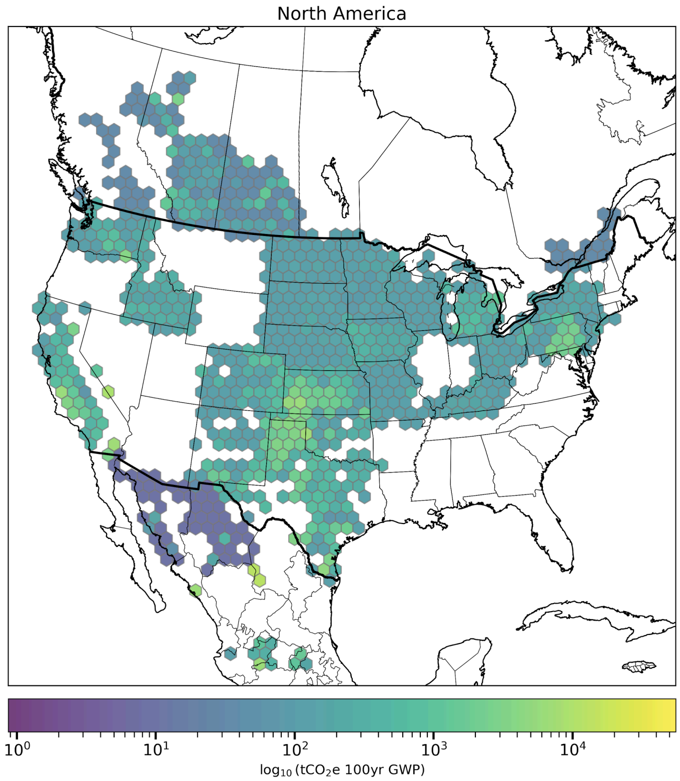
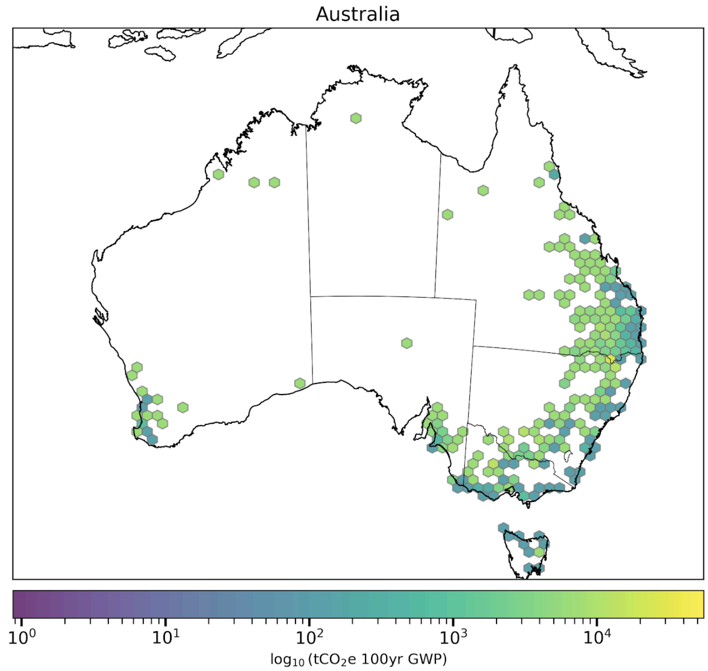


Figure 13 Top 10 U.S. cattle operations' quarterly emissions estimates for years 2015 to 2023. Top image: CH_4 from enteric fermentation; middle image: N_2O from manure management; button image: CH_4 from manure management. All cattle operations plotted, except for USA_Texas_OtherBeefCattle_21308 emissions spike in 2016 when the operation became active. Note, y-axis ranges differ for each image. Units are in metric tonnes (mt).

3.4 Spatially mapped emissions

Figure 14 provides examples of spatially binned CH_4 enteric fermentation emissions for cattle operations, represented as the mean tCO_2e 100yr GWP emissions for years 2015 to 2023. The regions shown are North America, South America, and Australia. The spatial maps here represent cattle operations, both beef and dairy, that were identified using AI tools and from reported data. In North America, there are higher emissions from concentrated cattle operations in the Texas panhandle, near the Central Valley of California, and eastern Pennsylvania. In South America, there are relatively higher cattle operation emissions in the Pampas region of Argentina compared to identified operations Mato Grosso, Goiás and Minas Gerais, which contain some of the largest operations for Brazil. Lastly, Australia displays higher cattle emissions along the eastern coast of Australia compared to the Outback. While not all Australian cattle operations were fully identified, New South Wales and Queensland in eastern Australia do contain some of the largest operations in the country.





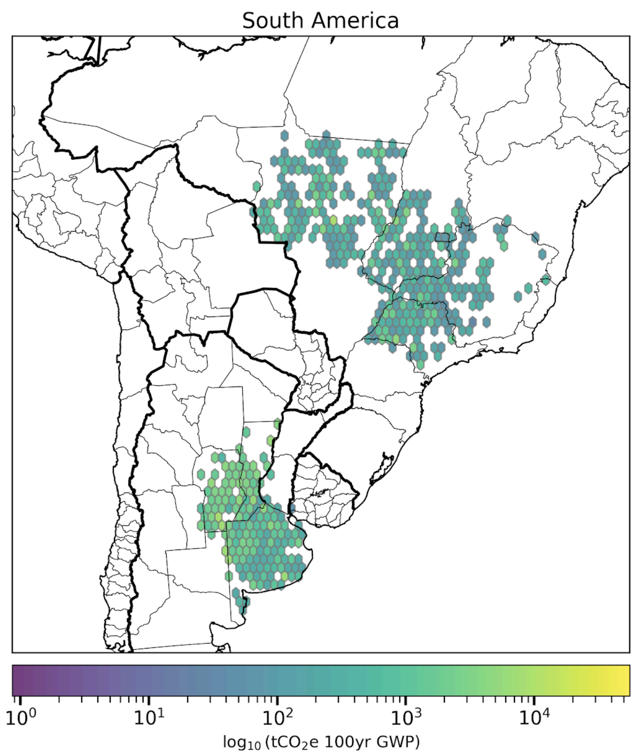


Figure 14 Spatially binned CH_4 enteric fermentation emissions for cattle operations, represented as the mean tCO_2e 100yr GWP emissions for years 2015 to 2023 (units in $\log_{10}$ scale). Top left: North America; Bottom left, South America; Top right: Australia.

4. Discussion and Conclusions

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, RAIC is only capable of correctly labeling cattle operations in contexts where the human eye can successfully differentiate a feedlot from nearby land uses. 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 RAIC tool. However, the Earth Index model was able to offer an improvement by identifying smaller operations via human input, which did improve and increase the number of cattle operations identified.

The Climate TRACE modeling approach works best when there are in situ, total head counts by cattle type at a representative portion of cattle operations within a country, and where manure management can be inferred. These conditions were not always present in beef and dairy producing regions, which may limit the applicability and precision of this approach. The population modeling requires some degree of local tuning to ensure that regional differences in management were captured, as shown in Figures 7 and 9. It is currently infeasible at this phase of the research to label the manure management practices at every cattle operation in the Climate TRACE dataset or indicate where operations may have had mixed beef and dairy production systems. Operations were labeled either beef or dairy operations, blurring the differences between integrated facilities. Differences in manure management between feedlots in a region were also difficult to capture in these results. All beef operations in a region were assigned a default regional manure management practice (as were all dairies) if more detailed information was not available. Additionally, there is the possibility some operations are misclassified - i.e. actually a swine facility instead of dairy or a crop field- possible false positives. While spatial joining of datasets was performed for all regions to minimize error and perform quality control, mislabeled and misidentified cattle operations may exist and we welcome users to report these operations if identified.

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 be to expand deployment of the AI models internationally. Climate TRACE only identified the largest cattle operations in each region. As a result, we only have a partially complete picture of the cattle operations present within a country but do capture some of the largest emitting sources for this sector. Future work will include identifying cattle operations in India and the rest of the European Union and Europe, and African countries. 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.

5. Supplementary information

Table S1 U.S. state CAFO data used to estimate cattle operations' emissions for Climate TRACE 2024 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 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.	KAZ	Petrick, M. and Götz, L. (2019)

ISO3 Code	Source	ISO3 Code	Source
BRA	Modernel et al. (2018);	MEX	USDA Report Dairy and Products Annual Mexico; Peel, D.S. (2010); Ibarrola-Rivas, M.J. et al. (2023).
BWA	UNEP Copenhagen Climate Centre (2023).	PAK	Zia (2009)
CAN	Government of Canada. (2021).	RUS	Korobkov et al. (2021).
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).	UKR	Tulush, L et al. (2023)
DEU	Gieseke, D. et al. (2018); Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.	URY	Modernel et al. (2018)
FRA	Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.	USA	United States. U.S. National Agricultural Statistics Service NASS.
GBR	Farm Accountancy Data Network (FADN), EUROSTAT for Agricultural prices and price indices- Structural Information.	ZAF	Scholtz et al. (2008); van Heerden, B. (2019)

Table S3 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 systems with an asterisk indicate Climate TRACE assumed manure management systems.

Manure management system identified	IPCC manure management system equivalent	IPCC description
• Aerobic treatment • Lagoon - aerobic • Treatment & Storage pond • Treatment pond • Vegetative Infiltration	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.

Manure management system identified	IPCC manure management system equivalent	IPCC description
Basin ● Wetland		
● 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	Liquid/slurry	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.
● Pit storage ● Pit storage - Deep	Pit storage below animal confinements	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 ● None* ● Roofed Storage Shed ● Solid storage	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.

Manure management system identified	IPCC manure management system equivalent	IPCC description
• Stockpiling Structure (covered or uncovered)		

5.1 RAIC Model

A continuation from section 2.2.1- RAIC detection results were presented as a list of entries in a comma-separated values (CSV) file, with each entry referring to a specific cattle operation tile found. In many instances, a whole cattle operation can cover a vast array of tiles, depending on the resolution of data ingested (Figure 2). For example, the same feedlot in NAIP data would be fewer tiles in PlanetScope data, given PlanetScope is ~3m and NAIP is ~1m. (Figure 5A and B). Following the export of the CSV values, there was a need to consolidate those results into groups, where each group represented a whole cattle operation. For that reason, RAIC created the Nearest Neighbors algorithm (not to be confused with the supervised K-NN learning algorithm). It was a process where all adjacent tiles were consolidated into a singular group. Following this, groups whose centroids were less than a minimum distance away from each other were merged to form a singular group of tiles representing the entire feedlot or dairy.

Each tile was assigned a unique tile ID as well as latitude and longitude coordinates that represent that tile's centroid. After a unique ID was generated, and the distance from each tile, *T*, was calculated to every other tile in the results CSV file. Once this distance was calculated, and compared to a minimum distance threshold, it was determined which tiles were adjacent neighbors. The immediate neighbors were grouped and assigned a unique ID.

At this point (the "Merging" stage), groups were checked to determine if they are too close to another group where they might also be associated. For each group, we calculated an average latitude and longitude based on its member tiles and checked with the Haversine distance, accounting for the shape of the Earth. If two or more groups were closer than ~1km, they were merged. The new merged group assumes a singular unique Group ID. The distance threshold of ~1km was determined to be a sufficient distance based on internal reviews of the data. There may be some cases where a few groups will be farther away from each other (>1km) yet still belong to the same cattle operation.

The final resultant file from this "nearest neighbors" process was a feature list of detections in a CSV format, with each tile having an additional Group ID column specifying which group the detection belongs to. Additionally, the Group Size was calculated for each group representing the number of tiles belonging to that Group ID. This can be used, for example, to detect the number of large cattle operations, e.g. exceeding 10 tiles (Figure 2).

5.2 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 AFO to small cattle farms) enteric fermentation CH_4, and 20yr and 100yr GWPs emissions
- Cattle operations (ranging from AFO to small cattle farms) manure management CH_4 and N_2O emissions, and 20yr and 100yr from feedlots and dairies

Emissions estimates were reported quarterly for years 2015 to 2023. The cattle emissions described here represent a subset of specific country-level emissions estimates from the Climate TRACE agriculture sector: "*Country-level Enteric fermentation and Manure Management Emissions Estimates from Cattle Operations*". Meaning", the country-level emissions encompass the subset of emissions contained in individual cattle operations' emissions estimates. For some countries, when individual cattle operations were aggregated and emissions 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 value 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 Table S2 to S4.

Table S2 Metadata for *Enteric Fermentation and Manure Management Emissions from Cattle Operations***.** 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 – 2023*
Temporal Resolution	*Quarterly*
Data format	*CSV*
Coordinate Reference System	*None. ISO3 country code provided*
Number of emitters available for download	*77,728 cattle operations in 18 countries (iso3 code): 'ARG', 'AUS', 'BLR', 'BRA', 'BWA', 'CAN', 'CHN', 'FRA', 'GBR', 'IRL', 'KAZ', 'MEX', 'PAK', 'RUS', 'UKR', 'URY', 'USA', and 'ZAF'.*

General Description	Definition
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 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 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 S3 Feedlot and dairy 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
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_capacity*"	If the asset-level "other2" column describes the asset's capacity derived by: *'fill'*: the σ is based on each years 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	*Dairy operations*: the σ of the lower, default, and upper capacity factor values: full capacity, full capacity w/ death & loss, full capacity w/ death & loss-10%, Ex. [1.0,0.996,0.8964]

Data attributes	Confidence Definitions	Uncertainty Definitions
	country or regional-level information; *Dairy operations:* assumed 100% or capacity factor =1.0 *High* All operations- farm-level specific capacity factor	*Beef operations:* for each year's quarter, the σ of the capacity was used
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 ranges
CO2_emissions_factor	Not estimated based on IPCC definition	
CH4_emissions_factor	*Medium*: based on IPCC emissions factors	IPCC ±50% uncertainty estimates based on the default EF
N2O_emissions_factor	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* Not estimated based on IPCC definition *Manure Mgmt:* IPCC uncertainty estimates, expressed as a percentage above or below the mean estimate (i.e. +/-XX%), or as an upper and lower bound
other_gas_emissions_factor	Not used; N/A	
CO2_emissions	Not estimated based on IPCC definition	
CH4_emissions	*Medium*: based on IPCC emissions factors	The σ of the lower, default, and upper emission values
N2O_emissions	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* Not estimated based on IPCC definition *Manure Mgmt*: The σ of the lower, default, and upper emission values
other_gas_emissions	Not used; N/A	

Data attributes	Confidence Definitions	Uncertainty Definitions
total_CO2e_100yrGWP	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* the σ CH4_emisisons *x* 100yr GWP of the lower, default, and upper emission values for each GHG *Manure Mgmt:* the combined σ of CH4_emisisons *x* 100yr GWP + N2O_emisisons *x* 100yr GWP of the lower, default, and upper emission values for each GHG
total_CO2e_20yrGWP	*Medium*: based on IPCC emissions factors	*Enteric fermentation:* the σ CH4_emisisons *x* 20yr GWP of the lower, default, and upper emission values for each GHG *Manure Mgmt:* the combined σ of CH4_emisisons *x* 20yr GWP + N2O_emisisons *x* 20yr GWP of the lower, default, and upper emission values for each GHG

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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.

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