HUMBERTO PAIVA FONSECA

Time2Graze
Brazil Workshop

LAPIG
Laboratório de Processamento
de Imagens e Geoprocessamento

METHANE FROM LIVESTOCK GLOBALLY: SATELLITE-BASED ESTIMATES

- Remote sensing
- Atmospheric modeling
- Sustainable solutions

GLOBAL COVERAGE
Consistent satellite-based estimates across regions and scales.

3-D REPRESENTATION
Uses 3-D atmospheric chemistry models to simulate methane transport.

COMPREHENSIVE CHEMISTRY
Includes detailed methane sources, sinks and interactions in the atmosphere.

OBSERVATION INTEGRATION
Combines multiple satellite datasets to improve constraints.

INVERSE MODELING CAPABLE
Links atmospheric observations and emissions for robust estimates.

Why Is Methane Important?

Methane (CH_4) is a powerful greenhouse gas. One tonne of CH_4 warms the atmosphere approximately 80 times more than one tonne of CO_2 over a 20-year period and between 27 and 30 times more over 100 years.

Although its atmospheric lifetime is relatively short—around 9 to 12 years—its high warming potential means that reducing methane emissions can produce more rapid climate benefits.

Its main sources include livestock production, wetlands, waste, rice cultivation, and fossil fuel extraction.

KEY FACTS

≈80x
stronger than CO_2 (20 years)

27–30x
stronger than CO_2 (100 years)

9–12
years atmospheric lifetime

MAIN SOURCES

- Livestock Production
- Wetlands
- Waste
- Rice Cultivation
- Fossil Fuel Extraction

What is a methane inventory?

A methane inventory is a structured description of where methane emissions come from, how they are organized, and how they can be estimated or observed.

1. WHAT IT DESCRIBES

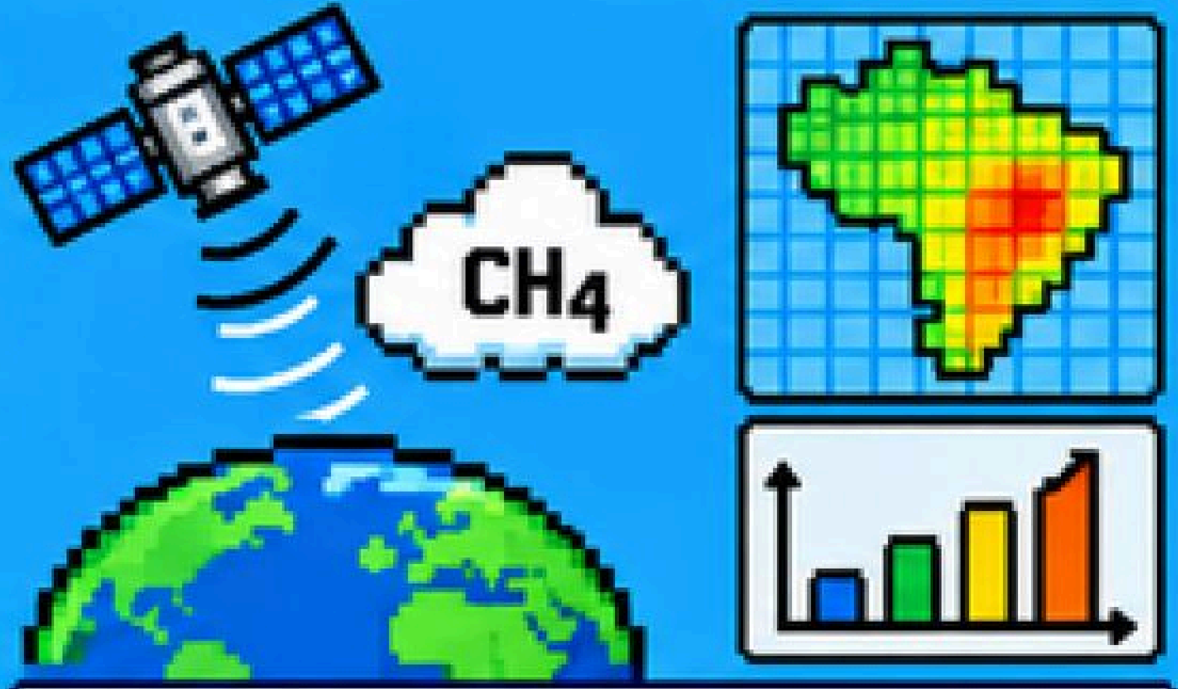
A methane inventory identifies the main sources of CH_4 emissions and organizes them by sector, place, and time.

2. BOTTOM-UP

Bottom-up inventories are built from activity information and sector knowledge. They describe emissions source by source and are commonly used for national and global reporting.

- Source-based
- Detailed by sector
- Useful for reporting

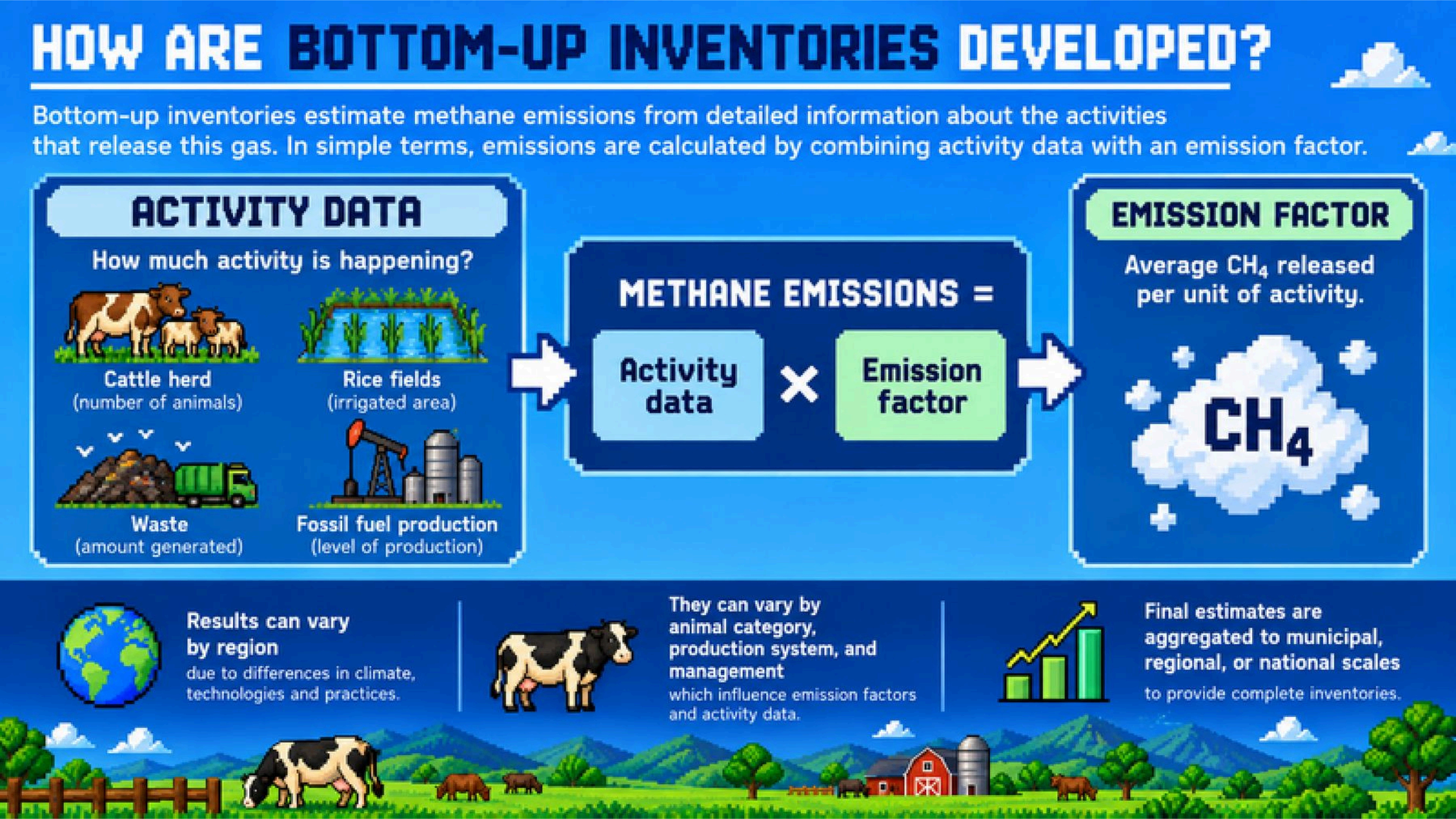
3. TOP-DOWN



Top-down inventories use atmospheric observations, such as satellites or in situ measurements, to infer emissions over a region. They are useful for evaluating patterns and checking consistency with bottom-up estimates.

- Observation-based
- Regional patterns
- Useful for evaluation

Bottom-up: process knowledge | Top-down: atmospheric constraints | Together: more complete understanding


HOW ARE BOTTOM-UP INVENTORIES DEVELOPED?
Bottom-up inventories estimate methane emissions from detailed information about the activities that release this gas. In simple terms, emissions are calculated by combining activity data with an emission factor.
ACTIVITY DATA
How much activity is happening?
Cattle herd
(number of animals)
Rice fields
(irrigated area)
Waste
(amount generated)
Fossil fuel production
(level of production)
METHANE EMISSIONS =
Activity data
×
Emission factor
EMISSION FACTOR
Average CH_4 released per unit of activity.
CH_4
Results can vary by region
due to differences in climate, technologies and practices.
They can vary by animal category, production system, and management
which influence emission factors and activity data.
Final estimates are aggregated to municipal, regional, or national scales
to provide complete inventories.

LEVELS OF BOTTOM-UP INVENTORIES

TIER 1

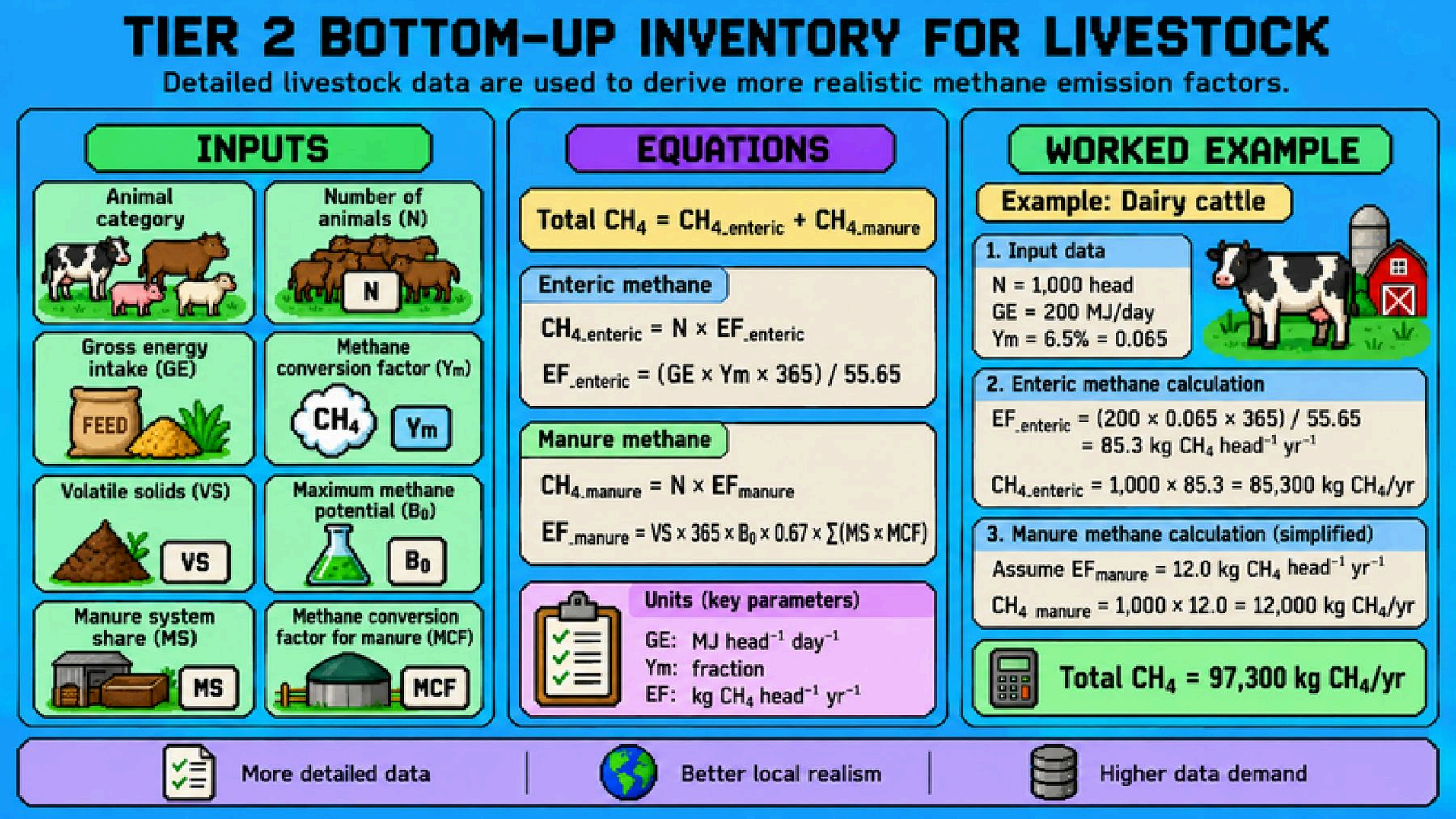
Uses activity data (for example, number of animals) together with default IPCC emission factors. It is the simplest approach, requires less data, and is useful for broad estimates, but it represents local production differences less well.

- Simplest approach
- Less data required
- Useful for broad estimates

TIER 2

Uses country- or region-specific emission factors and more detailed information on animal weight, diet, productivity, digestibility, and management. It requires more data, but better represents local conditions and usually gives more realistic estimates.

- More detailed information
- More data required
- Better represents local conditions


TIER 2 BOTTOM-UP INVENTORY FOR LIVESTOCK
Detailed livestock data are used to derive more realistic methane emission factors.
INPUTS
Animal category
Number of animals (N)
N
Gross energy intake (GE)
FEED
Methane conversion factor (Y_m)
CH_4
Ym
Volatile solids (VS)
VS
Maximum methane potential (B_0)
B_0
Manure system share (MS)
MS
Methane conversion factor for manure (MCF)
MCF
EQUATIONS
Total CH_4 = $CH_{4\_enteric}$ + CH_{4_manure}
Enteric methane
$CH_{4\_enteric} = N \times EF_{\_enteric}$
$EF_{\_enteric} = (GE \times Ym \times 365) / 55.65$
Manure methane
$CH_{4\_manure} = N \times EF_{manure}$
$EF_{\_manure} = VS \times 365 \times B_0 \times 0.67 \times \sum(MS \times MCF)$
Units (key parameters)
GE: MJ head^{-1} day^{-1}
Ym: fraction
EF: kg CH_4 head^{-1} yr^{-1}
WORKED EXAMPLE
Example: Dairy cattle
1. Input data
N = 1,000 head
GE = 200 MJ/day
Ym = 6.5% = 0.065
2. Enteric methane calculation
$EF_{\_enteric} = (200 \times 0.065 \times 365) / 55.65$
= 85.3 kg CH_4 head^{-1} yr^{-1}
$CH_{4\_enteric}$ = 1,000 × 85.3 = 85,300 kg CH_4/yr
3. Manure methane calculation (simplified)
Assume EF_{manure} = 12.0 kg CH_4 head^{-1} yr^{-1}
$CH_{4\ manure}$ = 1,000 × 12.0 = 12,000 kg CH_4/yr
Total CH_4 = 97,300 kg CH_4/yr
More detailed data
Better local realism
Higher data demand

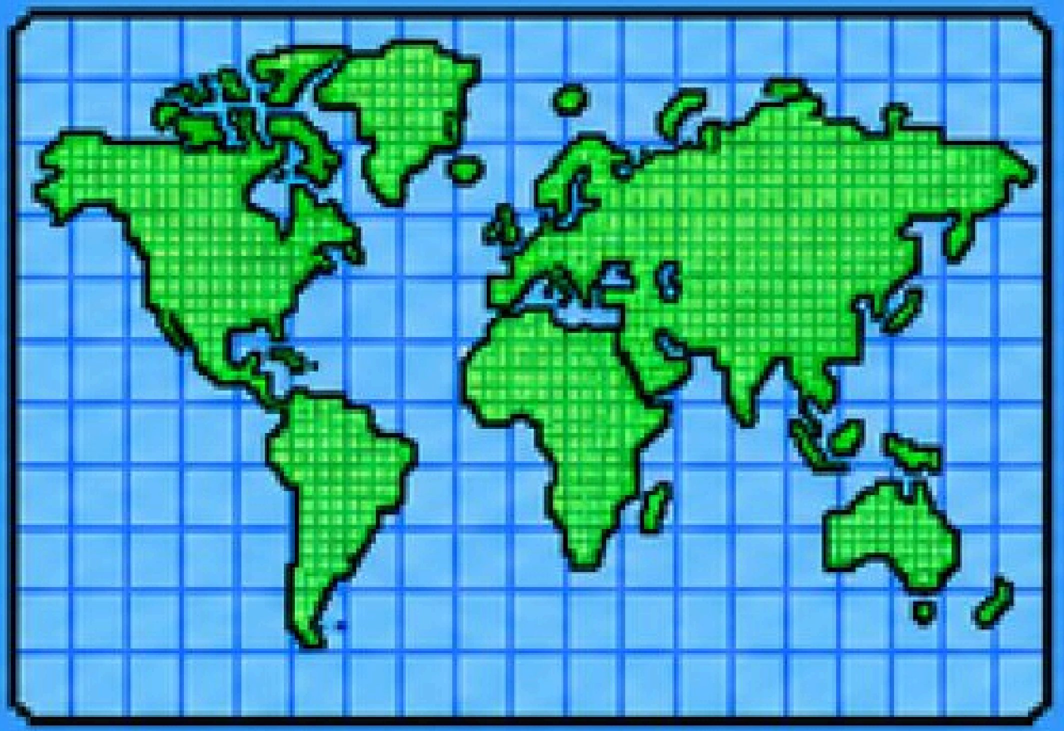
Spatial representation of bottom-up inventories

1. Administrative aggregation

Emissions are often reported by municipalities, states, regions, or countries.

Easy to compile, but explicit gridded detail is limited.

2. EDGAR



EDGAR is one of the few global inventories with explicit spatial grids.

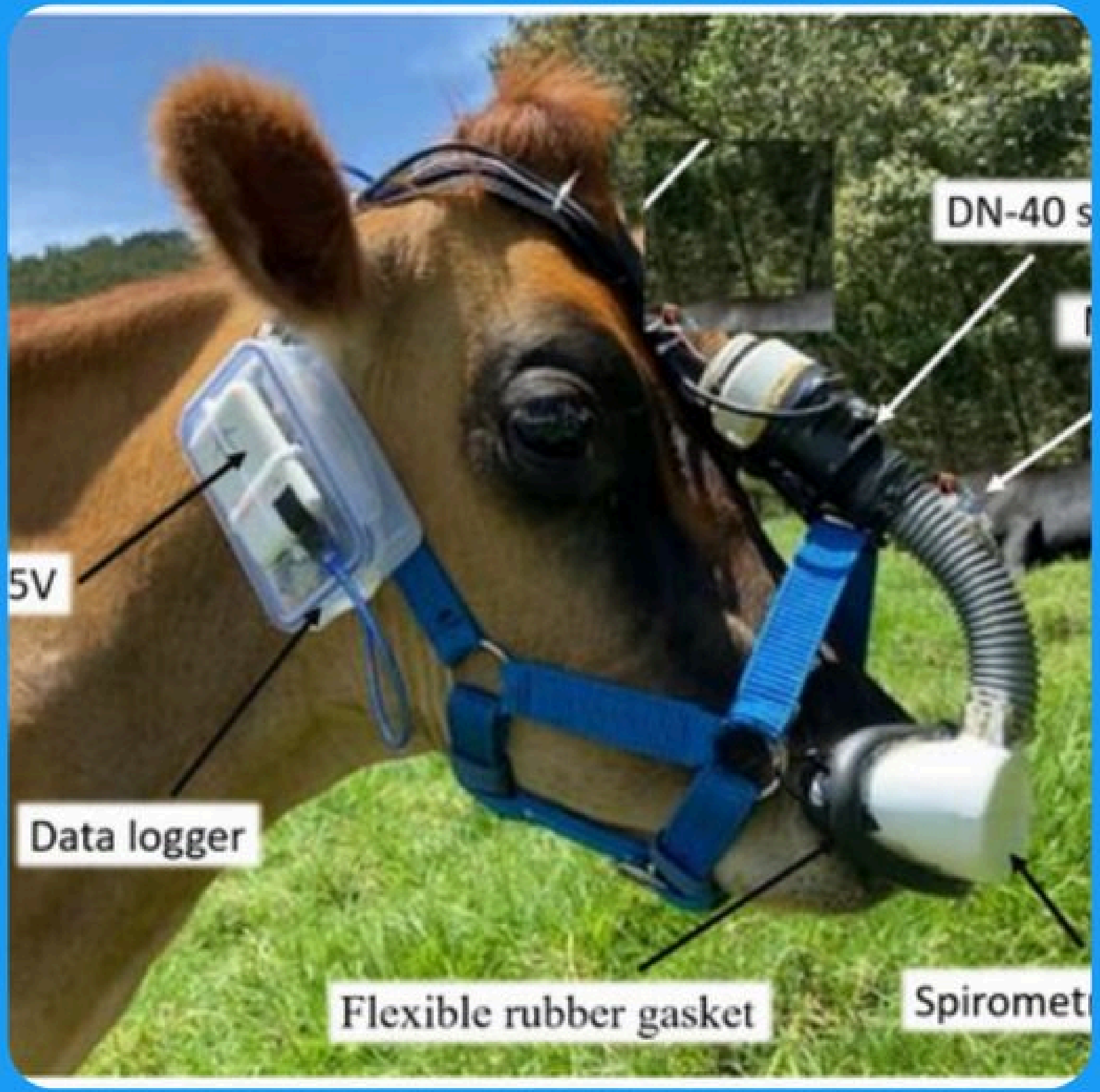
Resolution: 0.1° (~10 km).

3. LAPIG

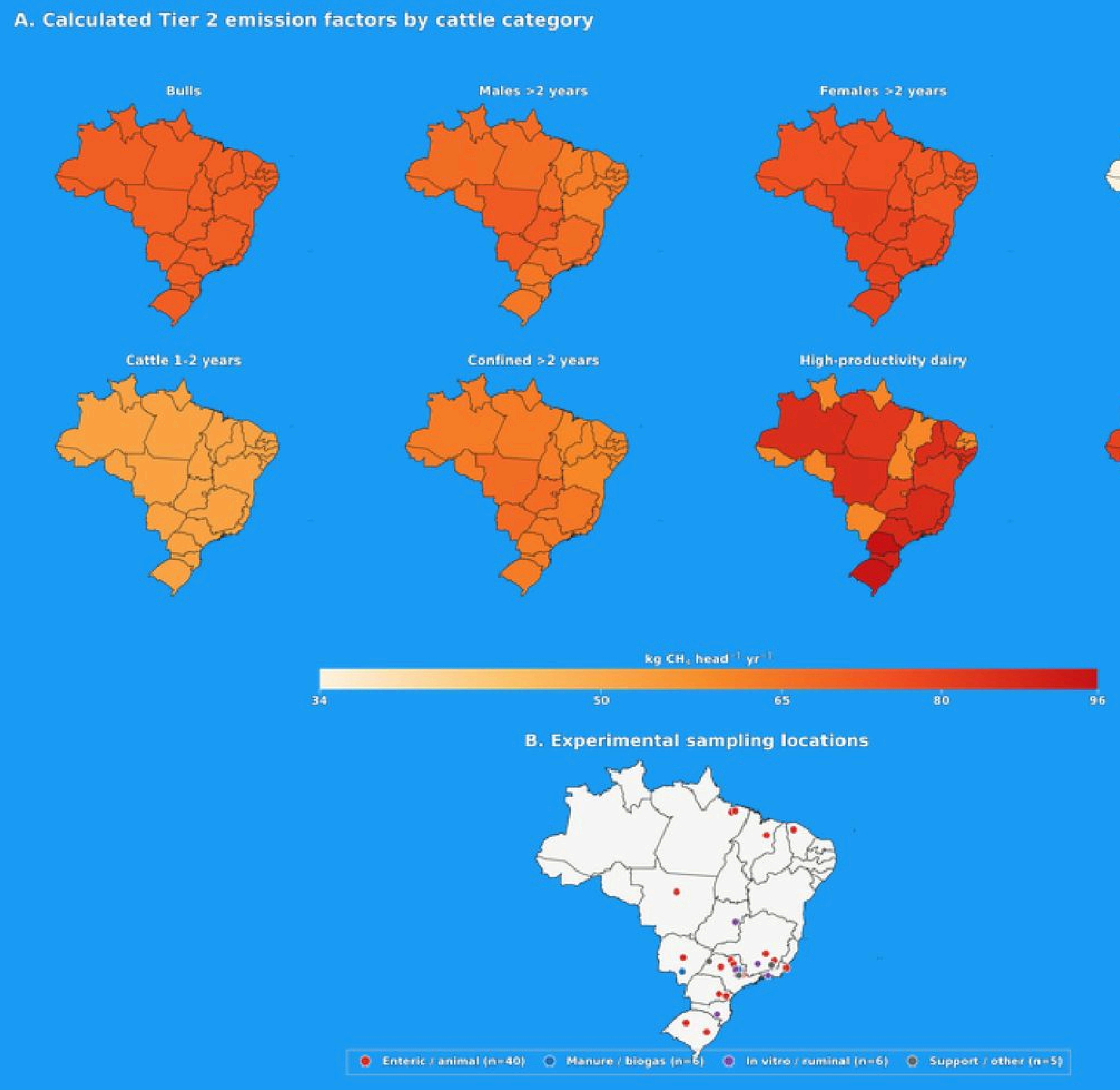
At LAPIG, we developed a livestock methane inventory using a Tier 1.5 bottom-up approach at 1 km resolution for 2000–2022.

This provides a more detailed view of the spatial distribution and historical evolution of methane emissions in Brazil.

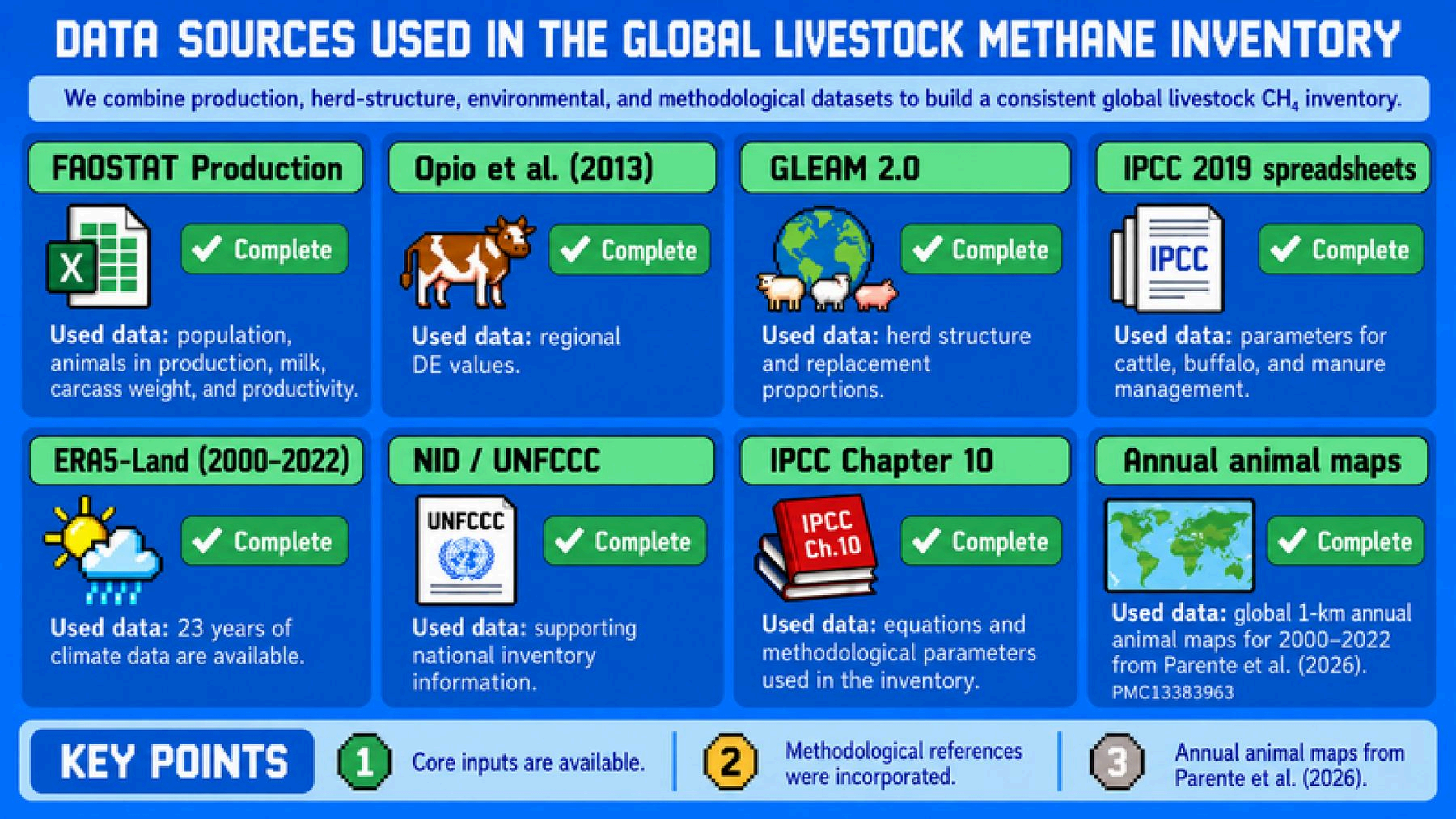
INTERESTING FACT: SOME WAYS TO ESTIMATE METHANE EMISSIONS IN THE FIELD.



METHODOLOGY ADOPTED AND RESULTS OF THE BOTTOM-UP INVENTORY



A. Calculated Tier 2 emission factors by cattle category
Bulls
Males >2 years
Females >2 years
Cattle <1 year
Cattle 1-2 years
Confined >2 years
High-productivity dairy
Low-productivity dairy
kg CH_4 head^{-1} yr^{-1}
34
50
65
80
96
B. Experimental sampling locations
Enteric / animal (n=40)
Manure / biogas (n=6)
In vitro / ruminal (n=6)
Support / other (n=5)


DATA SOURCES USED IN THE GLOBAL LIVESTOCK METHANE INVENTORY
We combine production, herd-structure, environmental, and methodological datasets to build a consistent global livestock CH_4 inventory.
FAOSTAT Production
X
✔ Complete
Used data: population, animals in production, milk, carcass weight, and productivity.
Opio et al. (2013)
✔ Complete
Used data: regional DE values.
GLEAM 2.0
✔ Complete
Used data: herd structure and replacement proportions.
IPCC 2019 spreadsheets
IPCC
✔ Complete
Used data: parameters for cattle, buffalo, and manure management.
ERA5-Land (2000–2022)
✔ Complete
Used data: 23 years of climate data are available.
NID / UNFCCC
UNFCCC
✔ Complete
Used data: supporting national inventory information.
IPCC Chapter 10
IPCC Ch.10
✔ Complete
Used data: equations and methodological parameters used in the inventory.
Annual animal maps
✔ Complete
Used data: global 1-km annual animal maps for 2000–2022 from Parente et al. (2026).
PMC13383963
KEY POINTS
1
Core inputs are available.
2
Methodological references were incorporated.
3
Annual animal maps from Parente et al. (2026).

Global distribution of cattle, horses, goats, sheep and buffaloes at 1 km resolution for 2000–2022 based on subnational census data and spatiotemporal machine learning

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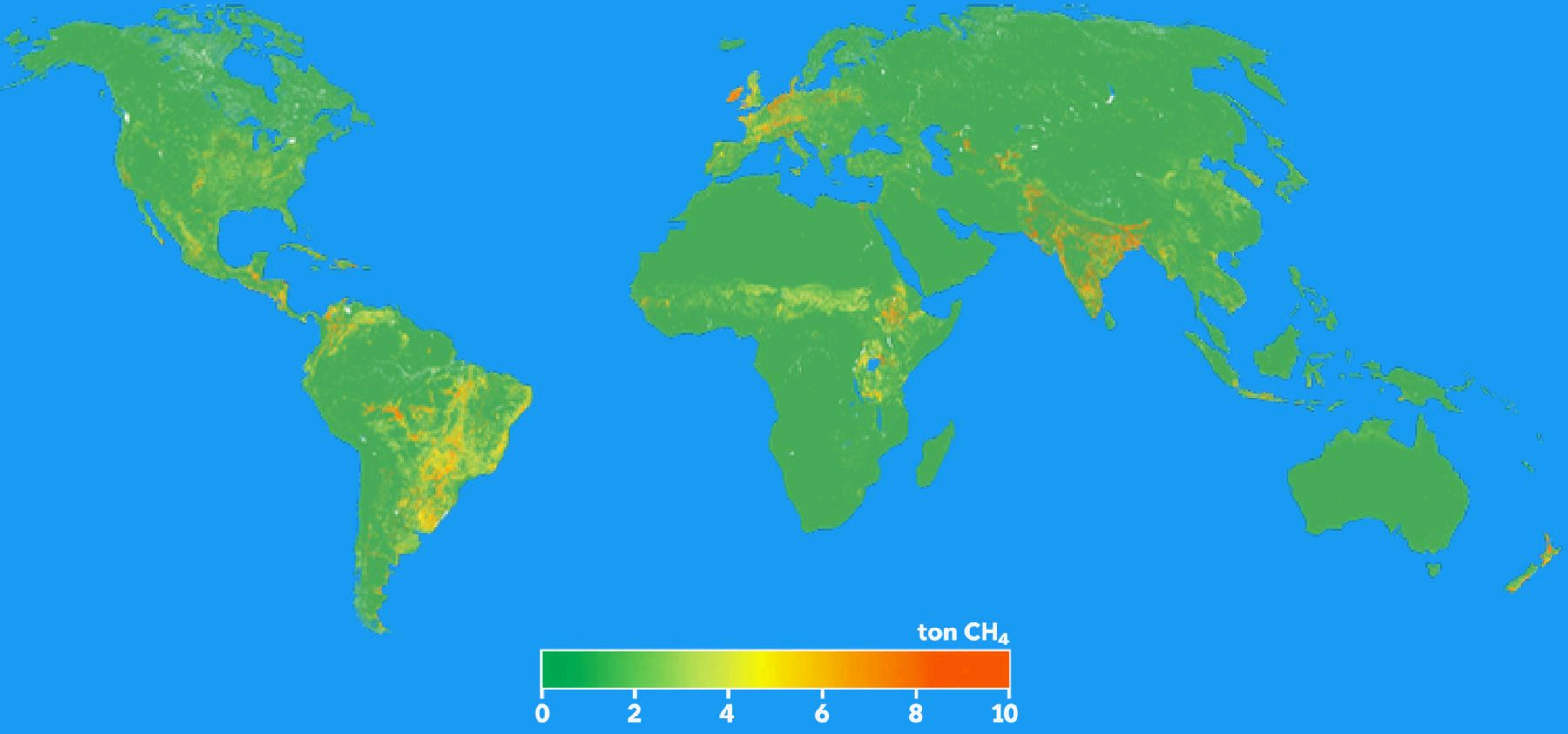
ABSTRACT

The article describes the production and evaluation of annual livestock densities and headcounts of cattle, horses, sheep, goats and buffaloes (including 95% probability prediction intervals) at 1 km spatial resolution for the 2000–2022 period using spatiotemporal machine learning. A compilation of subnational livestock census data has been imported, harmonized and used as reference data (55,336 census polygons and 939,257 individual data entries; covering 147 countries) to build predictive models. A large stack of multi-source harmonized raster data sets (128 individual layers) were used as features. Models were fitted using scikit-map and scikit-learn libraries with recursive feature elimination and Poisson criteria to represent the distribution of the target variable. Intermediate rasters estimating potential land for livestock production based on grassland and cropland extent, along with biophysical features, were used to estimate the spatial domain of livestock. The final predictions

LAPIG Global Livestock Methane Emissions Inventory at 1-km Spatial Resolution (2022)



Africa — Top 10 emitters

Cattle

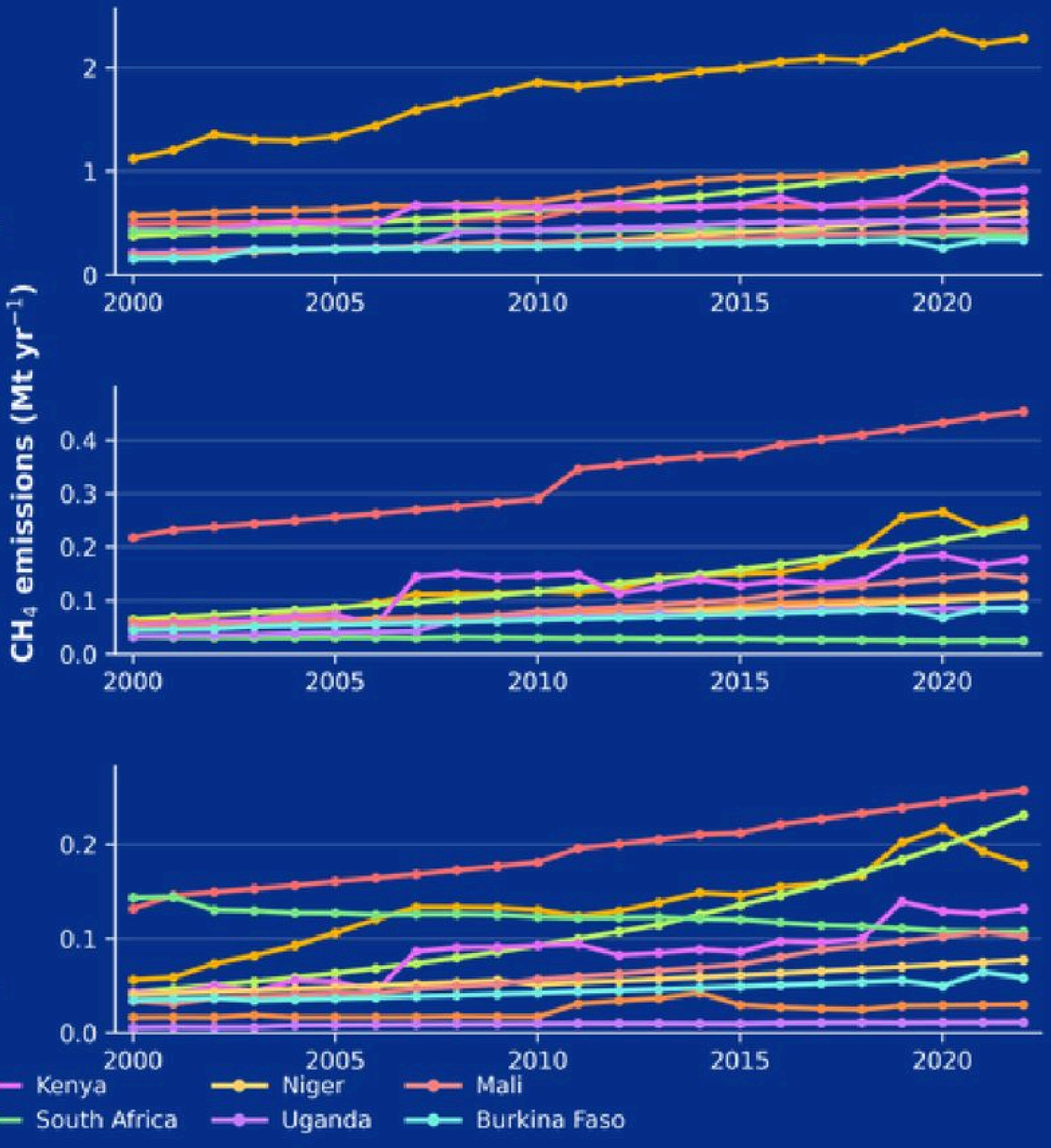
Ethiopia: τ=0.94, S=+0.053*
Nigeria: τ=0.98, S=+0.010*
Chad: τ=1.00, S=+0.034*
Tanzania: τ=1.00, S=+0.026*
Kenya: τ=0.77, S=+0.017*
South Africa: τ=-0.33, S=-0.002*
Niger: τ=0.99, S=+0.018*
Uganda: τ=0.96, S=+0.014*
Mali: τ=0.98, S=+0.011*
Burkina Faso: τ=0.91, S=+0.006*

Goat

Ethiopia: τ=0.96, S=+0.008*
Nigeria: τ=1.00, S=+0.011*
Chad: τ=1.00, S=+0.008*
Tanzania: τ=0.98, S=+0.003*
Kenya: τ=0.58, S=+0.005*
South Africa: τ=-0.86, S=-0.000*
Niger: τ=0.99, S=+0.003*
Uganda: τ=0.96, S=+0.003*
Mali: τ=0.98, S=+0.005*
Burkina Faso: τ=0.94, S=+0.002*

Sheep

Ethiopia: τ=0.84, S=+0.006*
Nigeria: τ=1.00, S=+0.006*
Chad: τ=1.00, S=+0.008*
Tanzania: τ=0.53, S=+0.001*
Kenya: τ=0.75, S=+0.004*
South Africa: τ=-0.94, S=-0.001*
Niger: τ=0.95, S=+0.002*
Uganda: τ=0.89, S=+0.000*
Mali: τ=0.98, S=+0.003*
Burkina Faso: τ=0.91, S=+0.001*



Ranking: total emissions across all successfully read species-years; τ = Kendall tau; S = Theil-Sen slope (Mt yr^{-1} yr^{-1}); * $p < 0.05$

Asia — Top 10 emitters

Cattle

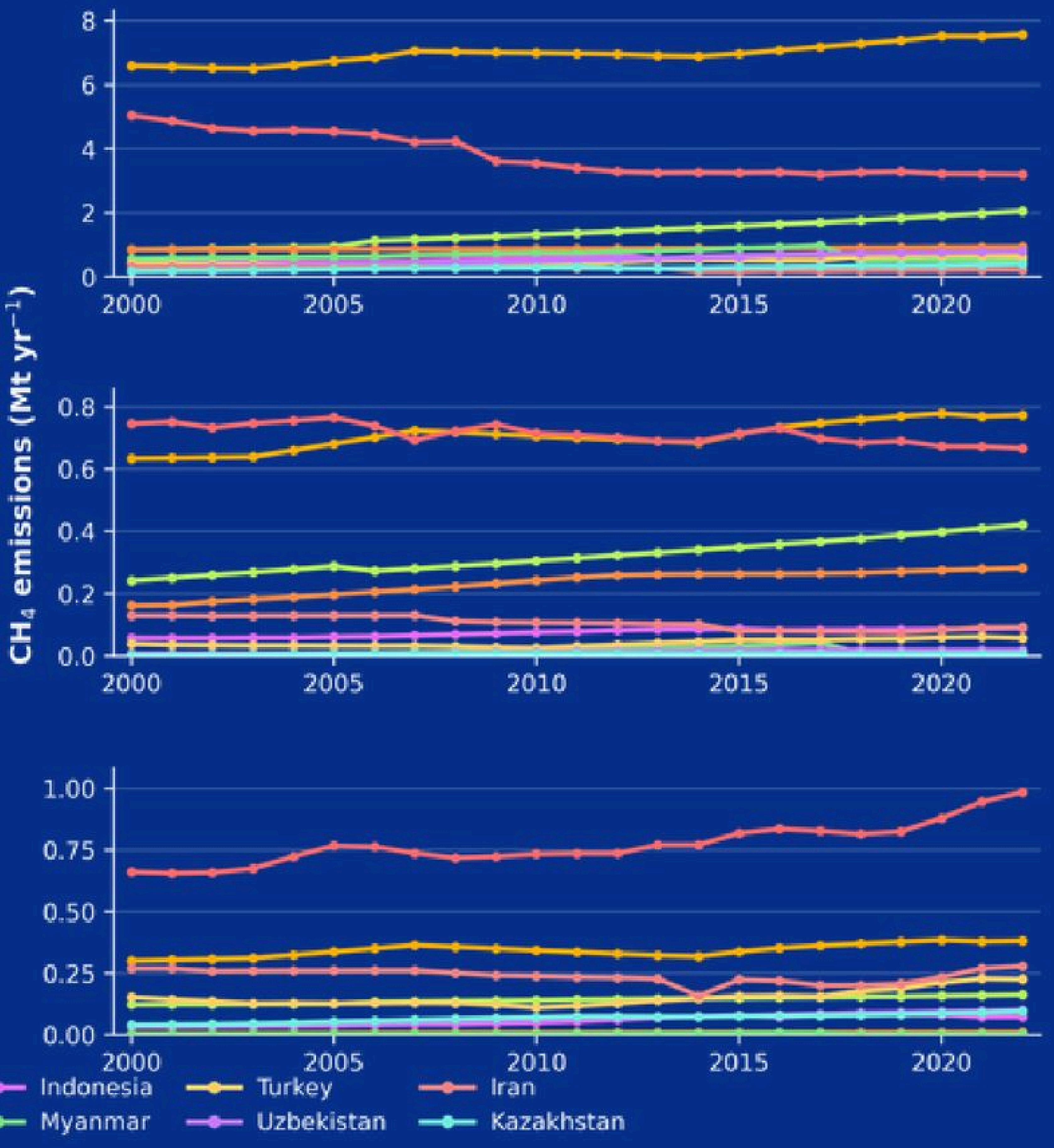
India: τ=0.68, S=+0.044*
China: τ=-0.85, S=-0.086*
Pakistan: τ=1.00, S=+0.055*
Bangladesh: τ=1.00, S=+0.004*
Indonesia: τ=0.83, S=+0.018*
Myanmar: τ=0.27, S=+0.016
Turkey: τ=0.70, S=+0.014*
Uzbekistan: τ=1.00, S=+0.025*
Iran: τ=-0.50, S=-0.005*
Kazakhstan: τ=0.88, S=+0.009*

Goat

India: τ=0.71, S=+0.006*
China: τ=-0.68, S=-0.004*
Pakistan: τ=0.98, S=+0.009*
Bangladesh: τ=1.00, S=+0.006*
Indonesia: τ=0.87, S=+0.002*
Myanmar: τ=0.54, S=+0.001*
Turkey: τ=0.49, S=+0.001*
Uzbekistan: τ=0.87, S=+0.001*
Iran: τ=-0.68, S=-0.002*
Kazakhstan: τ=0.18, S=+0.000

Sheep

India: τ=0.60, S=+0.003*
China: τ=0.79, S=+0.010*
Pakistan: τ=1.00, S=+0.002*
Bangladesh: τ=0.92, S=+0.000*
Indonesia: τ=0.87, S=+0.003*
Myanmar: τ=0.34, S=+0.000*
Turkey: τ=0.46, S=+0.003*
Uzbekistan: τ=1.00, S=+0.003*
Iran: τ=-0.42, S=-0.003*
Kazakhstan: τ=0.97, S=+0.002*



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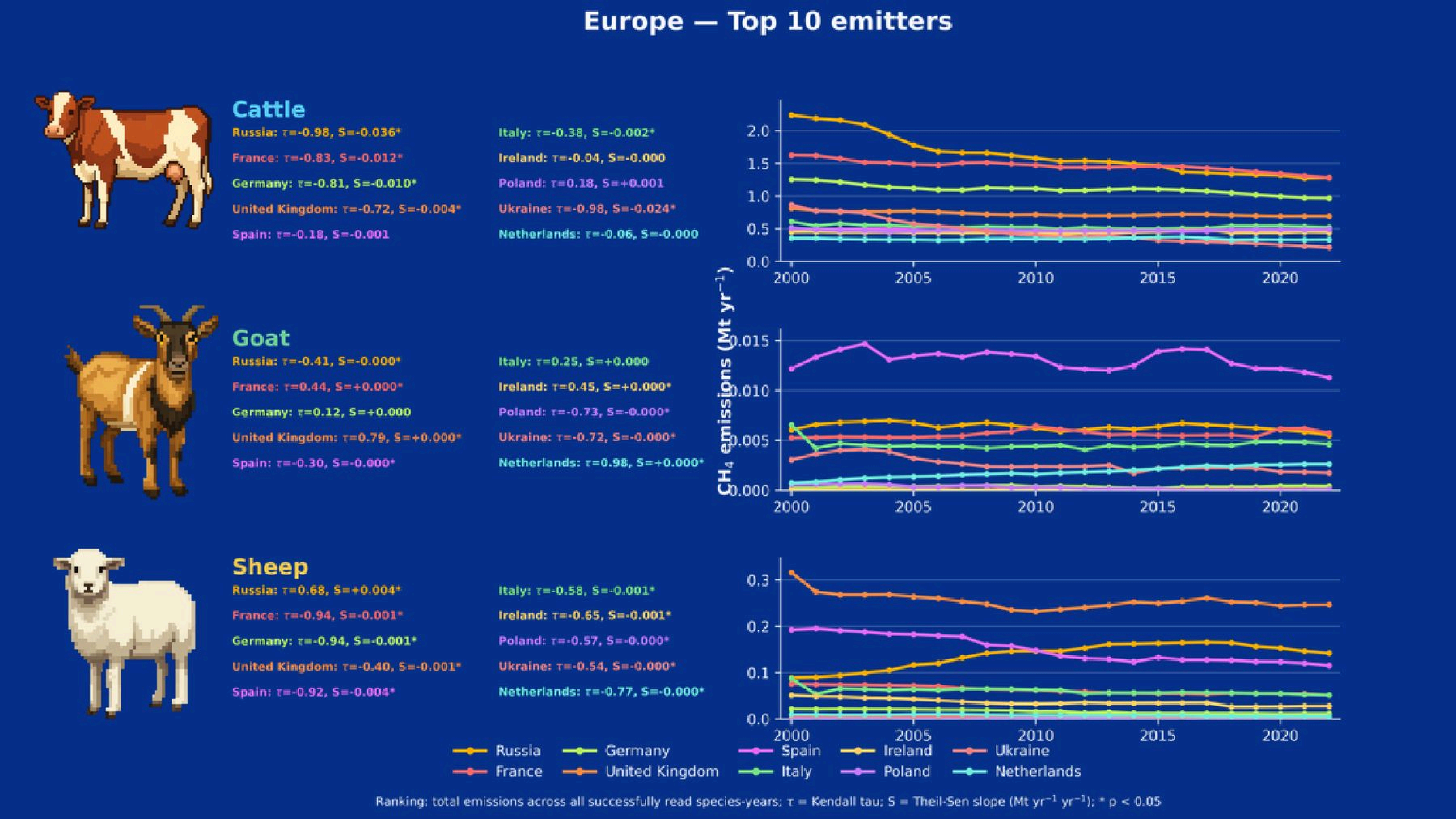


Europe — Top 10 emitters
Cattle
Russia: τ=-0.98, S=-0.036*
France: τ=-0.83, S=-0.012*
Germany: τ=-0.81, S=-0.010*
United Kingdom: τ=-0.72, S=-0.004*
Spain: τ=-0.18, S=-0.001
Italy: τ=-0.38, S=-0.002*
Ireland: τ=-0.04, S=-0.000
Poland: τ=0.18, S=+0.001
Ukraine: τ=-0.98, S=-0.024*
Netherlands: τ=-0.06, S=-0.000
Goat
Russia: τ=-0.41, S=-0.000*
France: τ=0.44, S=+0.000*
Germany: τ=0.12, S=+0.000
United Kingdom: τ=0.79, S=+0.000*
Spain: τ=-0.30, S=-0.000*
Italy: τ=0.25, S=+0.000
Ireland: τ=0.45, S=+0.000*
Poland: τ=-0.73, S=-0.000*
Ukraine: τ=-0.72, S=-0.000*
Netherlands: τ=0.98, S=+0.000*
Sheep
Russia: τ=0.68, S=+0.004*
France: τ=-0.94, S=-0.001*
Germany: τ=-0.94, S=-0.001*
United Kingdom: τ=-0.40, S=-0.001*
Spain: τ=-0.92, S=-0.004*
Italy: τ=-0.58, S=-0.001*
Ireland: τ=-0.65, S=-0.001*
Poland: τ=-0.57, S=-0.000*
Ukraine: τ=-0.54, S=-0.000*
Netherlands: τ=-0.77, S=-0.000*
CH4 emissions (Mt yr−1)
0.0
0.5
1.0
1.5
2.0
0.000
0.005
0.010
0.015
0.0
0.1
0.2
0.3
2000
2005
2010
2015
2020
Russia
Germany
Spain
Ireland
Ukraine
France
United Kingdom
Italy
Poland
Netherlands
Ranking: total emissions across all successfully read species-years; τ = Kendall tau; S = Theil-Sen slope (Mt yr−1 yr−1); * p < 0.05

North America — Top 10 emitters

Cattle

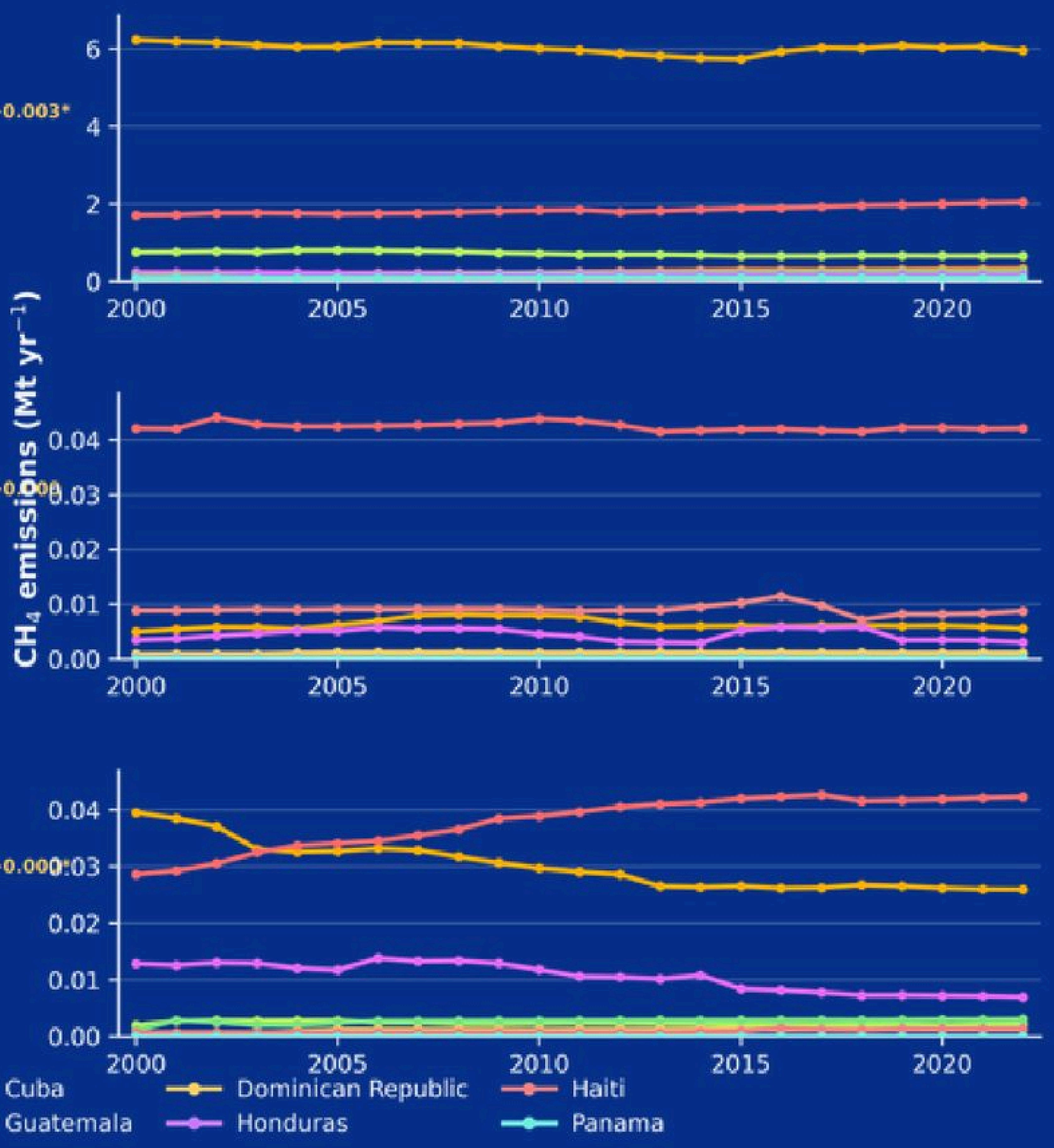
USA: τ=-0.46, S=-0.011*
Mexico: τ=0.88, S=+0.015*
Canada: τ=-0.66, S=-0.007*
Nicaragua: τ=0.97, S=+0.007*
Cuba: τ=-0.31, S=-0.001*
Guatemala: τ=0.95, S=+0.005*
Dominican Republic: τ=0.84, S=+0.003*
Honduras: τ=0.98, S=+0.002*
Haiti: τ=0.57, S=+0.000*
Panama: τ=0.02, S=+0.000

Goat

USA: τ=0.04, S=+0.000
Mexico: τ=-0.24, S=-0.000
Canada: τ=0.12, S=+0.000
Nicaragua: τ=-0.33, S=-0.000*
Cuba: τ=-0.08, S=-0.000
Guatemala: τ=0.03, S=+0.000
Dominican Republic: τ=0.05, S=+0.000
Honduras: τ=-0.48, S=-0.000*
Haiti: τ=-0.03, S=-0.000
Panama: τ=0.57, S=+0.000*

Sheep

USA: τ=-0.85, S=-0.001*
Mexico: τ=0.90, S=+0.001*
Canada: τ=-0.51, S=-0.000*
Nicaragua: τ=0.03, S=+0.000
Cuba: τ=-0.75, S=-0.000*
Guatemala: τ=0.86, S=+0.000*
Dominican Republic: τ=0.68, S=+0.000*
Honduras: τ=-0.19, S=-0.000
Haiti: τ=0.60, S=+0.000*
Panama: τ=NA, S=-0.000



Ranking: total emissions across all successfully read species-years; τ = Kendall tau; S = Theil-Sen slope (Mt yr^{-1} yr^{-1}); * $p < 0.05$

South America — Top 10 emitters

Cattle

Brazil: τ=0.82, S=+0.090*

Argentina: τ=0.06, S=+0.005

Colombia: τ=0.23, S=+0.005

Venezuela: τ=0.25, S=+0.002

Uruguay: τ=-0.00, S=-0.000

Paraguay: τ=0.72, S=+0.014*

Bolivia: τ=0.98, S=+0.011*

Peru: τ=0.82, S=+0.002*

Ecuador: τ=-0.33, S=-0.002*

Chile: τ=-0.64, S=-0.003*

Goat

Brazil: τ=0.29, S=+0.001

Argentina: τ=0.59, S=+0.000*

Colombia: τ=-0.03, S=-0.000

Venezuela: τ=0.82, S=+0.000*

Uruguay: τ=0.11, S=+0.000

Paraguay: τ=-0.38, S=-0.000*

Bolivia: τ=0.73, S=+0.000*

Peru: τ=-0.81, S=-0.000*

Ecuador: τ=-0.68, S=-0.000*

Chile: τ=-0.79, S=-0.000*

Sheep

Brazil: τ=0.92, S=+0.001*

Argentina: τ=-0.20, S=-0.000

Colombia: τ=-0.42, S=-0.000*

Venezuela: τ=0.85, S=+0.000*

Uruguay: τ=-0.87, S=-0.001*

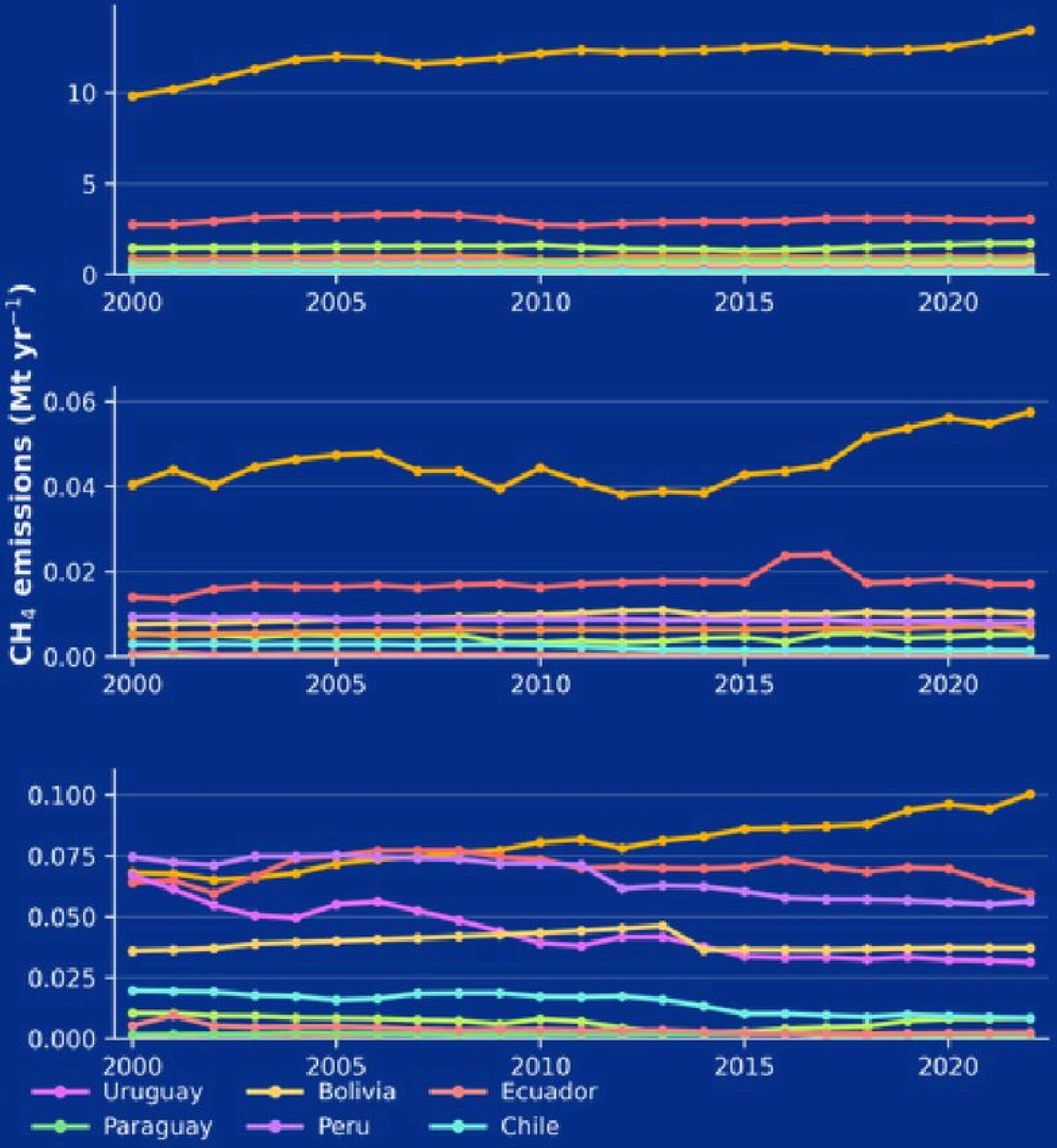
Paraguay: τ=-0.25, S=-0.000

Bolivia: τ=0.11, S=+0.000

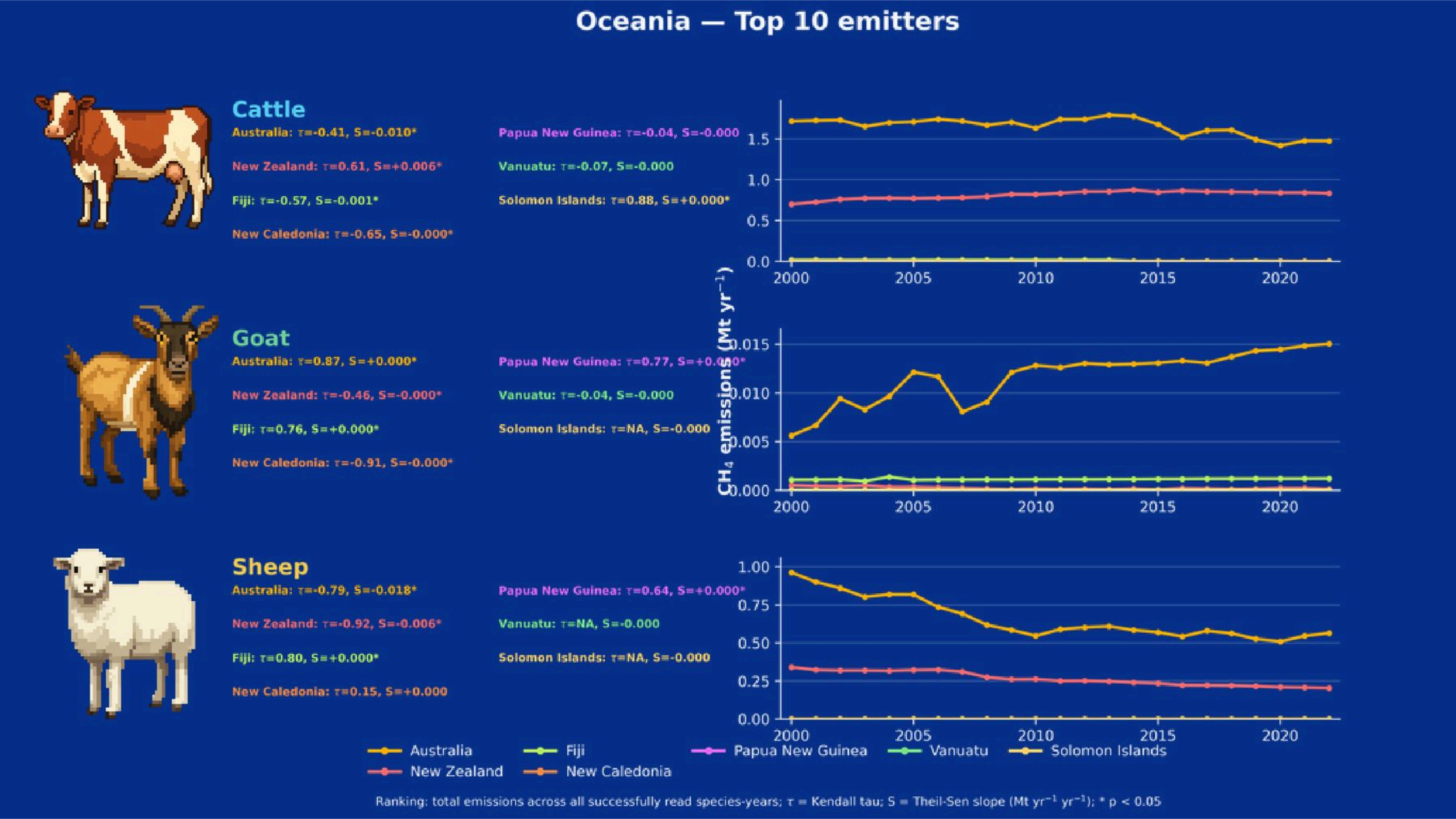
Peru: τ=-0.80, S=-0.001*

Ecuador: τ=-0.79, S=-0.000*

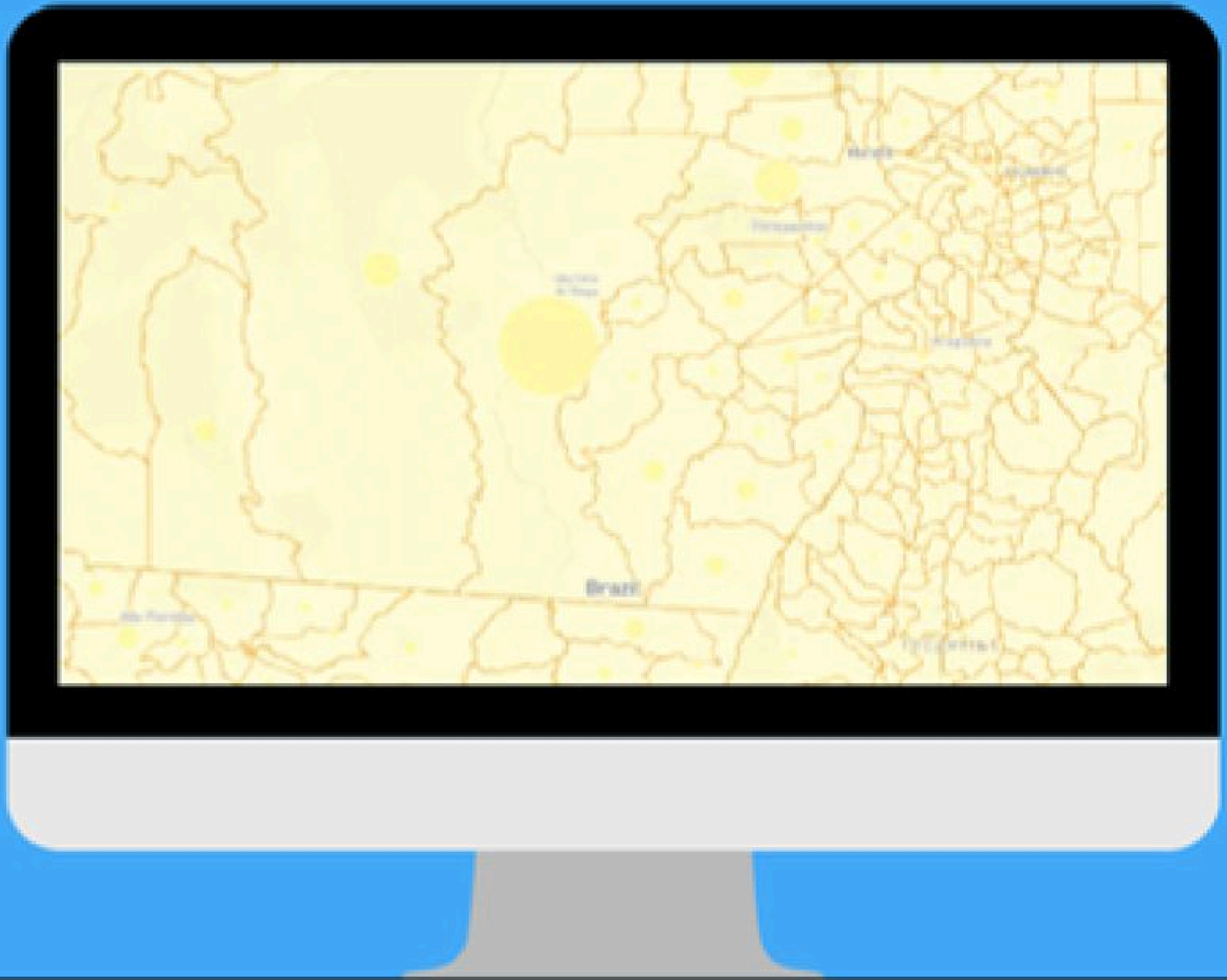
Chile: τ=-0.76, S=-0.001*



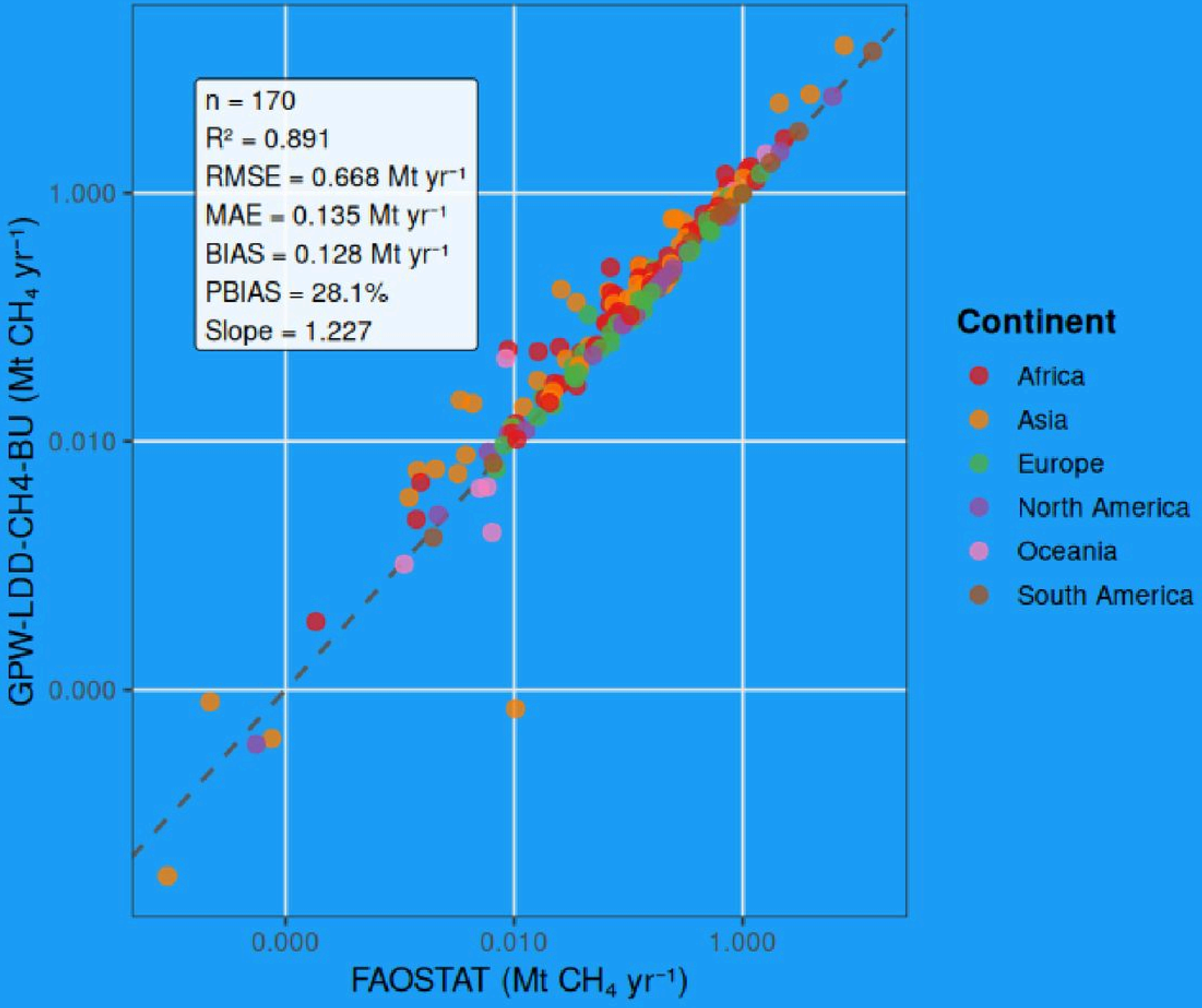
Ranking: total emissions across all successfully read species-years; τ = Kendall tau; S = Theil-Sen slope (Mt yr^{-1} yr^{-1}); * $p < 0.05$


Oceania — Top 10 emitters
Cattle
Australia: τ=-0.41, S=-0.010*
New Zealand: τ=0.61, S=+0.006*
Fiji: τ=-0.57, S=-0.001*
New Caledonia: τ=-0.65, S=-0.000*
Papua New Guinea: τ=-0.04, S=-0.000
Vanuatu: τ=-0.07, S=-0.000
Solomon Islands: τ=0.88, S=+0.000*
Goat
Australia: τ=0.87, S=+0.000*
New Zealand: τ=-0.46, S=-0.000*
Fiji: τ=0.76, S=+0.000*
New Caledonia: τ=-0.91, S=-0.000*
Papua New Guinea: τ=0.77, S=+0.000*
Vanuatu: τ=-0.04, S=-0.000
Solomon Islands: τ=NA, S=-0.000
Sheep
Australia: τ=-0.79, S=-0.018*
New Zealand: τ=-0.92, S=-0.006*
Fiji: τ=0.80, S=+0.000*
New Caledonia: τ=0.15, S=+0.000
Papua New Guinea: τ=0.64, S=+0.000*
Vanuatu: τ=NA, S=-0.000
Solomon Islands: τ=NA, S=-0.000
CH4 emissions (Mt yr−1)
0.0
0.5
1.0
1.5
0.000
0.005
0.010
0.015
0.00
0.25
0.50
0.75
1.00
2000
2005
2010
2015
2020
Australia
New Zealand
Fiji
New Caledonia
Papua New Guinea
Vanuatu
Solomon Islands
Ranking: total emissions across all successfully read species-years; τ = Kendall tau; S = Theil-Sen slope (Mt yr−1 yr−1); * p < 0.05

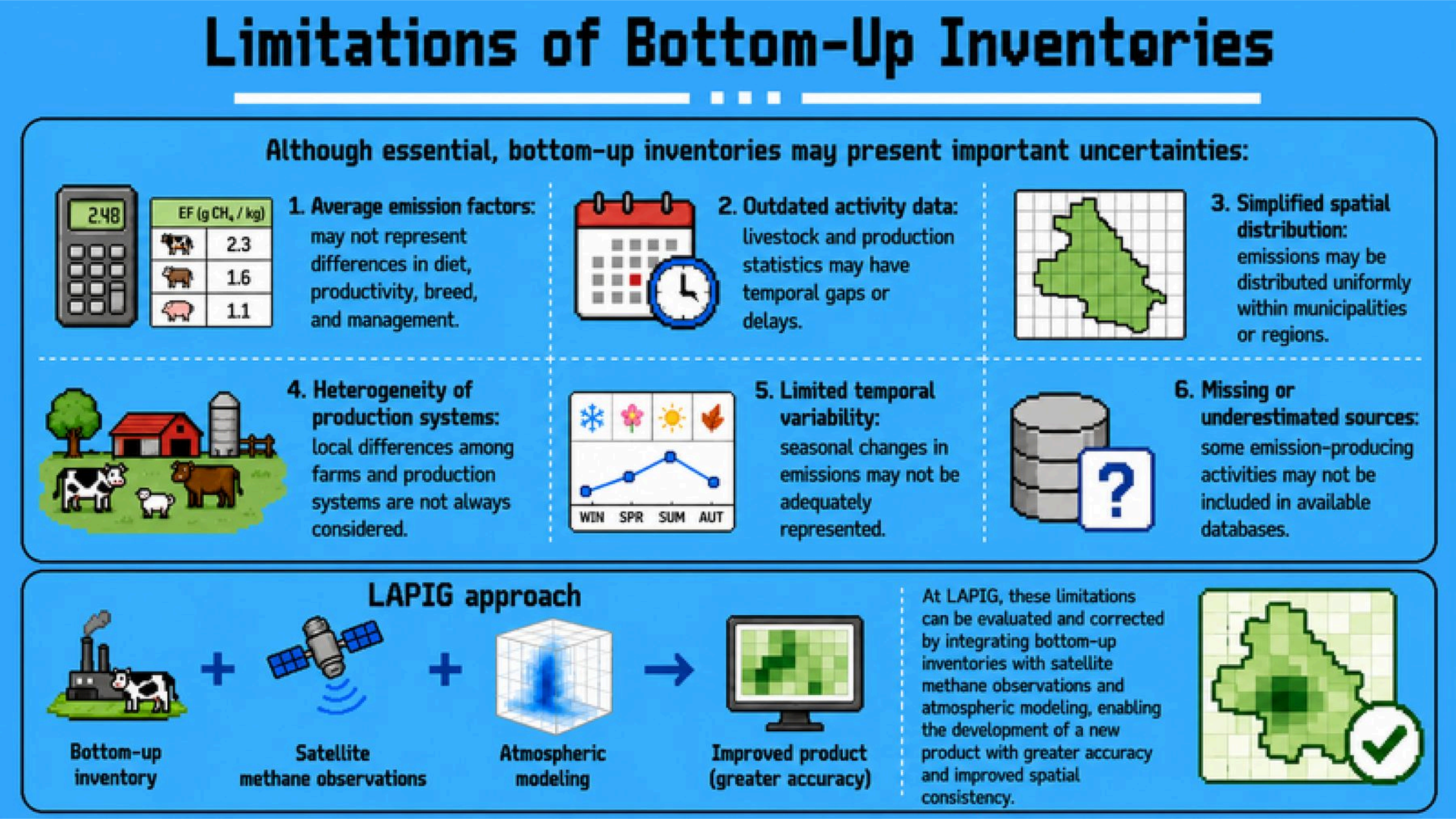
Traditional BU inventories

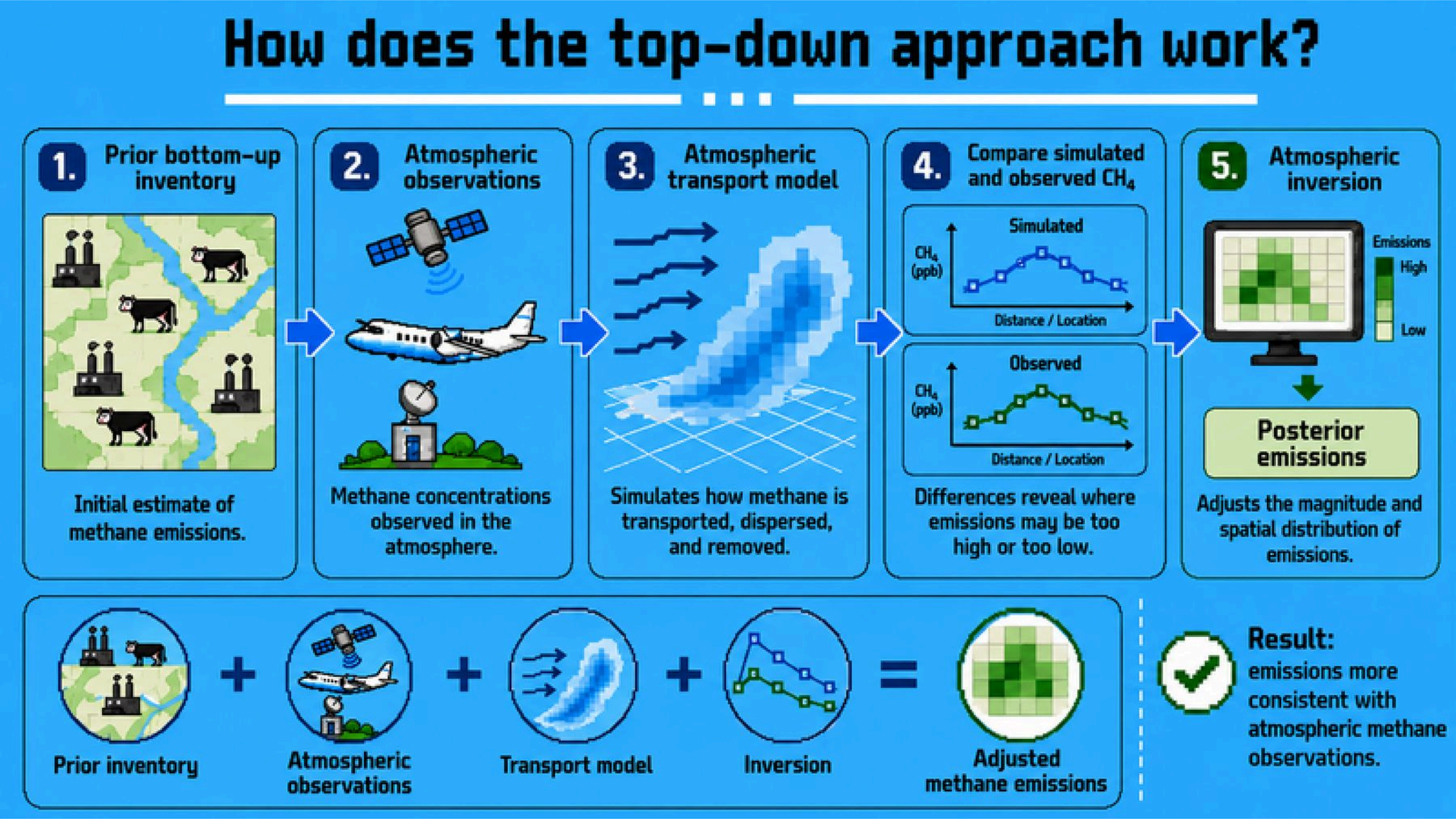


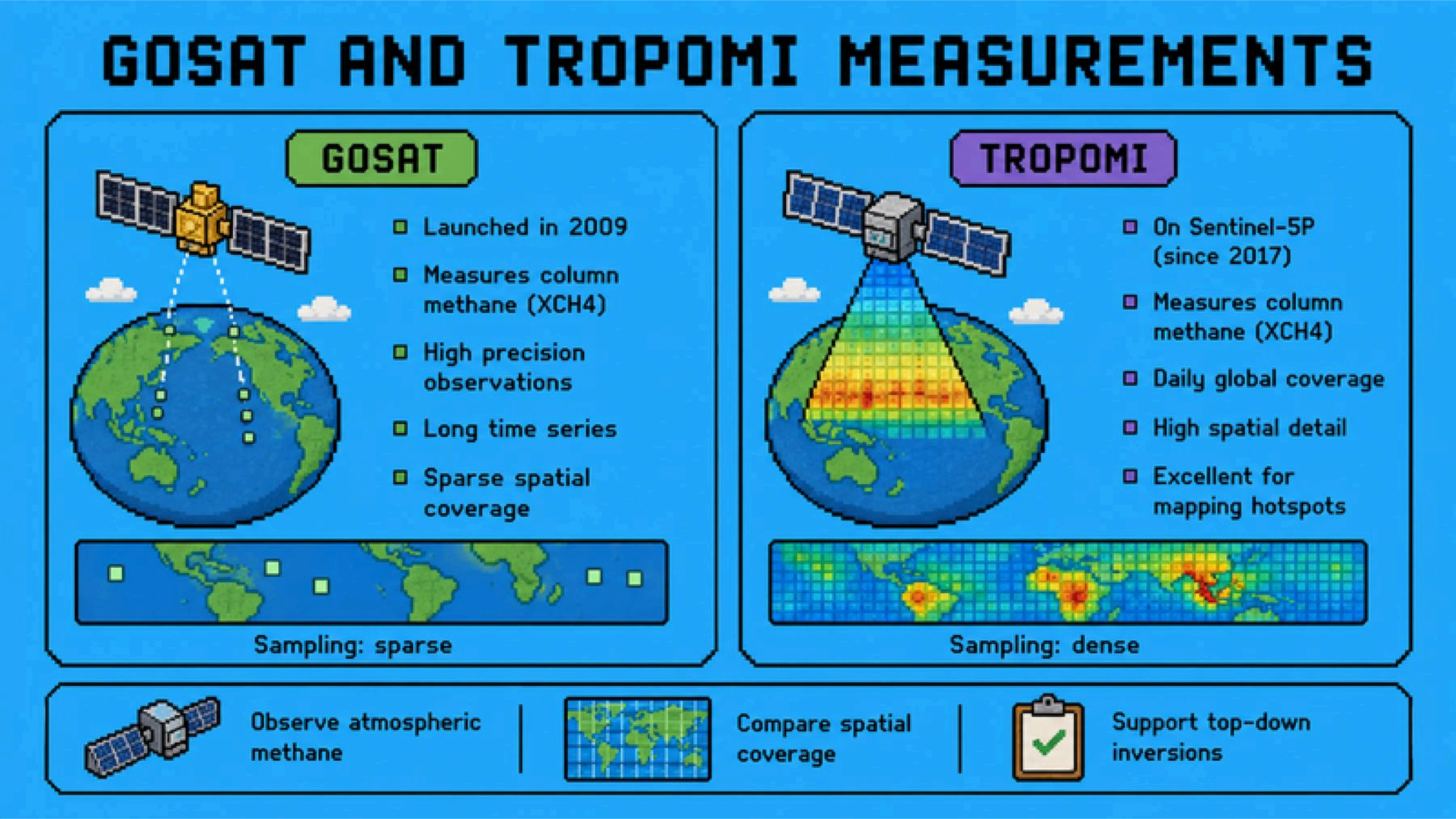
LAPIG BU Inventory

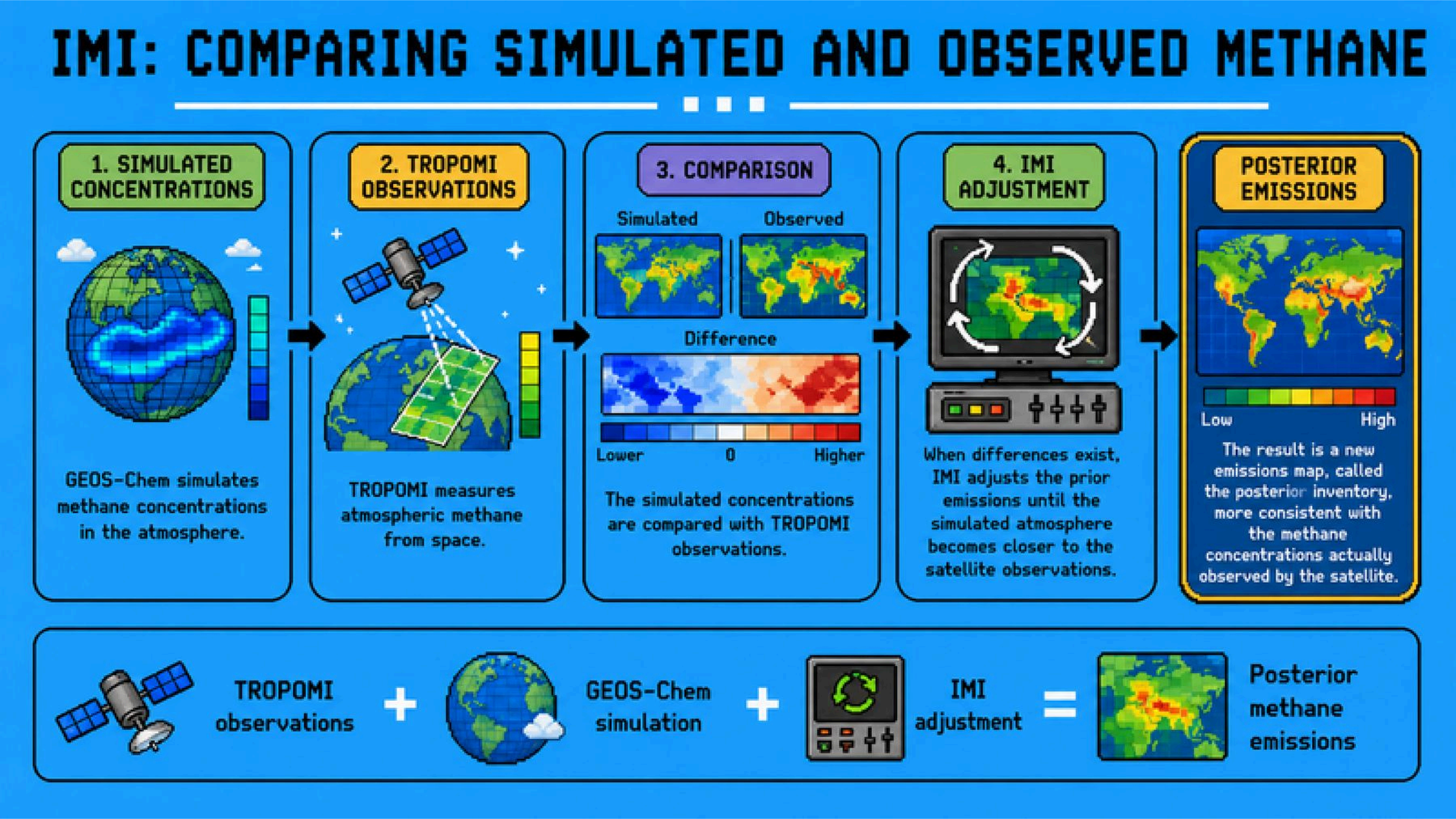


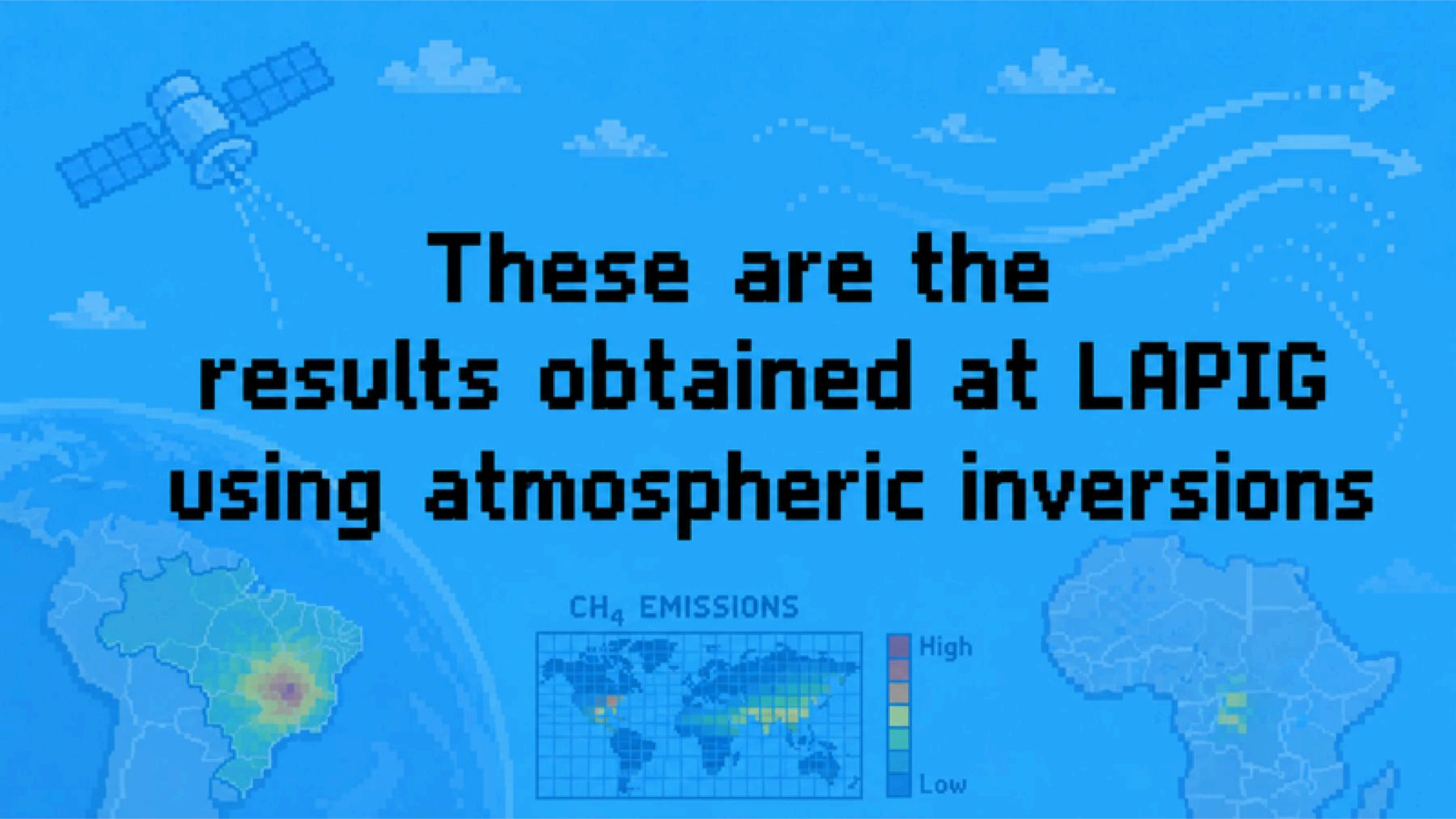
- Broad comparison base: 170 countries were evaluated (n = 170).
- Strong agreement: the model explained 89.1% of the FAOSTAT variability (R^2 = 0.891).
- Good accuracy: RMSE = 0.668 Mt CH_4 yr^{-1} and MAE = 0.135 Mt CH_4 yr^{-1}.
- Controlled bias: BIAS = 0.128 Mt CH_4 yr^{-1}, indicating a slight tendency toward overestimation.
- Percentage difference: PBIAS = 28.1%, highlighting opportunities for further refinement.
- Consistent response: the slope of 1.227 shows that the inventory effectively captures the variation in FAOSTAT emissions.


Limitations of Bottom-Up Inventories
Although essential, bottom-up inventories may present important uncertainties:
2.48
EF (g CH4 / kg)
2.3
1.6
1.1
1. Average emission factors: may not represent differences in diet, productivity, breed, and management.
2. Outdated activity data: livestock and production statistics may have temporal gaps or delays.
3. Simplified spatial distribution: emissions may be distributed uniformly within municipalities or regions.
4. Heterogeneity of production systems: local differences among farms and production systems are not always considered.
WIN SPR SUM AUT
5. Limited temporal variability: seasonal changes in emissions may not be adequately represented.
?
6. Missing or underestimated sources: some emission-producing activities may not be included in available databases.
LAPIG approach
Bottom-up inventory
+
Satellite methane observations
+
Atmospheric modeling
Improved product (greater accuracy)
At LAPIG, these limitations can be evaluated and corrected by integrating bottom-up inventories with satellite methane observations and atmospheric modeling, enabling the development of a new product with greater accuracy and improved spatial consistency.

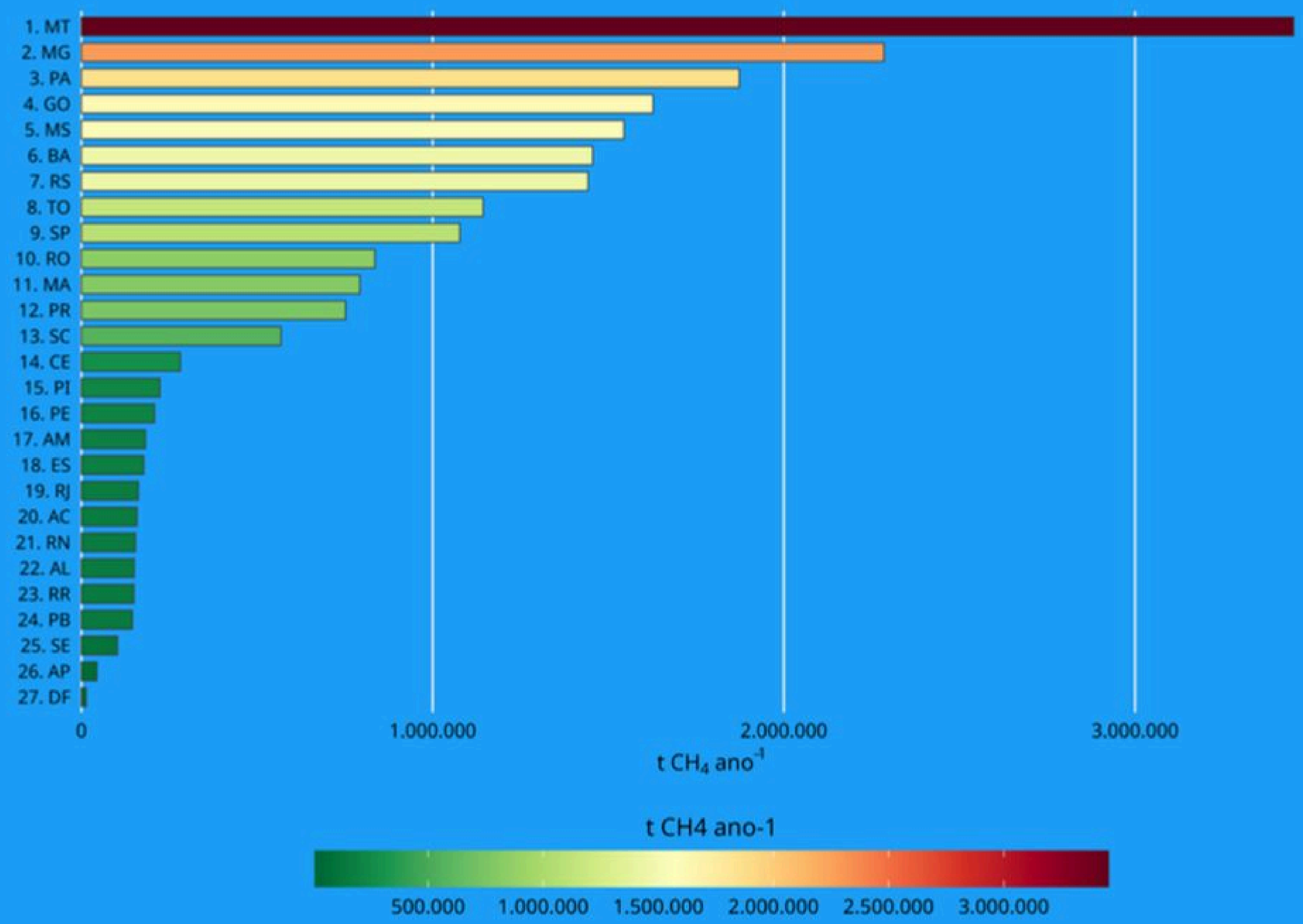

How does the top-down approach work?
1. Prior bottom-up inventory
Initial estimate of methane emissions.
2. Atmospheric observations
Methane concentrations observed in the atmosphere.
3. Atmospheric transport model
Simulates how methane is transported, dispersed, and removed.
4. Compare simulated and observed CH_4
Simulated
CH_4 (ppb)
Distance / Location
Observed
CH_4 (ppb)
Distance / Location
Differences reveal where emissions may be too high or too low.
5. Atmospheric inversion
Emissions
High
Low
Posterior emissions
Adjusts the magnitude and spatial distribution of emissions.
Prior inventory
+
Atmospheric observations
+
Transport model
+
Inversion
=
Adjusted methane emissions
Result:
emissions more consistent with atmospheric methane observations.

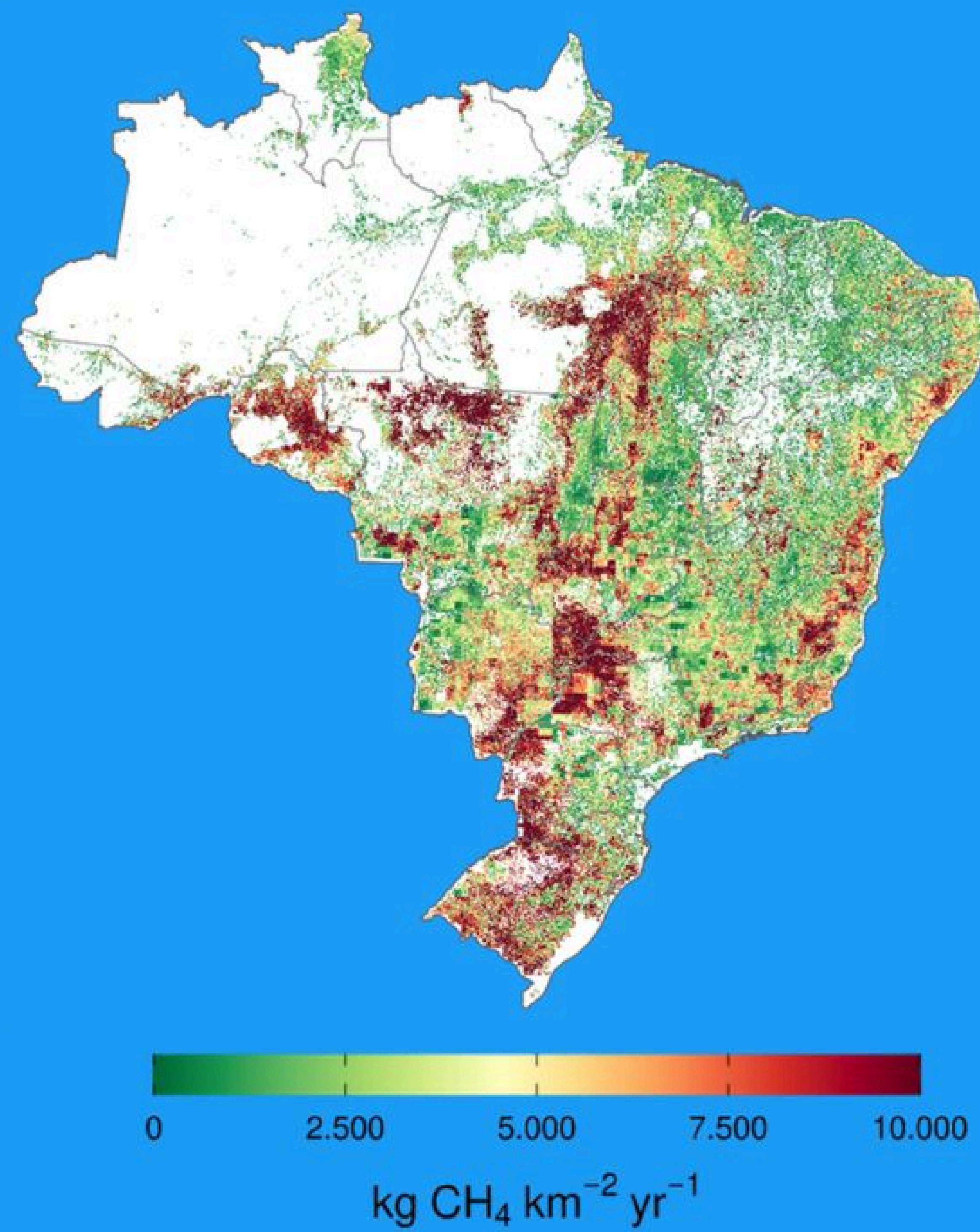

GOSAT AND TROPOMI MEASUREMENTS
GOSAT
Launched in 2009
Measures column methane (XCH4)
High precision observations
Long time series
Sparse spatial coverage
Sampling: sparse
TROPOMI
On Sentinel-5P (since 2017)
Measures column methane (XCH4)
Daily global coverage
High spatial detail
Excellent for mapping hotspots
Sampling: dense
Observe atmospheric methane
Compare spatial coverage
Support top-down inversions


IMI: COMPARING SIMULATED AND OBSERVED METHANE
1. SIMULATED CONCENTRATIONS
GEOS-Chem simulates methane concentrations in the atmosphere.
2. TROPOMI OBSERVATIONS
TROPOMI measures atmospheric methane from space.
3. COMPARISON
Simulated
Observed
Difference
Lower
0
Higher
The simulated concentrations are compared with TROPOMI observations.
4. IMI ADJUSTMENT
When differences exist, IMI adjusts the prior emissions until the simulated atmosphere becomes closer to the satellite observations.
POSTERIOR EMISSIONS
Low
High
The result is a new emissions map, called the posterior inventory, more consistent with the methane concentrations actually observed by the satellite.
TROPOMI observations
+
GEOS-Chem simulation
+
IMI adjustment
=
Posterior methane emissions

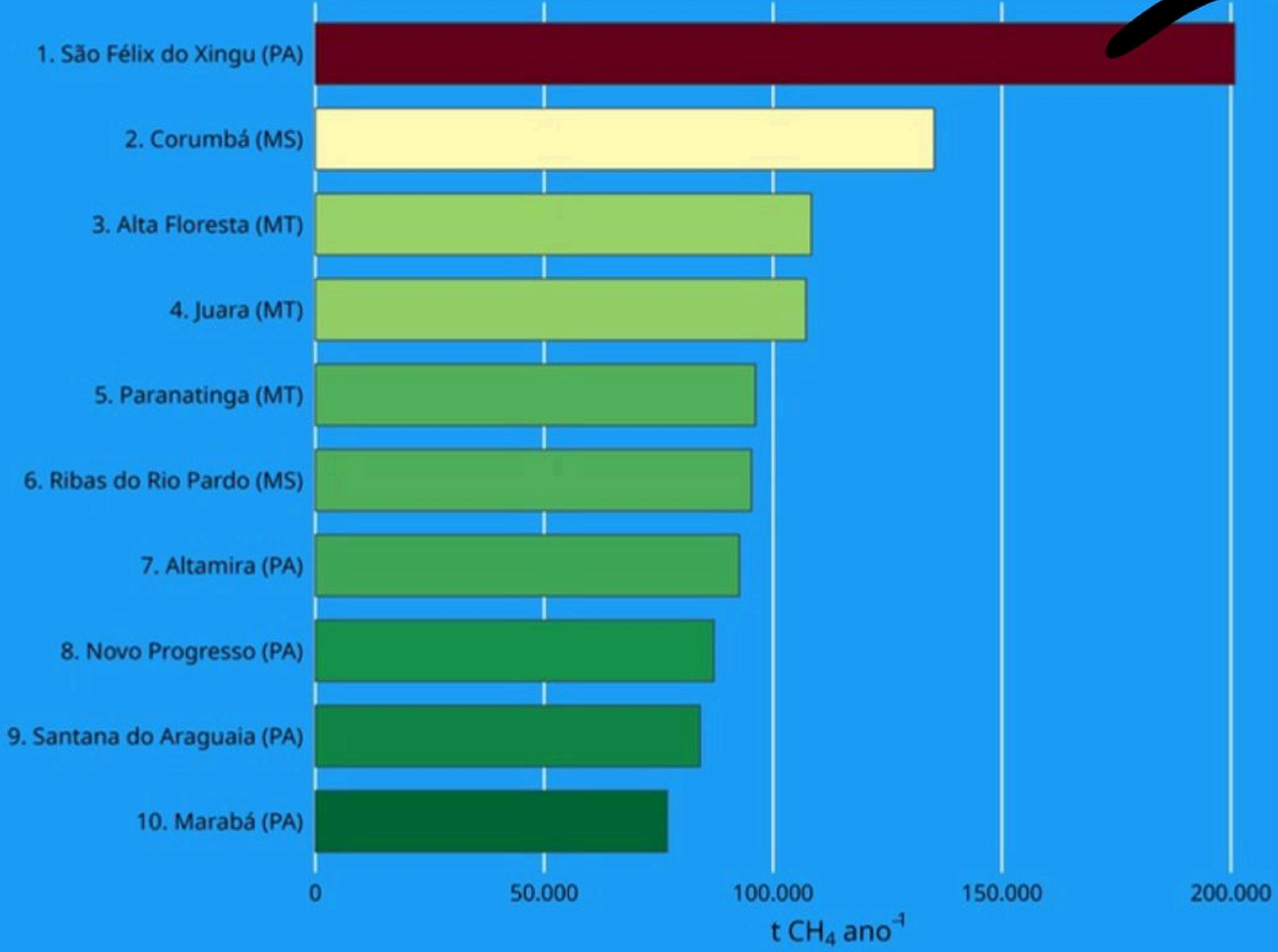

These are the
results obtained at LAPIG
using atmospheric inversions
CH4 EMISSIONS
High
Low

Overview of Brazilian emissions



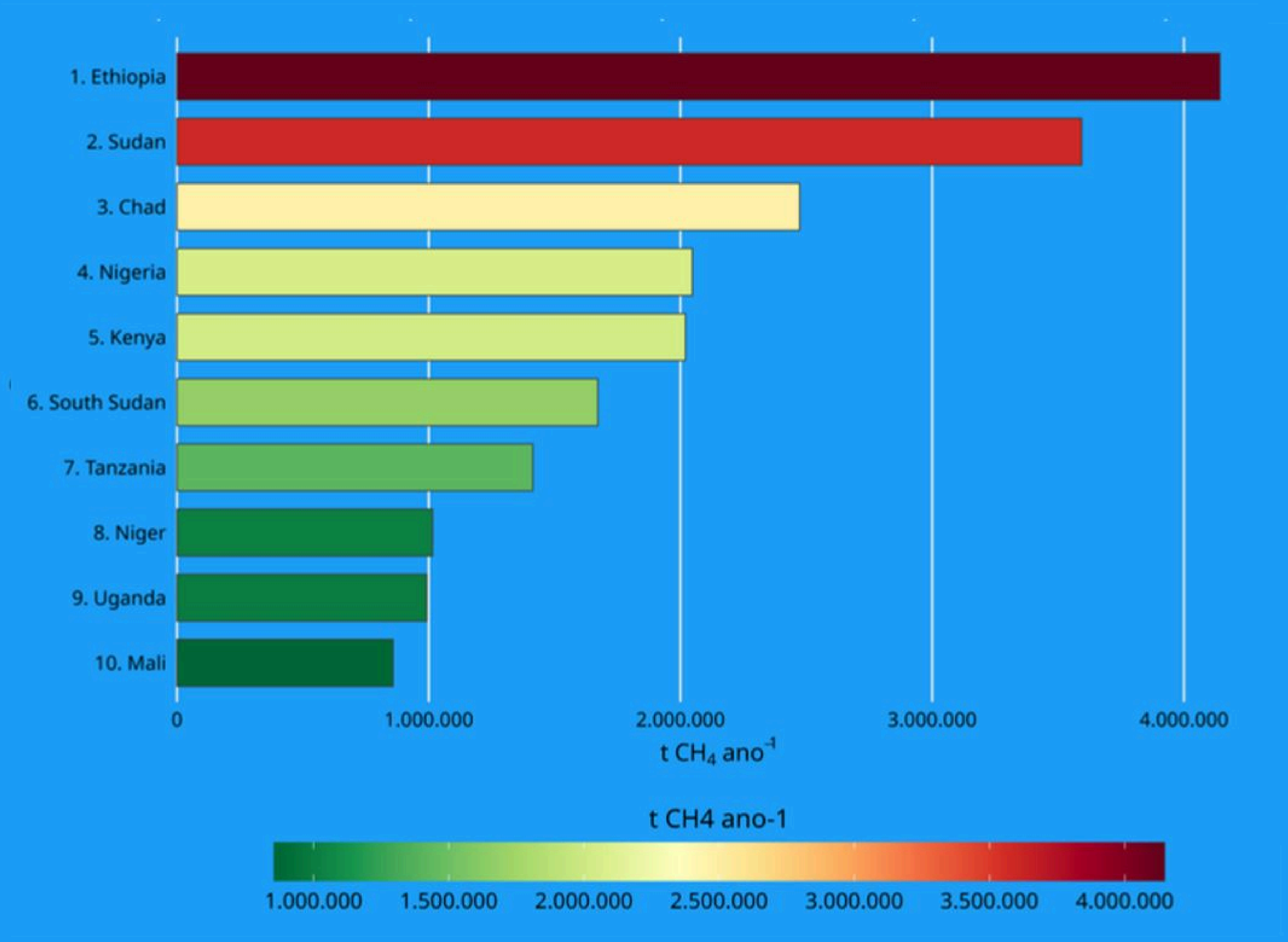


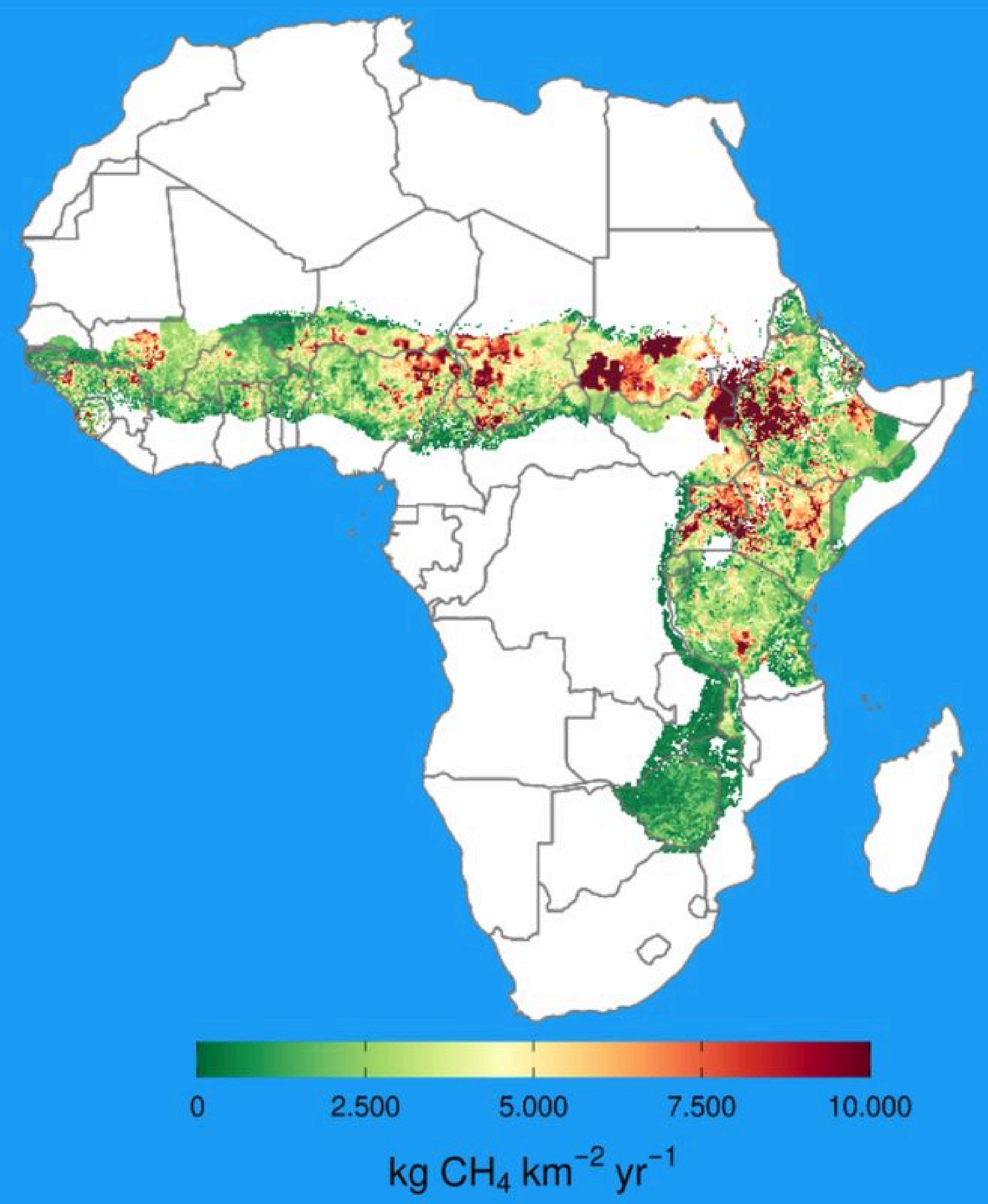
Overview of municipal emissions

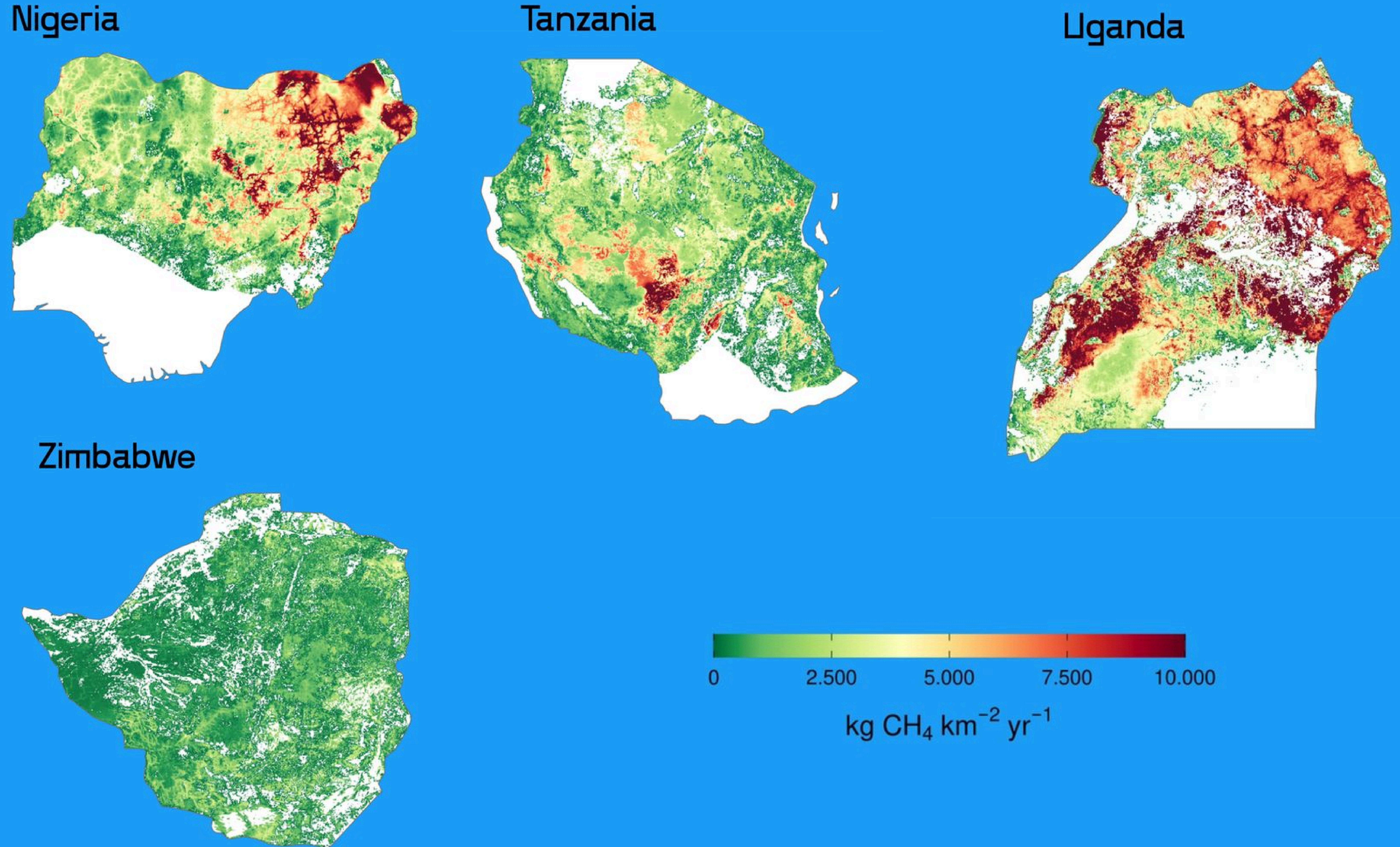


2.5 million head of cattle

Overview of emissions from African countries






Nigeria
Tanzania
Uganda
Zimbabwe
0
2.500
5.000
7.500
10.000
kg CH_4 km^{-2} yr^{-1}

A Global 1-km Inventory of Livestock Methane Emissions, 2000–2022: Integrating IPCC Methods with Annual Animal Population Maps

1 Introduction

Paragraph 1 — Relevance and global context. This paragraph should introduce livestock as a major anthropogenic source of methane, distinguish enteric fermentation from manure management, and explain the relevance of livestock CH_4 emissions to near-term climate mitigation, food production, and national greenhouse-gas reporting.

Paragraph 2 — Limitations of existing inventories. This paragraph should explain that global inventories differ because of their activity data, animal categorization, emission factors, temporal resolution, and spatial proxies. It should clarify that Tier 1 approaches generally apply broad default emission factors, whereas Tier 2 methods represent productivity, diet, animal characteristics, and manure-management practices more explicitly. The paragraph should also discuss the limitations of assigning national emissions to coarse or temporally static livestock maps.

Paragraph 3 — State of the art. This paragraph should summarize the progression from spatial inventories such as EDGAR and Gridded Livestock of the World to the long-term Tier 2 inventories developed by Dangal et al. and Zhang et al. It should highlight that Zhang et

The paragraph should emphasize the separation between enteric fermentation and manure management, the explicit treatment of animal categories, the conservation of national or regional totals, the documentation of the method applied to each estimate, the propagation of uncertainty, and the evaluation against national and independent global inventories.

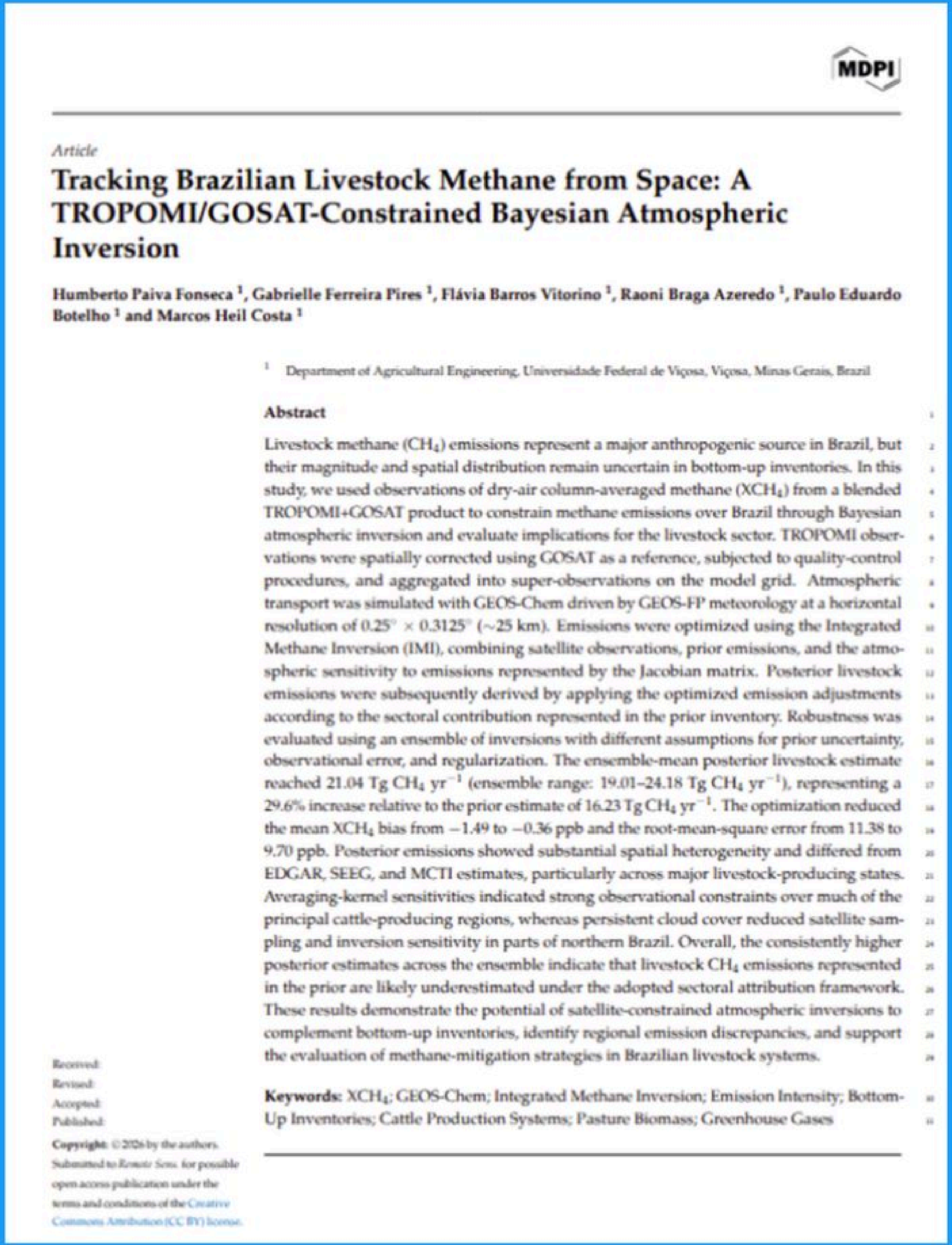
2 Materials and Methods

2.1 Inventory design and scope

The inventory will quantify annual methane emissions from livestock between 2000 and 2022. Emissions will be estimated separately for enteric fermentation and manure management and subsequently combined to obtain total livestock CH_4 emissions. The target spatial resolution will be 1 km in an equal-area grid.

The primary species will be cattle, buffaloes, sheep, goats, and horses, corresponding to the animals represented in the annual Global Pasture Watch (GPW) dataset [6]. Additional species, including pigs, camels, donkeys, and mules, may be incorporated only when a defensible species-specific spatial proxy is available.


It's almost over, I promise!



MDPI

Article

Tracking Brazilian Livestock Methane from Space: A TROPOMI/GOSAT-Constrained Bayesian Atmospheric Inversion

Humberto Paiva Fonseca [1], Gabrielle Ferreira Pires [1], Flávia Barros Vitorino [1], Raoni Braga Azeredo [1], Paulo Eduardo Botelho [1] and Marcos Heil Costa [1]

[1] Department of Agricultural Engineering, Universidade Federal de Viçosa, Viçosa, Minas Gerais, Brazil

Abstract

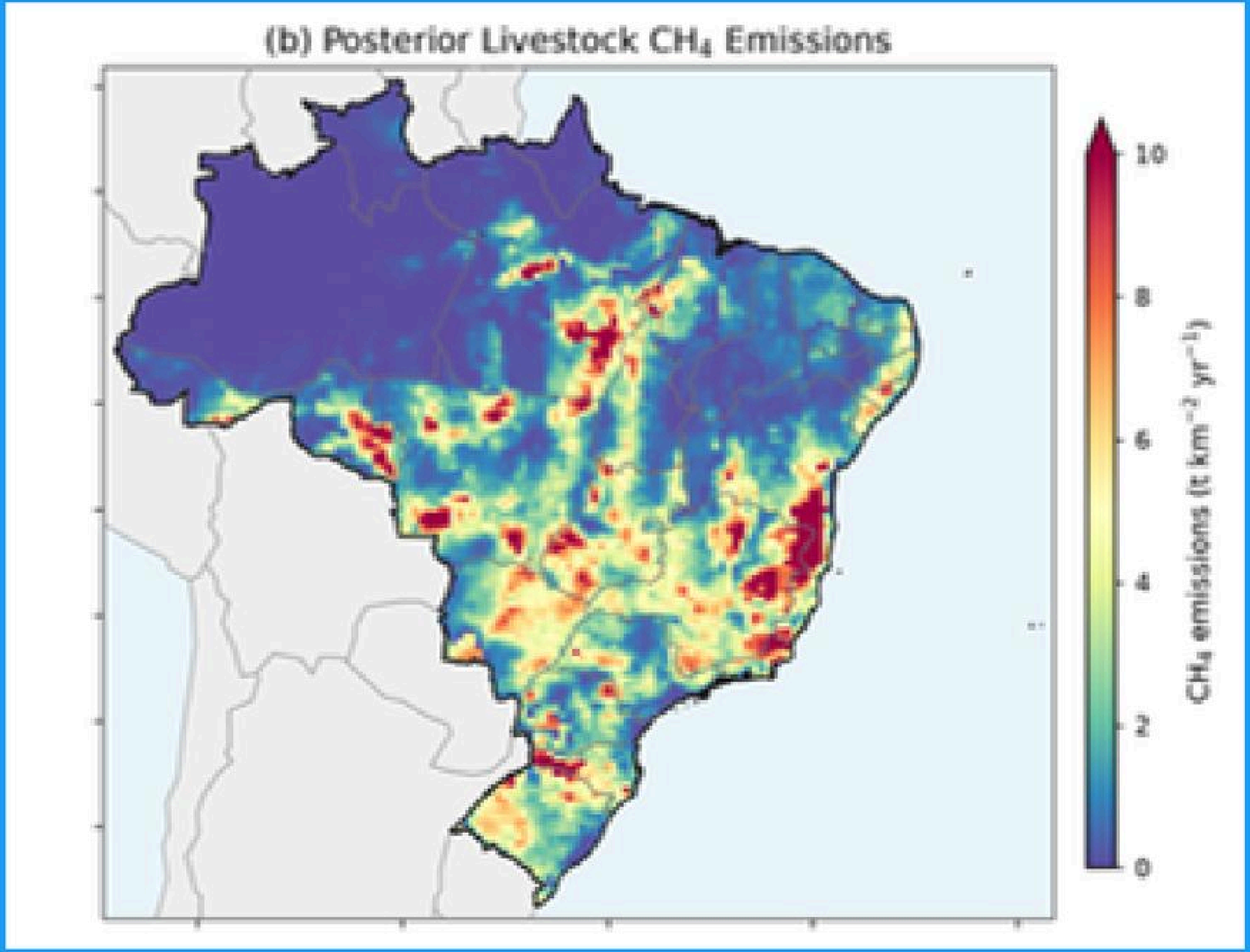
Livestock methane (CH_4) emissions represent a major anthropogenic source in Brazil, but their magnitude and spatial distribution remain uncertain in bottom-up inventories. In this study, we used observations of dry-air column-averaged methane (XCH_4) from a blended TROPOMI+GOSAT product to constrain methane emissions over Brazil through Bayesian atmospheric inversion and evaluate implications for the livestock sector. TROPOMI observations were spatially corrected using GOSAT as a reference, subjected to quality-control procedures, and aggregated into super-observations on the model grid. Atmospheric transport was simulated with GEOS-Chem driven by GEOS-FP meteorology at a horizontal resolution of $0.25^\circ \times 0.3125^\circ$ (~25 km). Emissions were optimized using the Integrated Methane Inversion (IMI), combining satellite observations, prior emissions, and the atmospheric sensitivity to emissions represented by the Jacobian matrix. Posterior livestock emissions were subsequently derived by applying the optimized emission adjustments according to the sectoral contribution represented in the prior inventory. Robustness was evaluated using an ensemble of inversions with different assumptions for prior uncertainty, observational error, and regularization. The ensemble-mean posterior livestock estimate reached 21.04 Tg CH_4 yr^{-1} (ensemble range: 19.01–24.18 Tg CH_4 yr^{-1}), representing a 29.6% increase relative to the prior estimate of 16.23 Tg CH_4 yr^{-1}. The optimization reduced the mean XCH_4 bias from −1.49 to −0.36 ppb and the root-mean-square error from 11.38 to 9.70 ppb. Posterior emissions showed substantial spatial heterogeneity and differed from EDGAR, SEEG, and MCTI estimates, particularly across major livestock-producing states. Averaging-kernel sensitivities indicated strong observational constraints over much of the principal cattle-producing regions, whereas persistent cloud cover reduced satellite sampling and inversion sensitivity in parts of northern Brazil. Overall, the consistently higher posterior estimates across the ensemble indicate that livestock CH_4 emissions represented in the prior are likely underestimated under the adopted sectoral attribution framework. These results demonstrate the potential of satellite-constrained atmospheric inversions to complement bottom-up inventories, identify regional emission discrepancies, and support the evaluation of methane-mitigation strategies in Brazilian livestock systems.

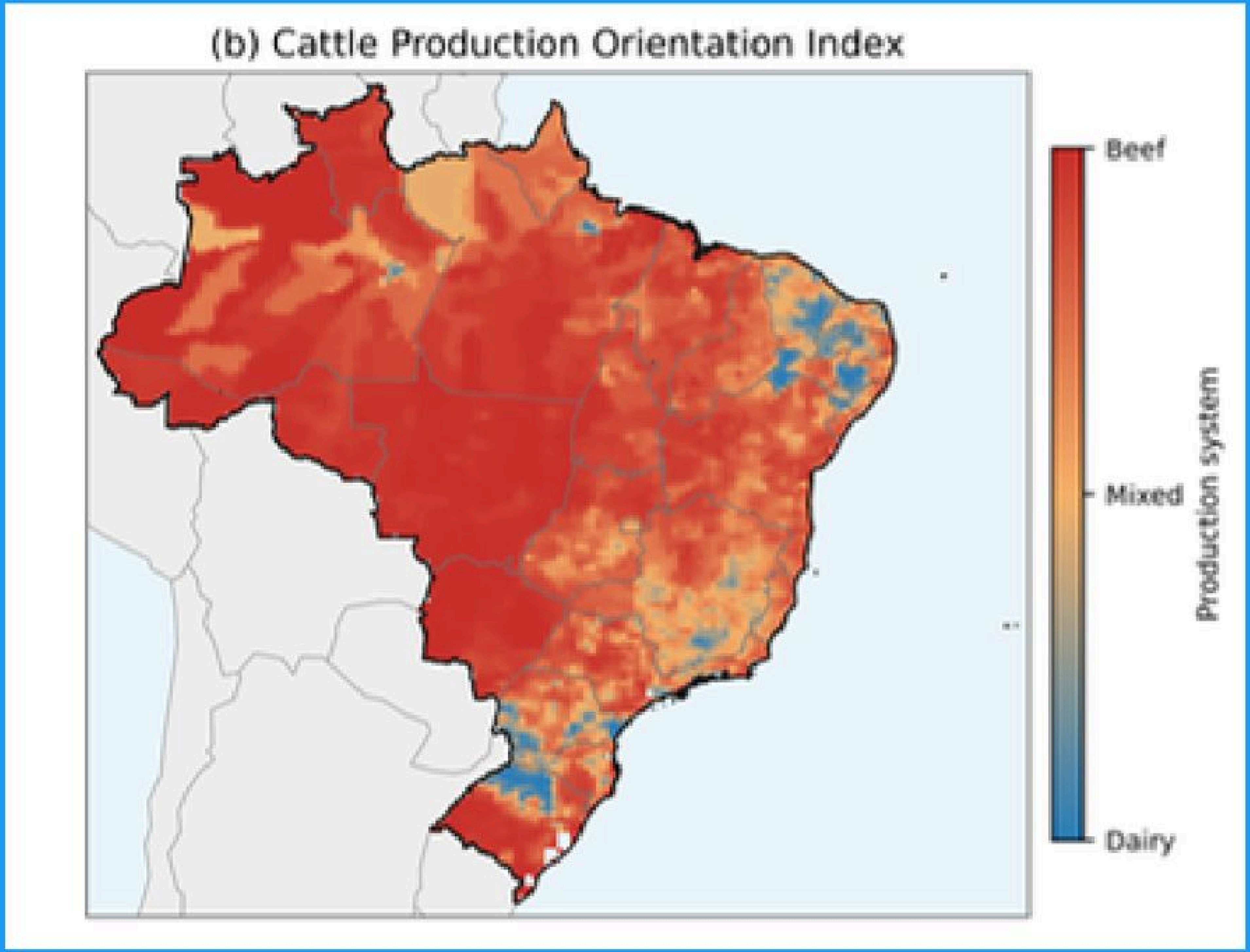
Keywords: XCH_4; GEOS-Chem; Integrated Methane Inversion; Emission Intensity; Bottom-Up Inventories; Cattle Production Systems; Pasture Biomass; Greenhouse Gases

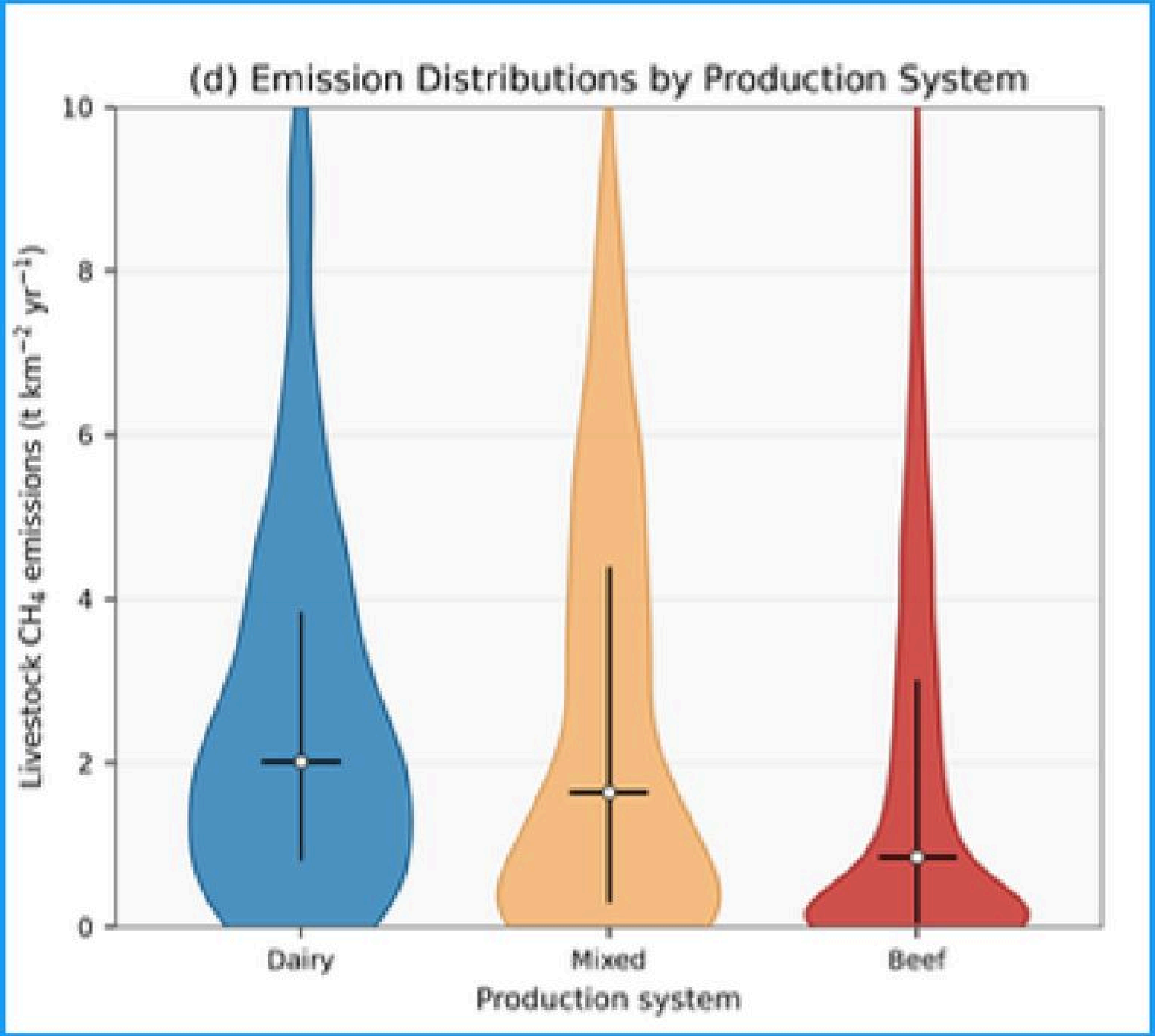
Received:
Revised:
Accepted:
Published:

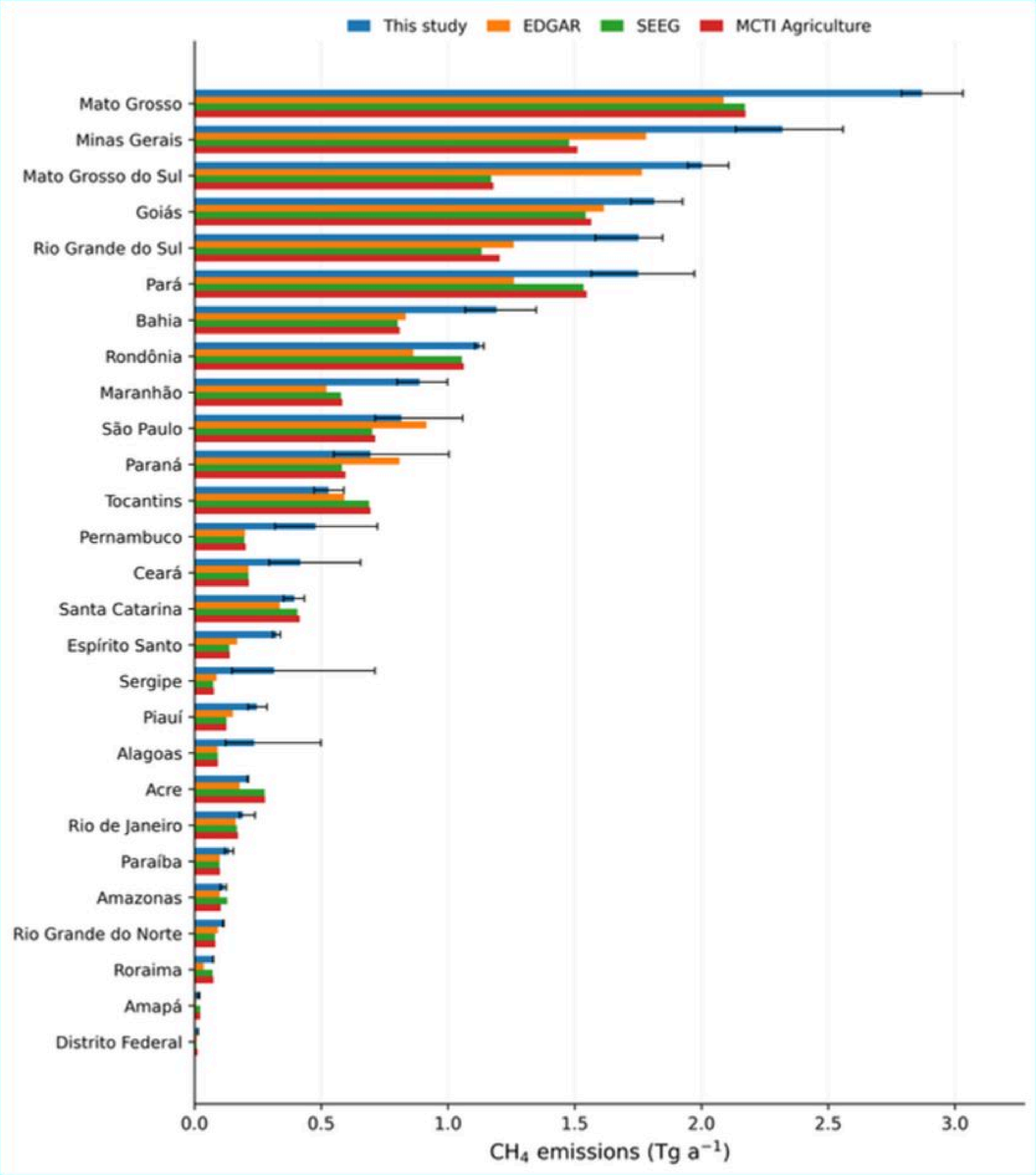
First-generation results with 25 km² resolution.

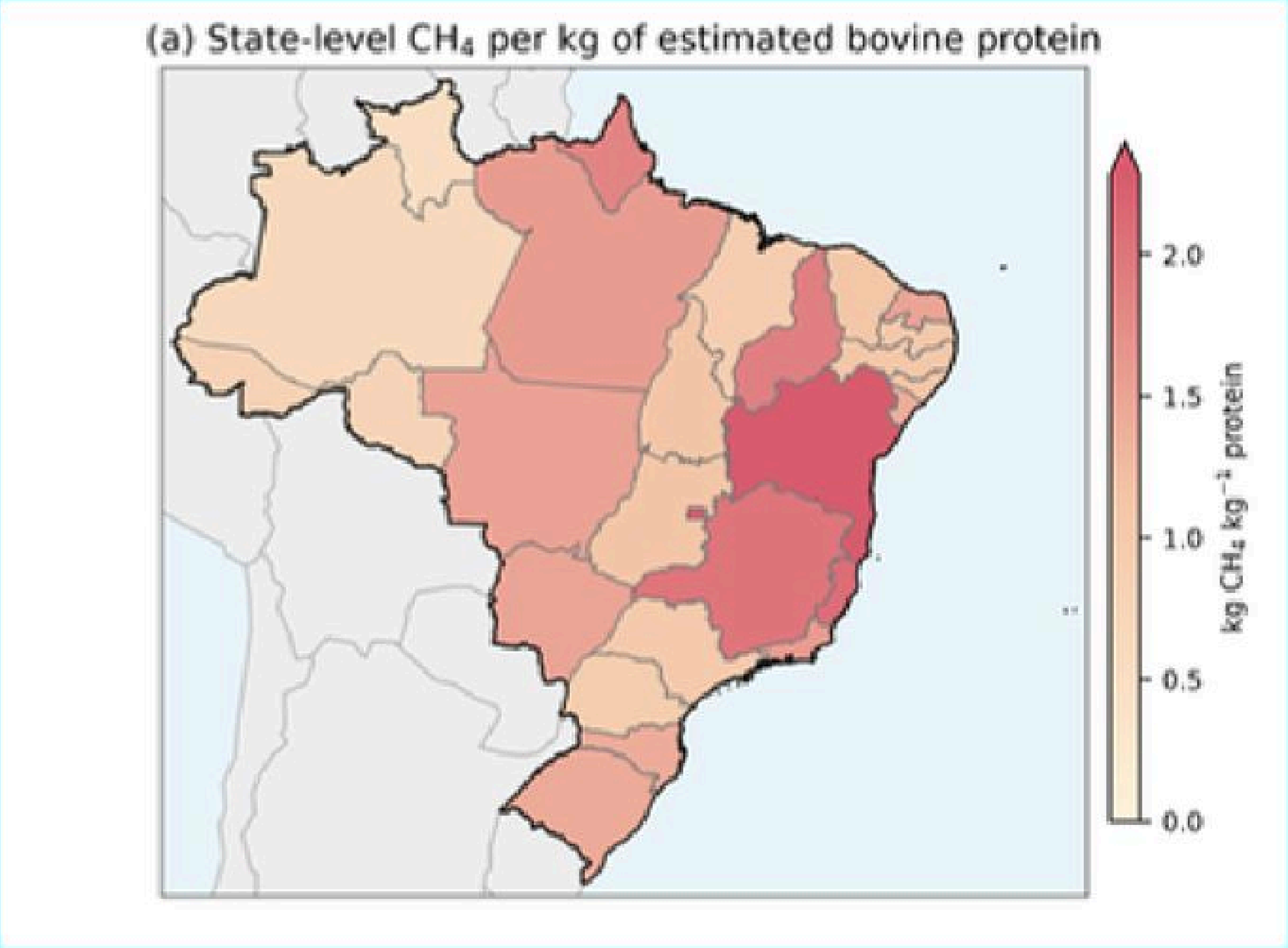
Fonseca et al. (submitted)

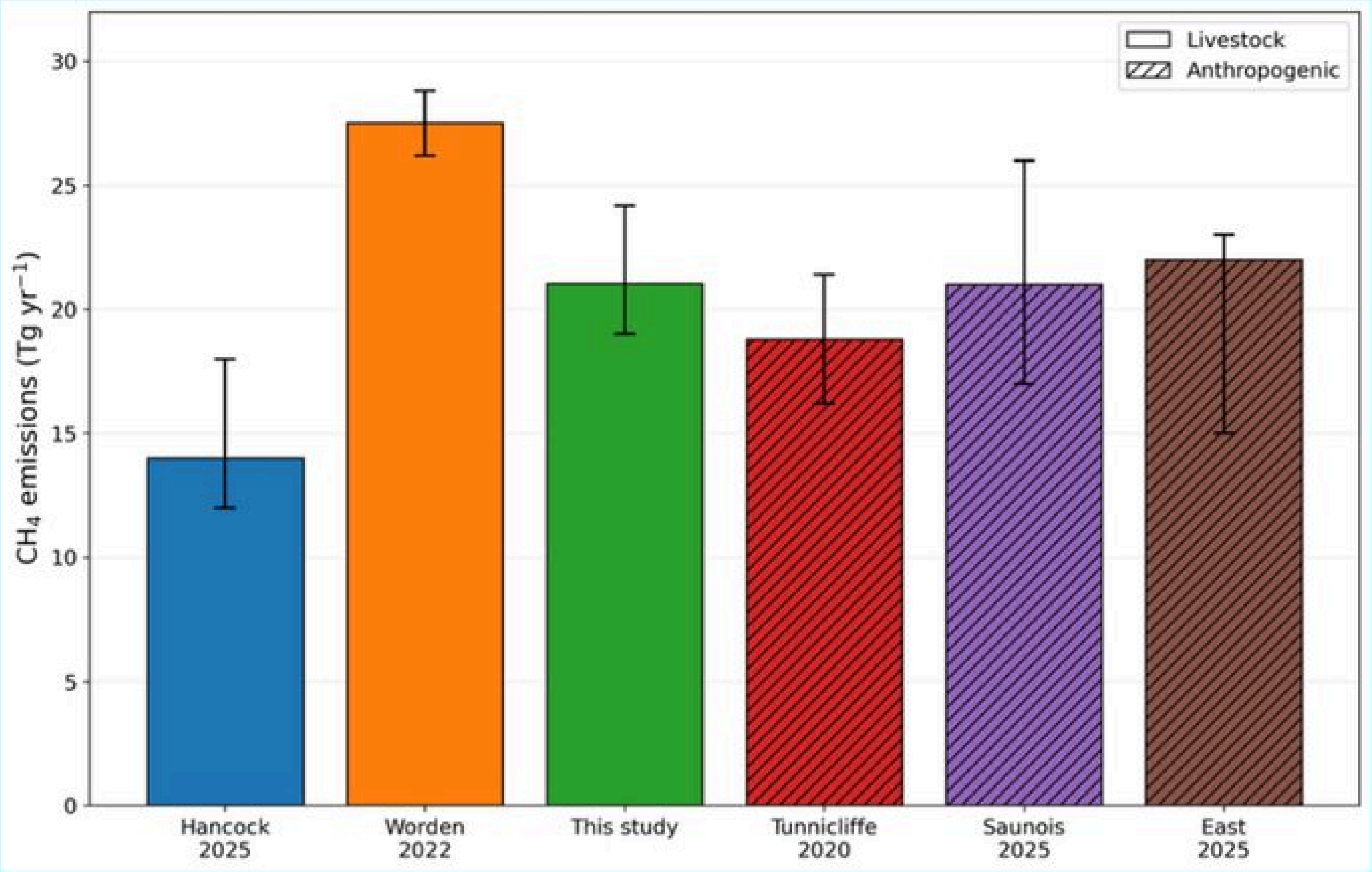



(b) Cattle Production Orientation Index
Beef
Mixed
Dairy
Production system


(d) Emission Distributions by Production System
Livestock CH_4 emissions (t km^{-2} yr^{-1})
0
2
4
6
8
10
Dairy
Mixed
Beef
Production system


This study
EDGAR
SEEG
MCTI Agriculture
Mato Grosso
Minas Gerais
Mato Grosso do Sul
Goiás
Rio Grande do Sul
Pará
Bahia
Rondônia
Maranhão
São Paulo
Paraná
Tocantins
Pernambuco
Ceará
Santa Catarina
Espírito Santo
Sergipe
Piauí
Alagoas
Acre
Rio de Janeiro
Paraíba
Amazonas
Rio Grande do Norte
Roraima
Amapá
Distrito Federal
0.0
0.5
1.0
1.5
2.0
2.5
3.0
CH_4 emissions (Tg a^{-1})


(a) State-level CH_4 per kg of estimated bovine protein
2.0
1.5
1.0
0.5
0.0
kg CH_4 kg^{-1} protein


Livestock
Anthropogenic
30
25
20
15
10
5
0
CH_4 emissions (Tg yr^{-1})
Hancock 2025
Worden 2022
This study
Tunnicliffe 2020
Saunois 2025
East 2025