COMPARISON OF THE NATIONAL-CONTRIBUTED EMISSIONS WITH THE CLIMATE TRACE'S GLOBAL EMISSIONS INVENTORY

by

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ABSTRACT

COMPARISON OF THE NATIONAL-CONTRIBUTED EMISSIONS WITH THE CLIMATE TRACE'S GLOBAL EMISSIONS INVENTORY

Accurate and transparent greenhouse gas (GHG) inventories are vital for tracking global climate commitments. With advances in satellite technologies and AI-integrated platforms, alternative inventories like Climate TRACE have emerged as complements or replacements for traditional systems such as the UNFCCC. This study compares GHG emissions reported by Climate TRACE and UNFCCC country submissions for 2015–2021. Eight countries—Australia, Belgium, Brazil, Germany, Japan, Poland, Turkey, and the United States—were selected for their data availability and regional diversity. Percentage differences between the two datasets were calculated for 13 sectors, and methodological consistencies were assessed using Principal Component Analysis (PCA) and K-means clustering. A heatmap visualization illustrated percentage differences across sub-sectors, highlighting areas of agreement and divergence. Results show substantial differences across most countries and sectors, with Climate TRACE often reporting higher emissions. The Waste sector and certain LULUCF sub-sectors had the largest discrepancies, largely due to methodological, scope, and data granularity differences. Climate TRACE's satellite- and AI-based methods—such as flaring inefficiency models, wastewater plant detection, and forest degradation monitoring—contributed to these gaps. Conversely, sectors like Enteric Fermentation in some countries (e.g., Belgium) showed higher alignment where Climate TRACE applied standard IPCC methodologies. The findings underscore how methodological heterogeneity—between and within inventories—affects comparability, highlighting the need for transparent methods and consistent sectoral definitions to improve global climate accountability.

ÖZET

ÜLKELERİN RAPORLADIĞI SERA GAZI SALIMLARININ CLIMATE TRACE KÜRESEL SERA GAZI ENVANTERİ İLE KARŞILAŞTIRILMASI

Doğru ve şeffaf sera gazı envanterleri, küresel iklim taahhütlerinin izlenmesi için kritik öneme sahiptir. Uydu teknolojilerindeki ve yapay zekâ tabanlı platformlardaki gelişmeler, UNFCCC gibi geleneksel sistemlere alternatif ya da tamamlayıcı envanterler olarak Climate TRACE gibi yeni veri kaynaklarını ortaya çıkarmıştır. Bu çalışma, 2015–2021 döneminde Climate TRACE ve UNFCCC'ye sunulan ülke verilerini karşılaştırmaktadır. Veri erişilebilirliği ve bölgesel çeşitlilik göz önünde bulundurularak Avustralya, Belçika, Brezilya, Almanya, Japonya, Polonya, Turkey ve Amerika Birleşik Devletleri seçilmiştir. İki veri seti arasındaki yüzde farklar 13 sektör için hesaplanmış, metodolojik benzerlikler ise Temel Bileşenler Analizi (PCA) ve K-means kümeleme yöntemi ile değerlendirilmiştir. Alt sektörler arasındaki farkları ve benzerlikleri göstermek amacıyla bir ısı haritası oluşturulmuştur. Sonuçlar, çoğu ülke ve sektörde belirgin farklar olduğunu ve Climate TRACE'in genellikle daha yüksek emisyonlar raporladığını göstermektedir. En büyük farklılıklar Atık sektörü ve bazı LULUCF alt sektörlerinde görülmüş; bunun başlıca nedenleri metodolojik ve kapsam farklılıkları ile veri toplamadaki ayrıntı seviyesidir. Uydu ve yapay zekâ tabanlı alev yakma verimsizliği, atıksu arıtma tesisi tespiti ve orman bozulumu izleme yöntemleri bu farklara katkı sağlamıştır. Öte yandan, Belçika'daki Enterik Fermentasyon gibi bazı sektörlerde, IPCC metodolojilerinin kullanılması daha yüksek uyum sağlamıştır. Bulgular, metodolojik çeşitliliğin karşılaştırılabilirliği zorlaştırdığını ve küresel iklim hesap verebilirliği için şeffaf, tutarlı yöntemlere ihtiyaç olduğunu ortaya koymaktadır.

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LIST OF SYMBOLS

CO_2	Carbon dioxide
CH_4	Methane
$GgCO_2e$	Gigagrams of CO_2 Equivalent
$ktCO_2e$	Equivalent $GgCO_2$ Equivalent
$MtCO_2e$	Equivalent $GgCO_2$ Equivalent
N_2O	Nitrous Oxide

LIST OF ACRONYMS/ABBREVIATIONS

ARG	Argentina
AUS	Australia
BEL	Belgium
BLR	Belarus
BRA	Brazil
BSA	Blue Sky Analytics
BWA	Botswana
CAN	Canada
CHN	China
COP	Conference of the Parties
DEU	Germany
EDGAR	Emissions Database for Global Atmospheric Research
EEA	European Environment Agency
FAOSTAT	Food and Agriculture Organization's Corporate Statistical Database
FOD	First Order Decay
FRA	France
GBR	United Kingdom
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
GWPs	Global Warming Potentials
IPCC	Intergovernmental Panel on Climate Change
IRL	Ireland
JPN	Japan
KAZ	Kazakhstan
LULUCF	Land-Use Change, and Forestry
MEE	Ministry of Ecology and Environment of the People's Republic of China

MEX	Mexico
MLO	Mauna Loa Observatory
MOEF	Ministry of Environment,Forest and Climate Change
NDC	Nationally Determined Contribution
NGHGIs	National Greenhouse Gas Inventories
NOAA	National Oceanic and Atmospheric Administration
PAK	Pakistan
PCA	Principal Component Analysis
POL	Poland
RUS	Russia
TRACE	Tracking Real-time Atmospheric Carbon Emissions
TUR	Turkey
UKR	Ukraine
UNFCCC	United Nations Climate Change Convention
URY	Uruguay
USA	United States of America
VIIRS	Visible Infrared Imag-ing Radiometer Suite
WWTPs	Wastewater Treatment Plants
ZAF	South Africa

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1. INTRODUCTION

Climate change has become one of the significant problems of the 21st century. Greenhouse gas concentration had been in a natural cycle. However, certain factors broke this harmony for a few centuries with the Industrial Revolution. Industrialisation has led to various side effects, such as rapid urbanization and consumption of fossil fuels. As a result, this combination of factors has affected the greenhouse balance. In the late 19th century, the increase of greenhouse gas concentrations like atmospheric carbon dioxide (CO_2), methane (CH_4), and nitrogen oxide (N_2O) became evident. This increase can be visualized through the graph known as "Keeling Curve". Since the 1950s, the curve has been updated with carbon dioxide measurements taken at the Mauna Loa Observatory (MLO) in Hawaii, and it shows that the CO_2 concentration is increasing over time. However, greenhouse gases are now accumulating faster than ever. Lately, the National Oceanic and Atmospheric Administration(NOAA) and Scripps Institution of Oceanography announced that there is an unprecedented rise in the atmospheric CO_2 levels, which increased by 2.9 ppm from May 2023 to May 2024 and reached 426.7 ppm. This is the fifth-largest annual increase in NOAA's 50-year record (Monroe, 2024, June 6)

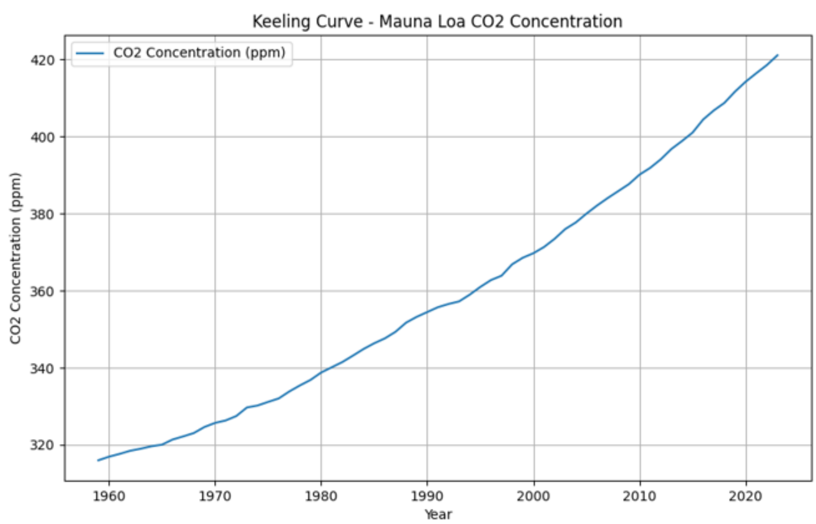

Figure 1.1. The Keeling curve shows CO_2 monthly data between 1958-2024 from the National Oceanic and Atmospheric Administration (NOAA).

As the evidence for anthropogenic climate change has grown stronger, not only scientists but also governments and policymakers have increasingly prioritized the measurement, reporting, and reduction of greenhouse gas (GHG) emissions. This became even more significant after the Paris Agreement, which established a global commitment for countries to reduce their GHG emissions. The Paris Agreement, which was established by the Kyoto Protocol, is an agreement that aims to keep the pre-industrial level below 1.5 degrees and assigns certain responsibilities to countries. The Nationally Determined Contribution (NDC) is each party's national climate commitment to reduce greenhouse gas emissions and explain how they will adapt to the impacts to achieve the 1.5°C global target under the Paris Climate Agreement. NDCs, which cover short and medium-term plans, are expected to be updated every 5 years to reach higher targets depending on the capacity and capabilities of countries and they are submitted to the United Nations Climate Change Convention (UNFCCC). The first NDCs were submitted in 2015, and the second-round submissions featured higher targets in 2020 (UNDP, 2022). The complexity in establishing emission targets is becoming one of the defining points in global discussions such as long-term temperature goals and greenhouse gas emissions (Dekker *et al.*, 2025). Considering that India and China represent nearly one-third of the world's population, it is important to assess the current strategies being implemented in these countries.

In India's case, it achieved two measurable targets in 2015. The first is to reduce the emission intensity of gross domestic product (GDP) by 33 to 35 percent of 2005 levels by 2030, and the second is to increase the total installed capacity of electric power from non-fossil fuel energy sources to about 40 percent by 2030. According to the Ministry of Environment (Ministry of Environment,Forest and Climate Change (MOEF), 2018), by October 2023, non-fossil fuel-based energy sources will account for 186.46 MW, 43.81% of the total electricity capacity. Furthermore, according to India's third national communication submitted to the UNFCCC in December 2023, the emissions intensity of the country's GDP was reduced by 33 percent between 2005 and 2019. It updated its earlier declarations in August 2022 for 2030, with a GDP target of 45 percent and a non-fossil fuel-based electricity target of 50 percent.

One way of achieving the emission reduction targets included in India's NDC is to create an additional "carbon sink" of 2.5 to 3 billion tons of CO_2 equivalent through additional forest and tree cover by 2030. For power generation, in the "National Action Plan" (MOEF, 2018), published in 2007, which has not been updated, the Department of Atomic Energy envisages increasing nuclear power generation to a total of about 300 GWe by 2050.

As a country with substantial influence on global greenhouse gas emissions, India's irregular, unregulated, and inconsistently structured contributions to emission reductions have raised concerns. The use of multiple emissions inventories to report clarify national contributions could lead to more reliable outcomes. Ensuring reliability is crucial, as the effective implementation of the Paris Agreement depends on countries' commitments to limit or reduce greenhouse gas emissions, namely their Nationally Determined Contributions (NDCs) (Deng *et al.*, 2022).

Although nations are supposed to enhance and progressively strengthen their Nationally Determined Contributions (NDCs), China has not established new emission target (Ministry of Ecology and Environment of the People's Republic of China (MEE), 2022) beyond the two previously reported files (MEE, 2019). Regarding carbon dioxide, the 2016 5-year national development plan states that "reducing energy consumption per unit of GDP by 15% and CO_2 emissions per unit of GDP by 18%" is a priority. "Reducing energy consumption per unit of GDP by 13.5% and CO_2 emissions per unit of GDP by 18%" is a part of the next five-year plan, which was developed in 2021 for 2035 (United Nations Framework Convention on Climate Change, 2022b).

As seen in the examples of India and China, where targets remain low and largely unchanged, transparent measurements and accurate targets for GHG emissions should be on an international level and should be monitored. For a fair distribution of responsibility, accurately measured emissions and correct targets can only enable the formulation of appropriate policies to prevent climate change.

The motto ‘you can’t improve what you don’t measure’ has shaped the core principle of climate policy and the success of United Nations Framework Convention on Climate Change (UNFCCC)’s depends heavily on the accurate measurement and reporting of emissions by the parties (Perugini *et al.*, 2021). Countries submit their GHG reports to the Climate Change Secretariat, and these submissions should provide requirements that the Climate Change Convention regulates. The Global Stocktake coordinated by the UNFCCC aims to use National Greenhouse Gas Inventories (NGHGIs) to assess countries’ collective climate progress under the Paris Agreement (Deng *et al.*, 2022). In this way, inventories have become a key tool for understanding how effective the NDCs are and how much progress has been made toward achieving global climate goals.

UNFCCC has GHG emissions reports worldwide, and it has become an open source GHG inventory. While the measurements, targets, and policies of India and China, the world’s most populous countries and significant contributors to greenhouse gas emissions, hold an important place in climate change, the data provided by these two countries, which fall under the non-annex1 category within the UNFCCC, are not in line with this. For India, data for the years 1994-2000-2010-2016 were presented, while China similarly presented its NDC targets with data for the years 1994-2005-2010-2012-2014. It is concerning that so limited data is available and accessible from countries that play such a crucial role in global climate efforts.

2. GREENHOUSE GAS INVENTORIES

2.1. United Nations Framework Convention on Climate Change (UNFCCC)

The UNFCCC mandates all Parties to develop, periodically update, publish, and submit to the Conference of the Parties (COP) national inventories of all greenhouse gas emissions and sinks not controlled by the Montreal Protocol. These inventories are expected to be transparent, consistent, comparable, complete, and accurate (TCCCA)(United Nations Framework Convention on Climate Change, 2009).

Greenhouse gas inventories are compiled according to the inventory methodology guidance provided by the Intergovernmental Panel on Climate Change (IPCC), which has been officially adopted by the Parties, as the IPCC serves as the source of best practices for the preparation of national greenhouse gas inventories. This guidance has been updated over time through various versions: the 1994 Guidelines, the Revised 1996 Guidelines, the Good Practice Guidance, the 2006 IPCC Guidelines, and the 2019 Refinement (Gillenwater, 2008; Perugini *et al.*, 2021).

2.1.1. UNFCCC Methodology

The IPCC guidelines outline three tiers of methodological detail-Tier 1, Tier 2, and Tier 3-for estimating emissions using emission factors and activity data, each offering increasing levels of complexity and accuracy. Tier 1 typically employs default emission factors and simpler activity data, such as nationally or globally available deforestation rates, agricultural production statistics, and global land cover map estimates.

Tier 2 utilizes country- or region-specific data and more complex calculations, requiring higher-resolution data aligned with land use categories. Tier 3 represents the most detailed approach relying on facility-specific measurements, advanced models, and high-resolution data-often sourced from geographic information system (GIS)-based tools (IPCC, 2006; UNFCCC, 2009).

The UNFCCC inventory utilizes six main categories: Energy, Industrial Processes, Agriculture, Land Use, Land-Use Change, and Forestry (LULUCF), and Waste, which are further subdivided into sub-sectors (Table 1). Regarding the methodologies applied within these sectors, while Tier 1, 2, and 3 approaches are used for CO_2 emissions in the energy sector, Tier 1 is generally not used for non-CO_2 emissions (CH_4, N_2O); instead, more specific emission factors provided by Tier 2 and Tier 3 methodologies are preferred. In the Industrial Processes sector, emissions are examined in relation to chemical reactions, and Tiers 1 or the more detailed Tier 2 are typically sufficient without the need for Tier 3. Unlike Industrial Processes, which exclude energy inputs, the Agriculture sector includes all anthropogenic emissions except fuel combustion and relies on both Tier 1 (default emission factors) and Tier 2 (e.g., animal population, soil characteristics) methodologies. The LULUCF sector incorporates all tier methods, including Tier 3, which utilizes high-resolution data sources such as GIS. Similarly, in the Waste sector, Tier 3 is applied when country-specific data are available, whereas Tier 1 and Tier 2 are used when only default data are accessible (UNFCCC, 2009).

2.2. UNFCCC Sectors

UNFCCC divided countries into two categories as Annex 1 and non-Annex 1. Annex 1 countries labeled as developed and industrialised. Annex 1 and non-Annex 1 have different obligations regarding their inventory submissions to UNFCCC.

Annex 1 parties should use CRF Reporter software while non Annex 1 parties are not obligated to do so but should use the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Moreover, as clearly presented in the inventory files provided in Excel format on the UNFCCC's website (UNFCCC, n.d.; see Table 1), certain sub-sectors exhibit differences between the two country groups. Notably, UNFCCC inventory, which relies on countries' self-reported data, shows significant discrepancies-particularly in CH_4 emission data for non-Annex 1 countries-when compared with other inventories (Petrescu *et al.*, 2024).

Table 2.1. UNFCCC Subsector Differences: Annex I vs. Non-Annex I.

Main Sector	**Annex I Subcategories**	**Non-Annex I Subcategories**
Energy	Energy industries Manufacturing industries and construction Transport Other sectors Other(not specified elsewhere) Fugitive emissions from fuels	Energy industries Manufacturing industries and construction Transport Other sectors Other Fugitive emissions from fuels
Industrial Processes	Mineral Products Chemical Industry Metal Production Non-energy Products from Fuels and Solvent Use Electronics industry Product Uses as Substitutes for ODS Other Product Manufacture and Use Other	Mineral Products Chemical Industry Metal Production Other Production Production of Halocarbons and SF_6 Consumption of Halocarbons and SF_6 Other
Solvents	(not included)	Solvents
Agriculture	Enteric Fermentation Manure Management Rice Cultivation Agricultural Soils Prescribed Burning of Savannas Field Burning of Agricultural Residues Liming Urea Application Other Carbon-containing Fertilizers Other	Enteric Fermentation Manure Management Rice Cultivation Agricultural Soils Prescribed Burning of Savannas Field Burning of Agricultural Residues Other

Table 2.1 UNFCCC Subsector Differences: Annex I vs. Non-Annex I. (cont.)

Main Sector	Annex I Subcategories	Non-Annex I Subcategories
LULUCF / LUCF	Forest Land Cropland Grassland Wetlands Settlements Other Land Harvested Wood Products Other	Changes in Forest and Other Woody Biomass Stocks Forest and Grassland Conversion Abandonment of Managed Lands Emissions and Removals from Soil Other
Waste	Solid Waste Disposal Biological Treatment of Solid Waste Incineration and Open Burning of Waste Wastewater Treatment and Discharge Other	Solid Waste Disposal on Land Wastewater Handling Waste Incineration Other
Adapted from National Inventory Submissions 2009, by United Nations Framework Convention on Climate Change, 2009, https://unfccc.int. Copyright 2009 by the United Nations Framework Convention on Climate Change.		

UNFCCC has a country-contributed inventory, and day by day, other GHG measurement projects and ensembles arise. Satellite imagery data is one of the types other than ground truth data. There are two methods used to measure greenhouse gas emissions. The first is the national-level bottom-up approach, which measures emissions at the national level from specific sectors and certain sources, such as the number of equipment and emission factors, which can also be referred to traditionally, to arrive at total emission values and UNFCCC is a kind of inventory. The second is the top-down approach, which is based on atmospheric measurements and uses models to estimate emissions (Petrescu *et al.*, 2024).

Additionally, new projects such as Climate TRACE have emerged, combining various types of data. Its name comes from Tracking Real-time Atmospheric Carbon Emissions, and it integrates diverse technologies and develops sector-specific models to sectoral GHG data to identify emissions gaps in the reports. Methodologies vary sector to sector, but the most common method is combining a predictor variable and ground truth data; they can be satellite imagery and sensor data (Climate TRACE). According to their explanation, Climate TRACE uses technologies like artificial intelligence (AI) and machine learning (ML) to analyze trillions of bytes of data from satellites, sensors, and numerous additional sources of emissions information worldwide (Climate TRACE, 2024)

2.3. Climate TRACE

Climate TRACE aims to provide comprehensive and up-to-date emissions data to the public. Access to such information enables faster and more effective climate action. By using a hybrid method to estimate the emissions, and elaborates the traditional bottom-up inventory method with satellite data and machine learning technologies. Thus, the missing points of the emissions declaration of the countries can be improved and more accurate and real-time tracking data could be available (Climate TRACE, 2024).

There is also some kind of data that Trace can provide and that perhaps the UNFCCC will never have. Trace shares the world's highest-emitting countries and sub-sectors annually for each sector on its website, 2021-2025 (partially) data is available. According to Trace, the global emissions for the agriculture sector in 2024 are 7.91 billion tons of CO_2e, with North Korea (PRK) in first place at 8.03 million tons of CO_2e, followed by rice paddies field (Climate TRACE, 2024).

2.3.1. Climate TRACE Sectors

Climate TRACE (2024) provides emissions data under seven main categories: agriculture, forestry, fossil fuels, manufacturing, power, transportation, and waste. Unlike the UNFCCC, it offers a much more detailed sub-sector classification. The Agriculture category includes detailed emission sources such as Enteric Fermentation (Cattle Operation and Cattle Pasture), Manure Management (Operation and Pasture), Manure Applied to Soils, Manure Left on Pasture, Synthetic Fertilizers, Other Agricultural Soils, Rice Cultivation, Crop Residues, and Cropland Fires.

The Forestry and Land Use sector encompasses land-based carbon flux categories, includingForest Land Degradation, Forest Land Fires, Net Forest Land, Net Shrubgrass, Net Wetland, Removals, Shrubgrass Fires, Water Reservoirs, and Wetland Fires.

Fossil Fuel Operations cover upstream emissions from extraction and processing, including Coal Mining, Natural Gas Processing, Natural Gas Transmission and Distribution, Oil Production, Other Fossil Fuel Operations, and Refining.

Manufacturing and Industrial Processes are represented with detailed subcategories such as Aluminum, Cement, Chemicals, Food, Beverage, and Tobacco, Glass, Iron and Steel, Lime, Other Chemicals, Other Manufacturing, Paper, Refineries, and Textiles.

Power Generation emissions are reported from various electricity generation modes including Electricity Generation - Domestic Aviation, Domestic Shipping, International Aviation, International Shipping, Electricity Transmission and Distribution, and Heat Plants.

Transportation includes both domestic and international movement emissions such as Domestic Aviation, Domestic Shipping, International Aviation, International Shipping, Railway, and Road Transportation.

Waste sector emissions are categorized under Biological Treatment of Solid Waste, Incineration and Open Burning of Waste, Solid Waste Disposal, and Wastewater Treatment and Discharge.

2.3.2. Climate TRACE Methodology

Climate TRACE aims to meet different methodological needs in each category by integrating various satellite and observational systems. For agricultural fires, data is used for vegetation classification; however, TRACE uses VIIRS (Visible Infrared Imaging Radiometer Suite) and it provides a significant advantage over MODIS (Kochhar, Ahmed, and Luong, 2023). In estimating emissions from enteric fermentation and cattle operations, pasture data from Food and Agriculture Organization's Corporate Statistical Database (FAOSTAT), and other inventories are utilized, while individual operations are identified using AI-based tools (Davitt *et al.*, 2024). In the forestry sector, in addition to Tier 1 IPCC emissions, Climate TRACE incorporates information from diverse sources such as weather, elevation data, reservoir surface areas, and water surfaces. For living biomass, satellite data are combined with machine learning algorithms (Yang and Saatchi, 2024).

In fossil fuel operations, metadata such as mine depth is used for coal mining, while oil and gas production relies on a combination of life cycle emission methodologies and estimators (Schmeisser *et al.*, 2023; Lewis, Tate, and Mei, 2024). In the manufacturing sector, facility-level data is used for aluminum and chemicals, whereas satellite imagery is incorporated for cement (Sinha, Crane, and Heal, 2023, 2024; Sinha and Crane, 2023). In the power sector, IPCC Tier 1 emission factors are applied for heat plants, while electricity generation integrates satellite imagery, proxy signals, and machine learning (Freeman, Sridhar, and Alvara, 2024; Freeman *et al.*, 2024). For the transportation sector, satellite imagery and machine learning are used for road emissions; Tier 3 methodology is employed for aviation, while automatic identification systems (AIS) and ML-based methods are applied to track ship activities (Saraswat, 2025; Mayes *et al.*, 2024; Kott *et al.*, 2024). In the waste sector, Climate TRACE uses satellite data and probabilistic programming packages to estimate emissions from solid waste disposal sites and has developed a satellite- and machine-learning-based approach for wastewater treatment plants, also incorporating data from diverse sources such as population statistics (Collins *et al.*, 2024; Raniga, 2024).

The fact that Climate TRACE, which utilizes multiple technologies, provides lower emission data than the UNFCCC in many areas makes it worthwhile to examine the reasons for the difference between them. In a study conducted specifically for

Brazil, it was stated that Climate TRACE does not account for emissions from liming and organic fertilizers, and that liming could be responsible for 10% to 50% of GHG emissions because it is a fundamental practice in Brazilian agriculture to balance the pH of acidic soils (da Costa *et al.*, 2025). Therefore, considering the categorical gaps in Climate TRACE data, it is essential to investigate the factors contributing to these differences.

Only the 2021 data are comparable between the UNFCCC and Climate TRACE emissions inventories for Annex I countries across the main sectors of agriculture, energy, LULUCF, and waste. This limitation arises because Climate TRACE provides data for these main categories only for the period 2021–2025, whereas the UNFCCC offers data spanning 1990–2021. Examination of selected Annex I countries reveals considerable inconsistencies between the sectoral data reported by the two inventories. A detailed comparative analysis is necessary, as one inventory reflects countries' self-declared emissions, while the other integrates advanced technologies into emission estimates. This thesis aims to investigate the underlying reasons for these discrepancies.

3. METHOD

3.1. Comparison of UNFCCC and Climate TRACE GHG Data

The comparison between Climate TRACE and UNFCCC begins with the selection of countries. Regional diversity was prioritized in the selection of countries. As previously mentioned, emissions data for Annex I countries are comparable for the years 2015–2021. Therefore, seven Annex I countries were selected: Australia (AUS), Belgium (BEL), Germany (DEU), Japan (JPN), Poland (POL), Turkey (TUR), and the United States of America (USA). In addition, Brazil (BRA), a non-Annex I country, was included based on the availability of data for the years 2015–2016. The first point of comparison between UNFCCC and Climate TRACE on a sectoral basis is the year 2021, as reported on both of their official platforms. However, this comparison is only feasible for Annex I countries. Among the selected Annex I countries, Australia was excluded due to the availability of Climate TRACE data only up to 2020. Therefore, the country-level emission comparison is conducted in table 2 for BEL, DEU, JPN, POL, TUR, and USA.

Table 3.1. 2021 emissions comparison (MtCO_2e) between Climate TRACE and UNFCCC for selected countries: BEL, DEU, JPN, POL, TUR, and USA.

Country	**All sectors**	**Year**	**UNFCCC (MtCO_2e)**	**TRACE (MtCO_2e)**	**Percentage Difference**
BEL	All sectors	2021	111.00	131.52	18.49%
DEU	All sectors	2021	76.035.801	862.73	13.46%
JPN	All sectors	2021	1.168.09	1.400	19.85%
POL	All sectors	2021	39.943.849	449.94	12.64%
TUR	All sectors	2021	56.438.975	672.84	19.22%
USA	All sectors	2021	6.340.23	6.780	6.94%

Figure 1 shows that the waste sector generally has the widest distribution. This indicates that methodological discrepancies between TRACE and UNFCCC are particularly evident in the waste sector.. The waste sector shows that TRACE makes much higher emission estimates, especially for Turkey, Germany, and Poland. This difference may stem from variations in the definitions and scope used for the subcomponents of the waste category.

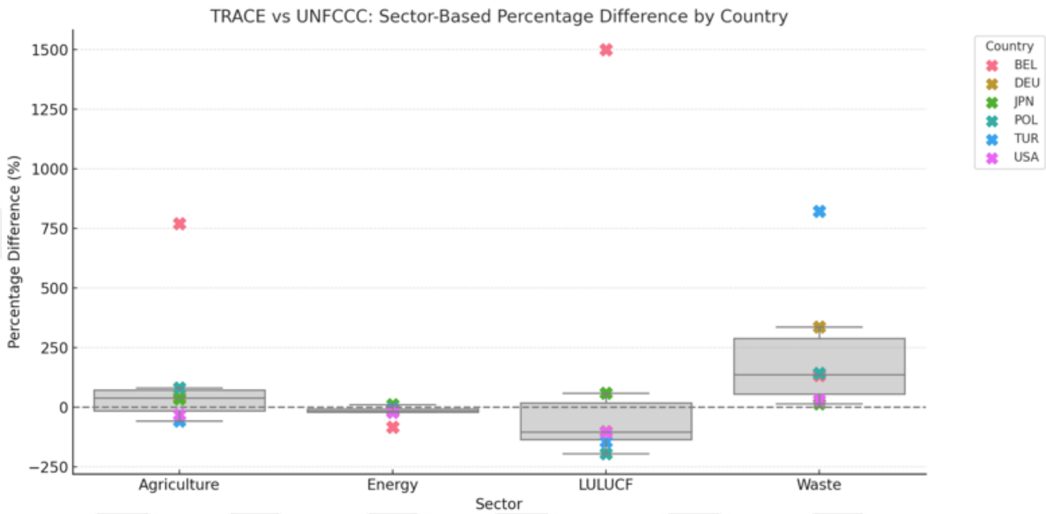

Figure 3.1. “Gray boxplots show the spread of percentage differences between TRACE and UNFCCC by sector. Wide boxes indicate greater variation between countries, narrow boxes indicate consistency. The dashed line marks 0% difference, and colored ‘X’s show each country’s value” (positive = higher TRACE estimates, negative = lower).

As previously mentioned, Climate TRACE and UNFCCC categorize emissions under different sub-sectors. Therefore, in order to achieve more meaningful comparisons, sub-sectors have been matched in accordance with the methodological frameworks of both inventories, as shown in Table 3. For instance, while the UNFCCC reports enteric fermentation as a single sub-sector under agriculture, Climate TRACE divides this into cattle operation and pasture. The UNFCCC category encompasses both. Additionally, there are sub-sectors such as manure management that can be directly compared due to their definitional alignment across both inventories.

Table 3.2. Comparable sub-Sectors: UNFCCC vs. climate TRACE.

Sector	**UNFCCC**	**Climate TRACE**
Agriculture	Enteric Fermentation	Enteric Fermentation Cattle Operation
		Enteric Fermentation Cattle Pasture
	Manure Management	Manure Management Cattle Operation
	Rice Cultivation	Rice Cultivation
	Agricultural Soils	Manure Applied to Soils
	Field Burning of Agricultural Residues	Crop Residues
Waste	Solid Waste Disposal	Solid Waste Disposal
	Biological Treatment of Solid Waste	Biological Treatment of Solid Waste and Biogenic
	Incineration and Open Burning of Waste	Incineration and Open Burning of Waste
	Wastewater Treatment and Discharge	Wastewater Treatment and Discharge
		Domestic Wastewater Treatment and Discharge
Energy	Energy Industries	Electricity Generation Heat Plants
	Transport	Domestic Aviation
		Domestic Shipping
		Railways
		Road Transportation
	Fugitive Emissions from Fuels	Coal Mining
		Oil and Gas Production
		Oil and Gas Transport
		Other Fossil Fuel Operations
		Other Solid Fuels
	Manufacturing Industries and Construction	Aluminum
		Cement
		Chemicals
		Food Beverage Tobacco

Table 3.2 Comparable sub-Sectors: UNFCCC vs. climate TRACE. (cont.)

Sector	**UNFCCC**	**Climate TRACE**
		Glass
		Iron and Steel
		Lime
		Other Chemicals
		Other Manufacturing
		Other Metals
		Petrochemical Steam Cracking
		Pulp and Paper
LULUCF	Forest Land	Net Forest
		Forest Land Fires
		Forest Land Degradation
		Forest Land Clearing
	Grassland	Net Shrubgrass
		Grassland Fires
	Wetlands	Net Wetlands
		Wetland Fires

Both systems express emissions in terms of carbon dioxide equivalents (CO_2e), taking into account the global warming potentials (GWPs) of various greenhouse gases (CO_2, CH_4, N_2O, HFCs, PFCs, and SF_6) (Davitt *et al.*, 2024). Climate TRACE uses the GWPs provided in the IPCC AR6 for these conversions (Davitt *et al.*, 2024). Similarly, the UNFCCC also relies on IPCC guidelines for its reporting, which use the unit of gigagrams of CO_2 equivalent (Gg CO_2e), corresponding to 1 kiloton (kt), and its data are generally presented in megatons (MtCO_2e) (IPCC, 2006). In contrast, Climate TRACE provides GHG emission data in kilotons (ktCO_2e), so its values were converted to MtCO_2e by dividing by 1,000 to ensure consistency with UNFCCC data.

As Climate TRACE periodically updates its data, the most current data from June 2025 has been utilized. This data is referred to as version v4, with file extensions *v4_4_0*. This specific versioning is highlighted because the previous dataset, accessed in October 2024, did not include this extension, and the emission data content changes with each new version.The Climate TRACE data, which is publicly available on www.climatetrace.org, currently provides country-level datasets covering the years 2015-2021. In contrast, the UNFCCC presents its country-specific GHG (Greenhouse Gas) emission data in both Excel and PDF formats.

To compare sectoral greenhouse gas (GHG) emissions reported by Climate TRACE and UNFCCC, a series of data processing scripts were developed in Python. Climate TRACE data were programmatically retrieved from their publicly accessible repository. The process involved iterating through relevant sector-specific files, applying filters to isolate data for the target country within the 2015-2021 timeframe, and then aggregating these emissions on an annual basis. The processed data were then consolidated into a unified structure for subsequent analysis.

Concurrently, national inventory data reported to the UNFCCC were extracted from a dedicated file containing sector-specific emission profiles. These data, originally expressed in kilotonnes of CO_2 equivalent (ktCO_2e), were transformed into a long format to ensure compatibility with the Climate TRACE dataset. A critical step involved normalizing the sector names across both datasets to account for differing nomenclature and facilitate accurate merging. Following data acquisition and normalization, the two datasets were merged based on common sectors and years. For each sector and year, both absolute and relative differences were calculated to assess consistency. The relative difference was computed using the formula:
$RelativeDifference(\%) = (TRACE - UNFCCC)/UNFCCC \times 100$

To maintain unit consistency, Climate TRACE emission values were converted from ktCO_2e to megatonnes of CO_2 equivalent (MtCO_2e) as necessary, aligning them with UNFCCC reporting units.

3.2. Country Profile Detection

To assess cross-country similarity in emission reporting discrepancies, Principal Component Analysis (PCA) and K-means clustering were employed (Figure 17).

First, the dataset was prepared. Emission differences between Climate TRACE and UNFCCC reports were calculated for each sector and country using the formula: [(TRACE-UNFCCC)/UNFCCC]$\times$100. A total of 13 emission sectors were considered across eight countries. Any country-sector combinations with missing data were excluded using listwise deletion (dropna) to ensure a complete matrix suitable for multivariate analysis. This resulted in each country being represented by a 13-dimensional vector of sectoral percentage differences. Missing values were not imputed or estimated; only existing data were used.

Prior to dimensionality reduction, the data were standardized using z-score normalization to ensure a mean of zero and a standard deviation of one for each sector, addressing PCA's sensitivity to input scale (Bro and Smilde, 2014). A covariance matrix was then computed to capture the relationships among the sectoral discrepancies, followed by eigenvalue decomposition to extract the principal components. PCA was chosen for its ability to reduce the dimensionality of this 13-dimensional dataset while preserving informative variance. This enabled a simplified and interpretable two-dimensional representation without significant loss of information. PCA 1 (the first principal component) captures the greatest variance, typically reflecting systematic over- or under-reporting across sectors. PCA 2, orthogonal to PCA 1, captures the next largest source of variability, often associated with sector-specific deviation patterns.

Each country's 13-dimensional difference vector was then projected onto this reduced two-dimensional space defined by PCA 1 and PCA 2. Consequently, countries are compared not by raw sectoral differences, but by their overall emission discrepancy profiles as captured by these principal components. For example, a country like the United States, with high positive scores on both PCA 1 and PCA 2, indicates a large overall discrepancy alongside distinct sectoral inconsistencies. Conversely, countries such as Turkey or Poland, positioned closer to the origin, show more moderate or balanced reporting differences.

Following the PCA projection, K-means clustering was applied to the resulting (PCA1, PCA2) coordinates. K-means is well-suited for identifying patterns in continuous, multidimensional data, enabling the grouping of countries with similar consistency profiles-those whose emission reporting discrepancies exhibit comparable structures, also it has been clearly demonstrated that K-means is a well-established and studied algorithm (Sinaga and Yang, 2020). The number of clusters was set to three, based on interpretability and visual inspection. The resulting scatter plot visualizes each country as a point in PCA space, with color-coded clusters indicating shared reporting characteristics. Proximity between countries suggests similarity in their TRACE–UNFCCC difference profiles, whereas separation indicates divergence either in magnitude (PCA 1) or in sector-specific anomalies (PCA 2). This combined PCA and K-means approach provides a compact and statistically grounded assessment of cross-country consistency in GHG reporting, offering deeper insights into systematic and sectoral reporting differences.

3.3. Sector Frequency Analysis

To visualize the distribution of consistency between Climate TRACE and UNFCCC emission estimates across various subsectors, a heatmap was constructed (Figure 19). Percentage differences, calculated for each country-sector-year combination using the formula [(TRACE–UNFCCC)/UNFCCC]×100, formed the basis of this visualization. The "Category" column, representing UNFCCC's top-level sector classifications (e.g., Solid Waste Disposal, Agricultural Soils), served as the primary grouping variable. Each calculated percentage difference was then binned into one of the following predefined discrepancy intervals using Python's *pd.cut*() function:

- Less than -100%
- Between -100% and -10%
- Between -10% and 10% (interpreted as consistent)
- Between 10% and 25%
- Between 25% and 50%

- Between 50% and 100%
- Greater than 100%

This categorization allowed us to represent the magnitude of discrepancy between TRACE and UNFCCC for each specific sector and country-year. A contingency table was then generated using pandas.crosstab() to count how many data points fell into each percentage range for every category.

For improved interpretability, a heatmap was created using seaborn.heatmap(). This visualization displayed the distribution of discrepancy magnitudes across sectors, where each cell indicates the number of observations within a specific percentage difference range. Darker colors represent higher counts, providing an intuitive overview of consistency across sectors.

For example, the Solid Waste Disposal category exhibits the highest concentration of observations (n = 41) in the -10% to 10% range, indicating strong agreement between TRACE and UNFCCC estimates in that sector. In contrast, sectors such as Crop Residues and Agricultural Soils show a notable number of data points in the >100% difference range (n = 19 and n = 16, respectively), highlighting significant inconsistencies, possibly due to methodological differences or reporting scope discrepancies.

This heatmap serves as a valuable visual tool for identifying sectors with higher or lower alignment between the two reporting systems, providing a strong foundation for further analysis of discrepancies.

4. COUNTRY SPECIFIC FINDINGS

Both Climate TRACE and the UNFCCC provide total country-level greenhouse gas (GHG) emission data, categorized by main sectors. For the UNFCCC, data for Annex I countries is available from 1990-2021, though Australia specifically provides data only up to 2020. For Non-Annex I countries, the reporting periods vary; for instance, Brazil (examined in this study) has data available from 1990-2016 (UNFCCC, n.d.). Climate TRACE, while also categorizing GHG emissions, offers total country-level GHG data only for the years 2021-2024.

Therefore, to ensure comparability between the two inventories, the main sector data for the common year 2021 has been visualized using graphs (Figure 4.1, Figure 4.3, Figure 4.5, Figure 4.7, Figure 4.9, Figure 4.11). Subsequently, sub-sectors that were matched according to the categorization in Table 3 were visualized using average relative difference graphs, based on their percentage differences.

These graphs are ordered from top to bottom, with the most compatible categories (smallest percentage difference) at the top, and the least compatible categories (largest percentage difference) at the bottom. The observed differences from this comparative analysis were then examined, supported by literature, primarily focusing on the methodologies of each inventory.

4.1. Belgium

In the case of Belgium, there is a significant discrepancy between Climate TRACE and UNFCCC in the agriculture sector, with a relative difference of approximately 770%. This corresponds to a numerical difference of around 72.5 MtCO_2e.

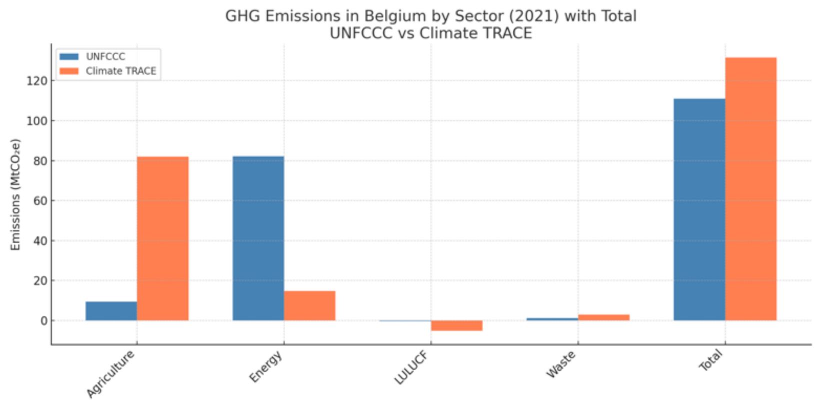

Figure 4.1. Sectoral and total GHG emissions in Belgium for 2021 from UNFCCC and climate TRACE ($MtCO_2e$).

When examining the agriculture subcategories, it is observed that while UNFCCC reports “NO – Not Occurring” for residues, Climate TRACE provides data ranging from 0.15 to 0.20 MtCO_2e for the 2015–2021 period. The primary divergence between the two inventories, however, stems from the manure management and agricultural soils subcategories, where the relative differences range between 71% and 77%.

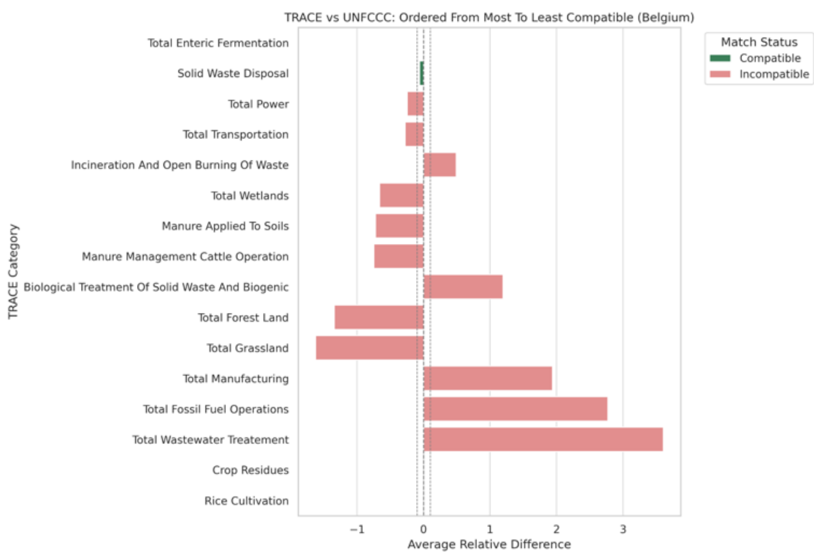

Figure 4.2. Y-axis shows TRACE subcategories; x-axis shows the average relative difference from UNFCCC values. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Subcategories are ranked by compatibility, with dashed lines at ±0.10 marking the ±10% threshold for incompatibility.

Manure management is a significant source of methane (CH_4) and nitrous oxide (N_2O) emissions, particularly from cattle. Climate TRACE identifies individual cattle operations (such as farms, feedlots, and dairies) using artificial intelligence (AI) models and remote sensing imagery.

It estimates animal numbers or activity by analyzing the facility's footprint area, assuming a proportional relationship between facility size and herd size. When comparing its own data to FAOSTAT, Climate TRACE has reported cases where its facility-level data produced higher emissions-especially for N_2O-due to more detailed manure management observations (Davitt *et al.*, 2024).

On the UNFCCC side, countries are required to report livestock population data in their inventory tables. According to IPCC (2006a), methane emissions from manure management are influenced by both temperature and animal population size. However, the use of national average temperatures or default management system distributions in national reporting may deviate from the finer-scale estimates produced by Climate TRACE (Davitt *et al.*, 2024). Consequently, Climate TRACE's incorporation of granular activity data and local environmental conditions, such as temperature, directly into its calculations may result in significant divergences from the more aggregated and average-based UNFCCC estimates.

For Belgium, however, the opposite trend is observed in the case of enteric fermentation. The difference between Climate TRACE and UNFCCC estimates for this category ranges only between 0.27% and 1.94% from 2015 to 2021.

Climate TRACE employs artificial intelligence and remote sensing to estimate emissions at the individual facility level in specific sectors (e.g., cattle operations, power plants). However, the availability of such high-resolution data is limited to 77,728 cattle operations across 18 countries: ARG, AUS, BLR, BRA, BWA, CAN, CHN, FRA, GBR, IRL, KAZ, MEX, PAK, RUS, UKR, URY, USA, and ZAF (Davitt *et al.*, 2024). Since Belgium is not among the countries where this high-resolution modeling has been fully implemented, and enteric fermentation sources in the country largely conform to standard assumptions, the close similarity between inventories is likely due to both Climate TRACE and UNFCCC relying on IPCC's standard methodologies and default emission factors.

4.2. Germany

For Germany, which reports energy as its largest emission sector, the 2021 data show that TRACE estimates are 12.23% lower than those reported by the UNFCCC. On the other hand, the discrepancy in the waste sector-where TRACE reports emissions 337.25% higher than the UNFCCC-warrants closer examination.

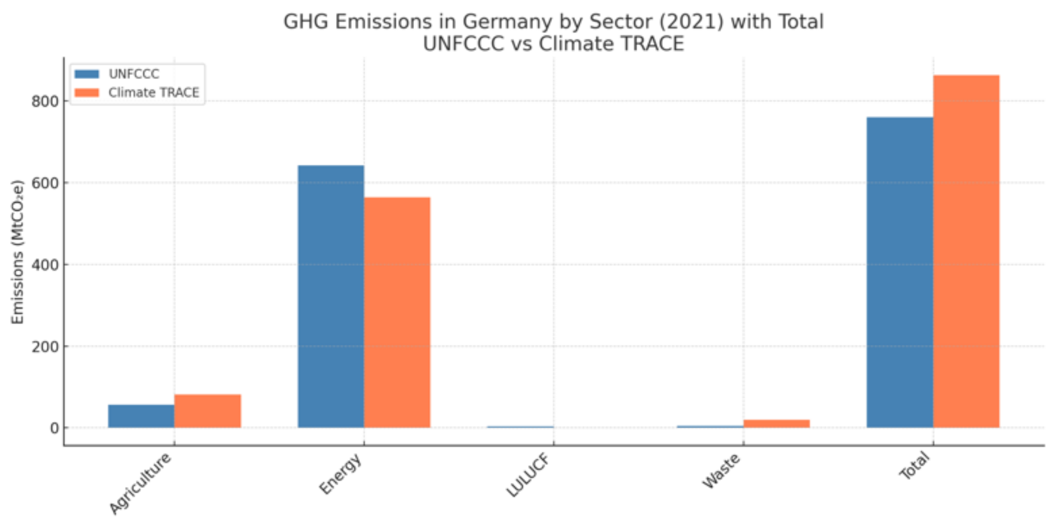

Figure 4.3. Sectoral and total GHG emissions in Germany for 2021 from UNFCCC and Climate TRACE ($MtCO_2e$).

Although both are Annex I countries and EU member states, the difference in the agriculture sector is 770% for Belgium, while it is only 44% for Germany. This suggests that even among European countries, it may be misleading to assume that emissions data are derived from similarly structured sources or methodologies.

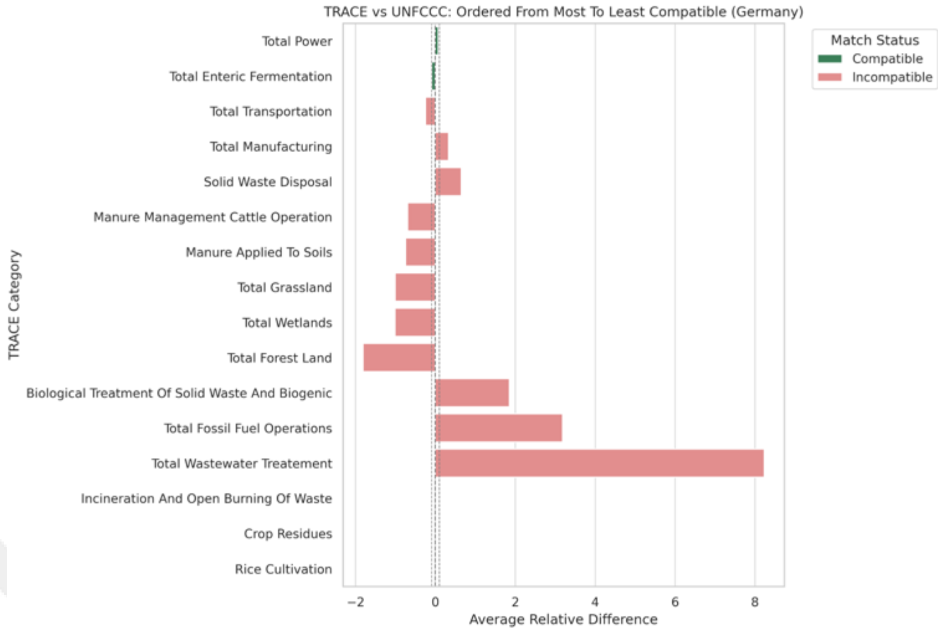

Figure 4.4. Y-axis shows TRACE subcategories; x-axis shows the average relative difference from UNFCCC values. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Subcategories are ranked by compatibility, with dashed lines at ±0.10 marking the ±10% threshold for incompatibility.

When examining the subcategories within the waste sector, it is observed that the wastewater treatment category exhibits discrepancies as high as 900% between the two inventories. One notable explanation for this, particularly in the case of Germany, stems from a methodological distinction introduced by Climate TRACE. Climate TRACE has developed a novel satellite imagery and machine learning-based model to detect wastewater treatment plants (WWTPs). This model is specifically trained to identify WWTPs based on distinct visual features, such as circular tanks (clarifiers) commonly found in treatment facilities. It was applied within a 5-kilometer radius around the world's 125 largest cities. In Germany, the model detected 373 centralized WWTPs across the country's 80 most populous cities, whereas only 219 centralized WWTPs were officially reported by the European Environment Agency (EEA) for the same locations (Collins *et al.*, 2024). The additional 154 WWTPs identified by the model may explain the significant discrepancy in emissions.

From another perspective, IPCC guidelines state that methane recovery or flaring at wastewater treatment facilities should be subtracted from total emissions (IPCC, 2006). However, it is noted that the current Climate TRACE model does not fully estimate the quantities of flaring or methane recovery, nor does it completely distinguish between aerobic and anaerobic treatment processes. These methodological limitations may also contribute to the divergence in methane emission estimates (Collins *et al.*, 2024).

4.3. Japan

In terms of percentage differences, Japan exhibited the most consistent results among all countries in the 2021 comparison of main sectors.

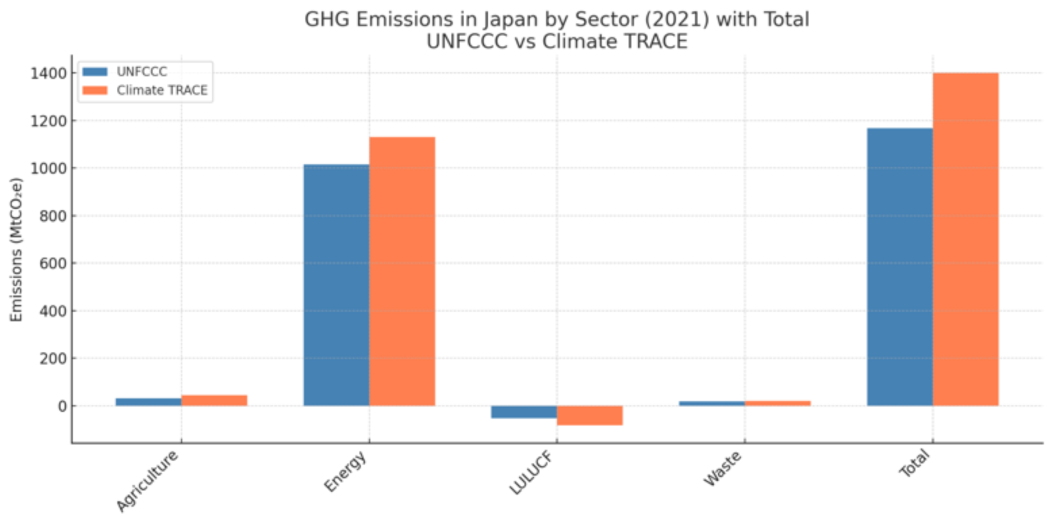

Figure 4.5. Sectoral and total GHG emissions in Japan for 2021 from UNFCCC and Climate TRACE ($MtCO_2e$).

While every other country analyzed had at least one sector exceeding a 100% difference threshold, Japan's sectoral discrepancies were as follows: agriculture (36.13%), energy (11.34%), LULUCF (60%), and waste (14.84%), with Climate TRACE consistently reporting higher emissions across all sectors. However, when analyzing subsectors over the period 2015–2021, significant discrepancies emerge in fossil fuel operations, where differences range between 1500% and 1900%.

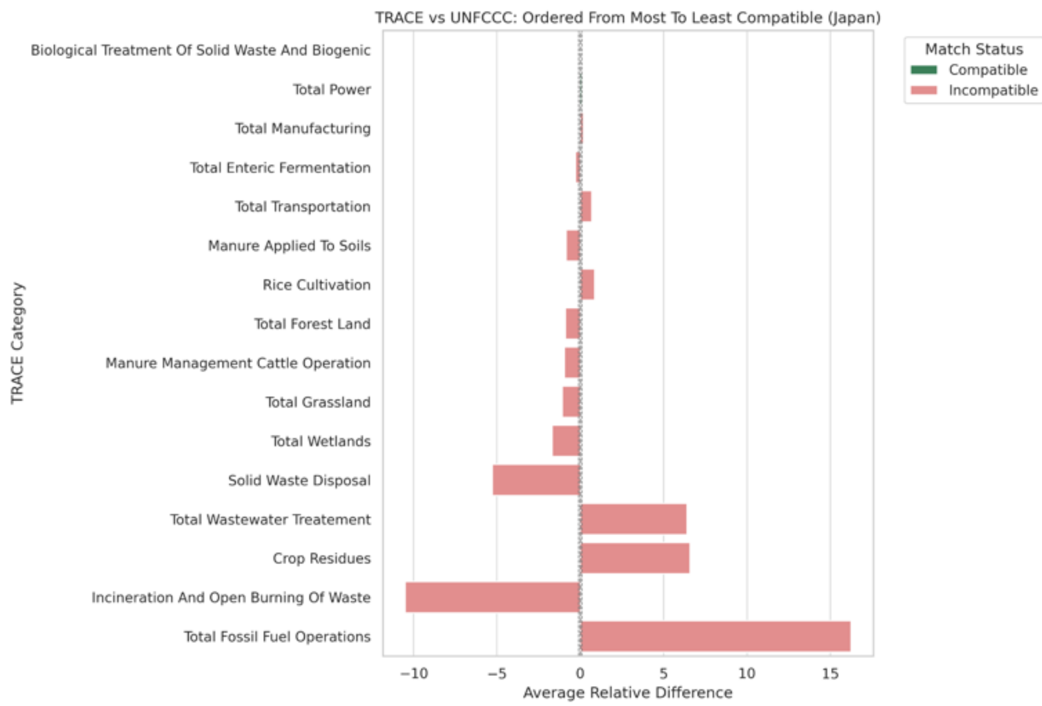

Figure 4.6. Y-axis shows TRACE subcategories; x-axis shows the average relative difference from UNFCCC values. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Subcategories are ranked by compatibility, with dashed lines at ±0.10 marking the ±10% threshold for incompatibility.

While there wouldn't be a difference in methodology specifically for Japan, flaring efficiency may help explain the significant differences observed. National inventories may lower flaring emissions assuming high flaring efficiency, but real-world field studies may show that efficiency is lower. Climate TRACE uses the Oil Climate Index + Gas (OCI+) methodology, which integrates VIIRS (Visible Infrared Imaging Radiometer Suite) satellite data to estimate flaring emissions from the oil and gas production and transportation sectors.

This method detects global flaring activity every 24 hours at a resolution of 750m and explicitly accounts for flaring inefficiency (such as 10% unburned methane) (Schmeisser *et al.*, 2023), which can increase emissions and consequently widen the gap with other inventories.

Another technology used by Climate TRACE also considers what are called ultra-emitters, which are large, intermittent methane releases detected by instruments such as the TROPOMI satellite, including equipment failures or during maintenance (Schmeisser *et al.*, 2023). It is stated that these super-emitters account for 8%-12% of global oil and gas production methane emissions, and such large releases are often overlooked in current national inventory estimates (Lauvaux *et al.*, 2022). UNFCCC inventories, however, may have significant underestimations, particularly for fugitive emissions in the oil sector (Lu *et al.*, 2022; Scarpelli *et al.*, 2022).

4.4. Poland

In the case of Poland, the largest discrepancy among the main sectors in 2021 is observed in the LULUCF category, where the UNFCCC reports 194% more emissions than Climate TRACE.

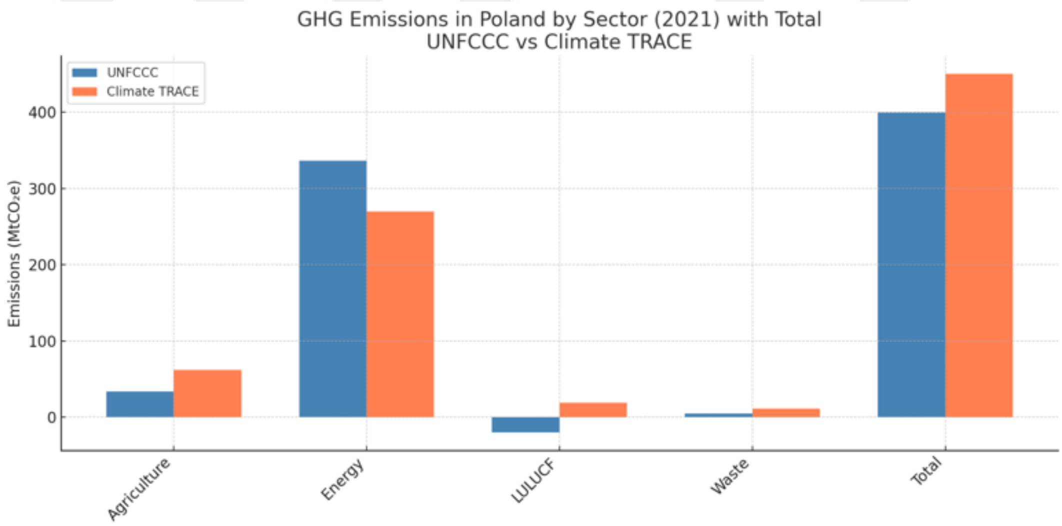

Figure 4.7. Sectoral and total GHG emissions in Poland for 2021 from UNFCCC and Climate TRACE ($MtCO_2e$).

When examining sub-sectoral differences over the 2015–2021 period, a significant divergence of approximately 5000% is found in the crop residues subcategory between the two inventories.

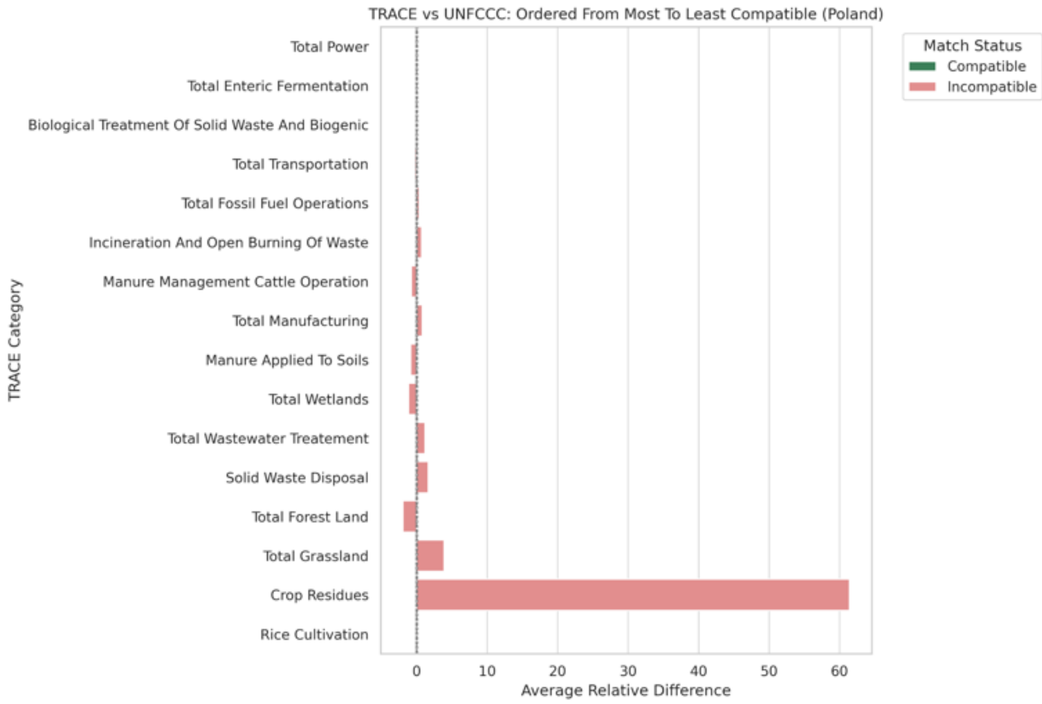

Figure 4.8. Y-axis shows TRACE subcategories; x-axis shows the average relative difference from UNFCCC values. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Subcategories are ranked by compatibility, with dashed lines at ±0.10 marking the ±10% threshold for incompatibility.

The significant discrepancy observed in the Crop Residues category may be attributed more to UNFCCC's reporting guidelines than to the technologies used by Climate TRACE. This is because UNFCCC national communications require reporting only anthropogenic fires (i.e., those on managed lands); therefore, their estimates may reflect only a subset of the fires captured by the Climate TRACE model (Kochhar, Ahmed, and Luong, 2023).

Another rule followed under UNFCCC guidelines excludes CO_2 emissions from national totals if they originate from biogenic materials (e.g., paper, food, wood waste) and are assumed to be reabsorbed by vegetation in the following growing season (IPCC, 2006).

In contrast, Climate TRACE statistically derives burn rates specific to cropland by regressing satellite-derived Aerosol Optical Depth (AOD) and Fire Radiative Power (FRP) data. However, acknowledged by the Climate TRACE expertise that regional emission estimates may differ when compared to other global inventories (Kochhar, Ahmed, and Luong, 2023).

4.5. Turkey

In the comparison of Turkey's main sectors for the year 2021, the largest discrepancy is observed in the waste sector, where Climate TRACE reports emissions that are 823% higher than those reported by the UNFCCC.

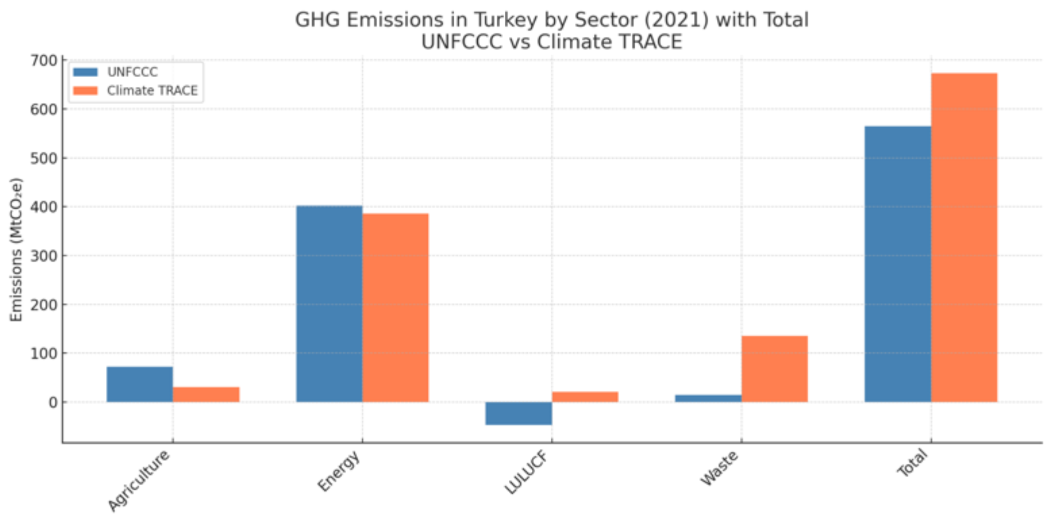

Figure 4.9. Sectoral and total GHG emissions in Turkey for 2021 from UNFCCC and Climate TRACE ($MtCO_2e$).

Conversely, the smallest difference is found in the energy sector, where TRACE estimates are 4.22% lower.

A strong correlation (R = 0.998) has been found between Climate TRACE and EDGAR in estimating country-level CO_2 emissions for the energy sector (Smalley *et al.*, 2024). Significant differences in subcategories of the waste sector are also evident throughout the 2015–2021 period.

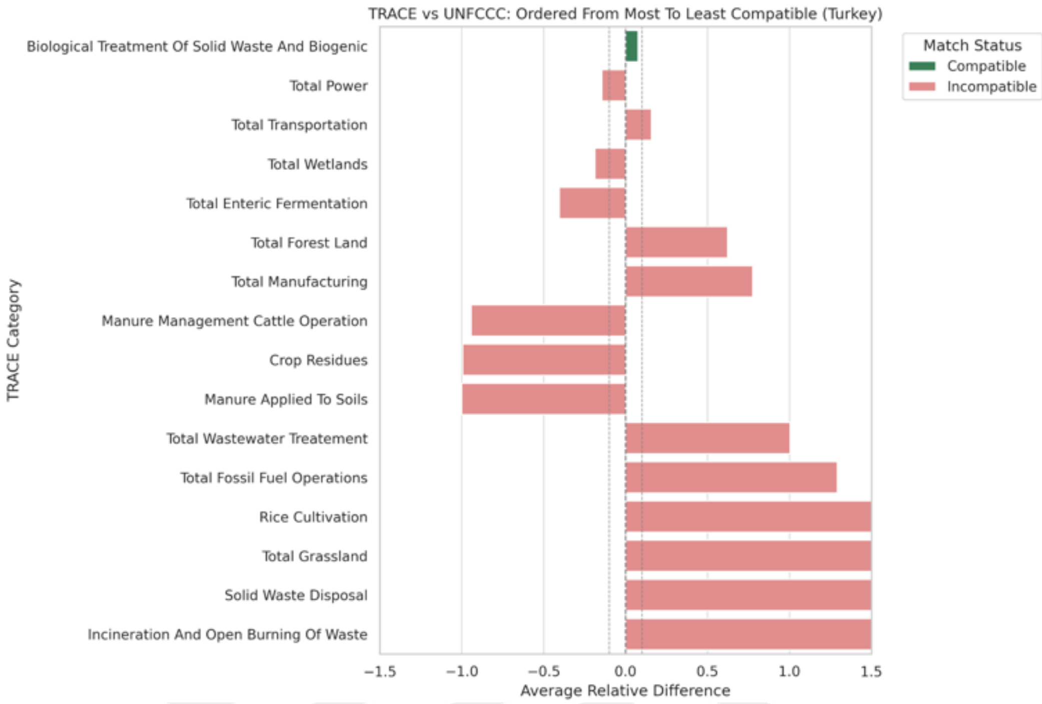

Figure 4.10. Y-axis shows TRACE subcategories; x-axis is limited to -1.5 to 1.5 for clarity in Turkey's chart. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Dashed lines at ±0.10 mark the ±10% incompatibility threshold.

In the case of Turkey, it is notable that the two sub-sectors showing the largest discrepancies both fall under the main category of Waste, while the sub-sector with the highest alignment between the two inventories-Biological Treatment-also belongs to the Waste category.

The UNFCCC guidelines (IPCC, 2006) state that open burning is common in many developing countries, but statistics on such practices are often unavailable. This can lead to underreporting of open burning emissions in national inventories. For estimating CH_4 emissions from solid waste disposal, the UNFCCC employs the First Order Decay (FOD) model, which requires historical waste disposal data. However, it has been noted that very few countries have sufficient historical waste data available (IPCC, 2006).

One of the critical aspects of solid waste emissions is that Climate TRACE does not directly model or estimate CO_2 and N_2O but republishes them when reported by facilities (Raniga, 2024). As a result, if a facility includes biogenic CO_2 in its total GHG reporting, the total CO_2e value in Climate TRACE may be higher than that in the UNFCCC.

Another striking point in Climate TRACE is its own critique of its 2024 methane emission estimates from Solid Waste Disposal Sites. In its 2024 (v3) data release, Climate TRACE applied a Bayesian regression modeling approach for estimating emissions from solid waste disposal, whereas its earlier 2022 (v1) methodology used a modified first-order decay equation for sites with specific metadata (Raniga, 2024).

This new data-driven approach was selected to produce more accurate estimates based on available information and to provide a globally consistent framework for estimating emissions.

It integrates detailed facility-level data, open datasets, and satellite emission measurements from GHGSat and Carbon Mapper (Raniga, 2024). The overestimation resulting from the combination of self-reported data and satellite-based emission estimates may raise broader concerns that could apply to other sectors as well.

4.6. USA

For the USA, the 2021 comparison of major sectors reveals that the largest discrepancy appears in the LULUCF sector, with a difference of -103.55%, where the UNFCCC reports significantly higher emissions.

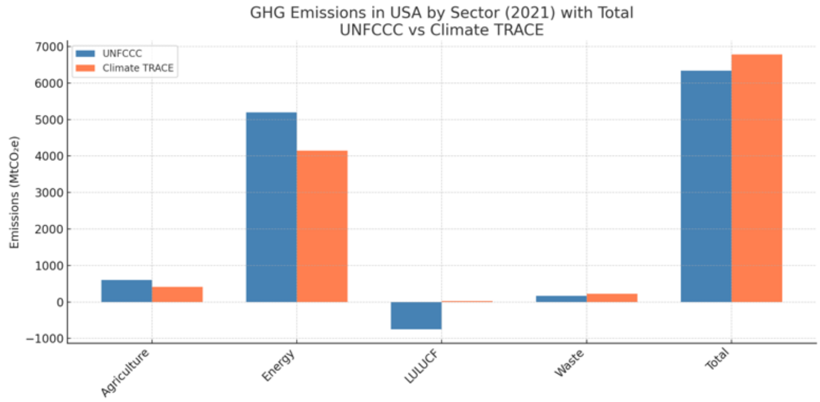

Figure 4.11. Sectoral and total GHG emissions in USA for 2021 from UNFCCC and Climate TRACE ($MtCO_2e$).

However, it is important to note that the UNFCCC reports a negative emission value, while Climate TRACE presents a positive emission figure for LULUCF. A similar situation is also observed in Australia and Brazil for this category. The underlying reasons for these discrepancies are analyzed in detail under the Australia graph.

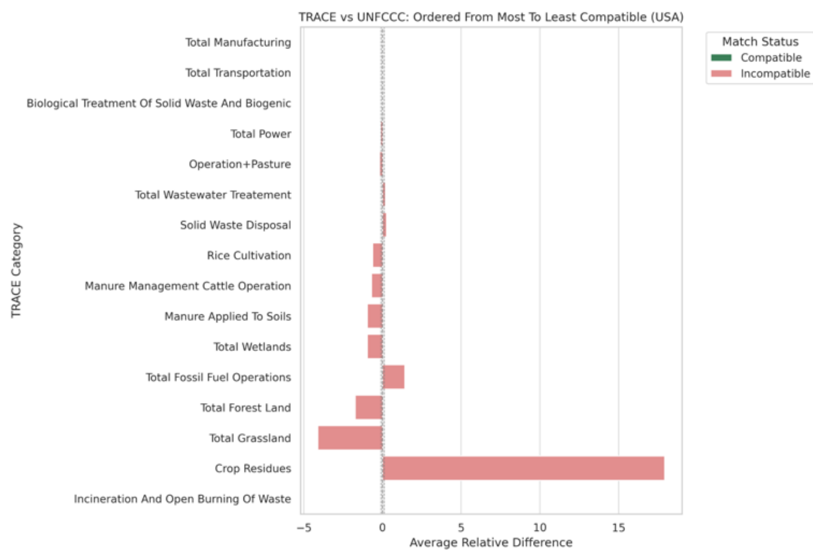

Figure 4.12. Y-axis shows TRACE subcategories; x-axis shows the average relative difference from UNFCCC values. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Subcategories are ranked by compatibility, with dashed lines at ±0.10 marking the ±10% threshold for incompatibility.

When examining the 2015–2021 period, extreme discrepancies-such as those observed in the Crop Residues sub-sector for Poland, where differences reach around 1700%-indicate that TRACE emission estimates are substantially higher than those reported by the UNFCCC. In contrast to Poland, a key difference for the USA is that it is one of the 12 countries for which BSA (Blue Sky Analytics) estimates were generated, which is a methodology integrated into Climate TRACE. BSA estimates are employed by the Climate TRACE coalition to monitor and predict global greenhouse gas (GHG) emissions, and the USA is among the countries analyzed for carbon dioxide (CO_2) emissions from total crop residue burning. In particular, for categories such as Field Burning of Agricultural Residues, Climate TRACE utilizes a satellite-based modeling approach developed and implemented by Blue Sky Analytics (Kochhar, Ahmed, and Luong, 2023).

While BSA estimates for India and Australia are explicitly noted to be higher than other inventories (e.g., GFAS and GFED), and lower for countries like Brazil, no direct comparison as “higher” or “lower” is specified for the USA in the same sentence (Kochhar, Ahmed, and Luong, 2023). At this point, the alignment of TRACE’s methodology with other inventories for this category in the USA invites further scrutiny of the country’s official UNFCCC submissions. Given that the USA plays a significant role in global emissions and is expected to report its reduction targets based on its declared emissions, this large discrepancy could also be explored from a political perspective.

4.7. Australia

Specifically for Australia, the most significant differences were in the Forest Land and Solid Waste Disposal categories. From 2015 to 2020, Climate TRACE reported emissions for Forest Land ranging from 570% to 2342%, which were significantly lower than those reported by the UNFCCC.

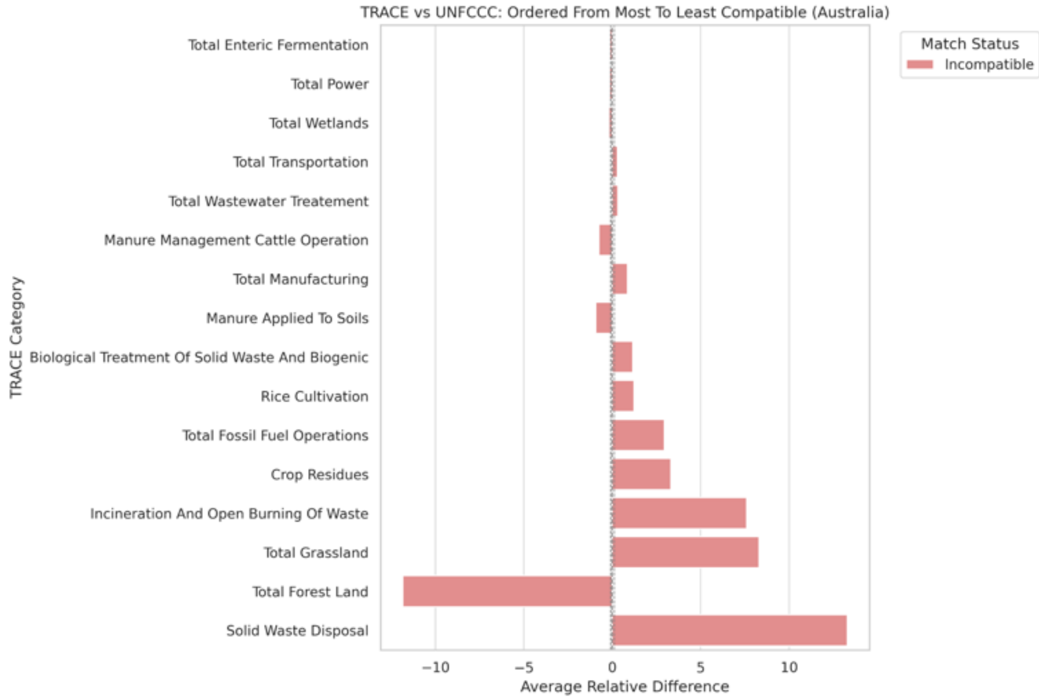

Figure 4.13. Y-axis shows TRACE subcategories; x-axis shows the average relative difference from UNFCCC values. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Categories are ranked by compatibility, with dashed lines at ±0.25 marking the ±25% incompatibility threshold.

Although Australia is in the Annex I category, unlike other countries, its 2021 data is not available in the UNFCCC; therefore, a 2021 main sector emission comparison between TRACE and UNFCCC could not be conducted as it was done for the other Annex I countries. If we look at the reasons for this difference in forest land, Climate TRACE combines many technologies. In collaboration with the organization CTrees, it combines advanced remote sensing datasets that estimate forest canopy structure and biomass aboveground using radar data such as GLAS and ALOS PALSAR, along with land use and land cover changes (Yang and Saatchi, 2024).

Furthermore, it integrates data such as Land Surface Temperature and burned area information from MODIS using machine learning (Yang and Saatchi, 2024). CTrees' integrated methodology facilitates the identification of seasonal spatiotemporal variabilities, as its calculations indicate a greater carbon imbalance relative to previous global greenhouse gas inventories (da Costa *et al.*, 2025). Since Climate TRACE estimates emissions using seasonal spatiotemporal variables, it has at times classified the forestry sector as a net emitter in countries where the UNFCCC reports it as a net sink (da Costa *et al.*, 2025).

Secondly, although the UNFCCC defines 'forest' based on specific thresholds-such as areas larger than 0.5 hectares, trees taller than 5 meters, and a canopy cover greater than 10% (IPCC, 2006)-countries may integrate these thresholds differently into their national inventories.

While Climate TRACE does not explicitly disclose its forest definition in its methodology documents, a paper authored by its members and shared by Climate TRACE indicates the adoption of a 30% canopy cover threshold (Xu *et al.*, 2021). If this threshold is applied, areas considered forests by the UNFCCC but characterized by low-density or degraded (high-emission) conditions may be excluded.

Consequently, this could lead to lower gross emission estimates within the 'forest land' category as defined by Climate TRACE.

4.8. Brazil

Brazil is the only non-Annex I country examined in this study. The main reason for the lack of broader observations regarding non-Annex I countries is the mismatch between the years they reported to the UNFCCC and the 2015–2016 period covered by TRACE data. For Brazil, only the years 2015 and 2016 allowed for a comparison between the two inventories.

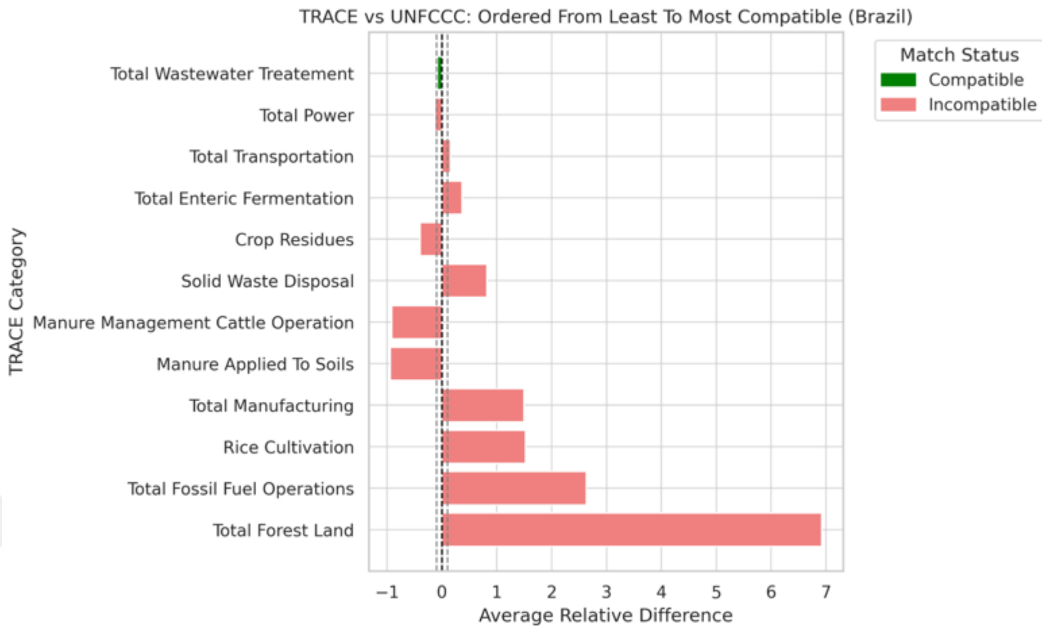

Figure 4.14. Y-axis shows TRACE subcategories; x-axis shows the average relative difference from UNFCCC values. Zero indicates perfect alignment; positive values mean higher TRACE estimates, negative values mean lower. Subcategories are ranked by compatibility, with dashed lines at ±0.10 marking the ±10% threshold for incompatibility.

Looking at the Forest Land comparison for 2015, there is approximately a 708% difference between the two inventories, corresponding to a discrepancy of 1,651.38 MtCO_2e. In 2016, the difference reached approximately 675%, equivalent to 1,963.82 MtCO_2e, with TRACE reporting significantly higher emissions. Forestry and land use, along with the agricultural sector, are commonly identified as the primary sources of greenhouse gas emissions in Brazil. According to Climate TRACE data, the forestry and land use sector in Brazil acts as a net source of emissions (positive values) in some years, and as a net carbon sink (negative values) in others (da Costa *et al.*, 2025). Although this discrepancy is thought to arise from TRACE's consideration of seasonal variations (da Costa *et al.*, 2025), as previously mentioned, differing definitions of forest and other methodological differences may also contribute to these discrepancies.

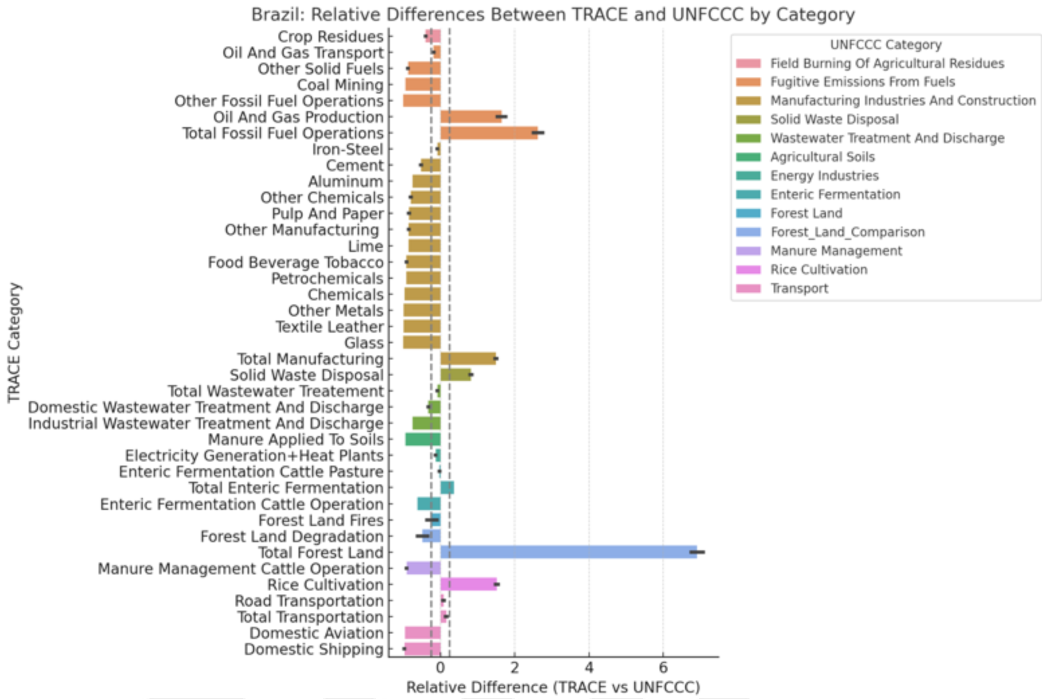

Figure 4.15. Y-axis shows TRACE subcategories, color-coded by their UNFCCC sector; x-axis shows the relative difference from UNFCCC values. Values near zero indicate better alignment; positive values mean higher TRACE estimates, negative values mean lower. Dashed lines at ±0.25 mark the threshold for significant inconsistency.

In the case of Brazil, a different aspect is also worth highlighting. We observe that some TRACE subcategories show a much better match than others within the same UNFCCC category. At the beginning of this study, while examining sub-sectors, TRACE subcategories that could correspond to UNFCCC's subcategories were selected based on methodological alignment. However, it was found that in some cases, individual TRACE subcategories aligned more closely with UNFCCC data than the aggregated TRACE totals that were expected to correspond to the UNFCCC categories. For example, the UNFCCC "Transport" category was compared with the sum of TRACE's domestic aviation, domestic shipping, road transportation, and railway emissions. While the aggregated comparison for Brazil resulted in a relative difference of about 15–20%, the alignment between UNFCCC's transport value and TRACE's road transportation alone was within a narrower range of 6–10%.Similarly, under the

Enteric Fermentation category, the "Cattle Pasture" subcategory shows better agreement with the UNFCCC estimates than either "Cattle Operation" or the total Enteric Fermentation emissions. These findings suggest that in some instances, more granular TRACE categories may provide a closer match to national inventory data than aggregated or total sectoral values.

5. COUNTRY PROFILES

The scatter plot visualizes the clustering of eight countries based on the consistency profiles of their greenhouse gas emissions data from Climate TRACE and UNFCCC, using Principal Component Analysis (PCA) followed by K-means clustering. Each country is represented as a point in a two-dimensional space defined by the first two principal components (PCA 1 and PCA 2), which together capture the most significant variation in the percentage differences across 13 emission sectors.

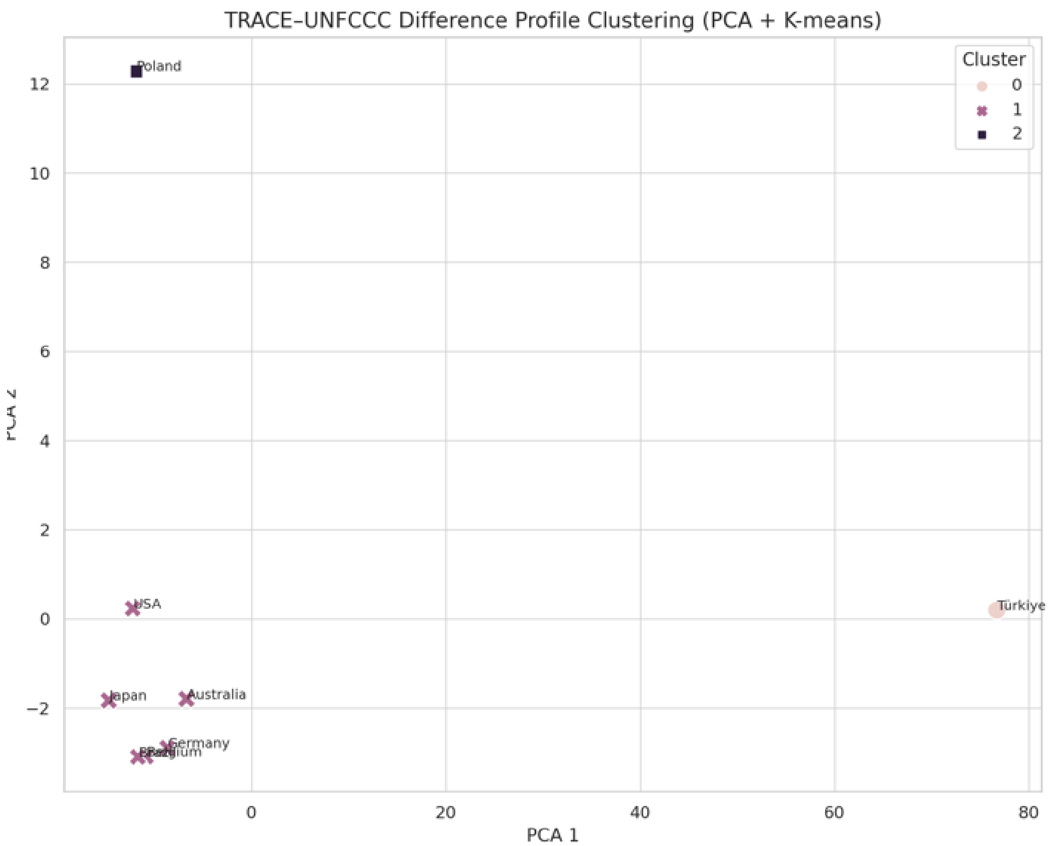

Figure 5.1. PCA + K-means visualization of eight countries (Turkey, Germany, Belgium, Brazil, Japan, Poland, USA, Australia) based on sectoral percentage differences between TRACE and UNFCCC. Data profiles were reduced to two dimensions with PCA and clustered using K-means according to similarity in discrepancy patterns.

Cluster 0: Turkey Turkey stands out due to significantly higher TRACE–UNFCCC discrepancies compared to the other countries. Its distinctly isolated position in the PCA plot reflects the substantial impact of these differences in the high-dimensional space.

Cluster 1: Germany, Belgium, Brazil, Japan, United States, Australia Countries in this cluster exhibit generally similar and moderate levels of discrepancy. The differences among them do not involve extreme deviations, indicating more consistent and comparable methodological profiles across these nations.

Cluster 2: Poland Poland forms a cluster on its own, having demonstrated exceptionally high positive or negative differences in certain sectors compared to other countries. These extreme values in a few specific sectors have driven its separation into an individual cluster.

In this plot, Turkey appears as an outlier on the far right with a high positive PCA 1 score, indicating a strong overall discrepancy-specifically, a systematic overestimation in TRACE data compared to UNFCCC across most sectors. In contrast, countries such as Germany, Australia, Brazil, and Japan are grouped closely together in the lower-left quadrant with negative PCA 1 and PCA 2 scores, suggesting relatively smaller and more uniform differences between TRACE and UNFCCC estimates, forming a cluster with higher consistency.

USA stands slightly apart within the same cluster due to modest differences in certain sectors but still exhibits relatively moderate discrepancies. Poland, located at the top with a high PCA 2 value and moderate PCA 1, displays a distinct deviation pattern-likely indicating significant variation in only a few specific sectors rather than a systematic bias. These spatial separations support the interpretation that PCA 1 captures the overall magnitude and direction of the reporting differences (e.g., TRACE consistently higher or lower), while PCA 2 reflects sector-specific inconsistencies. The color-coded clusters further reinforce the similarity profiles: countries in the same cluster (e.g., Germany, Brazil, Japan) exhibit comparable discrepancy patterns, whereas isolated countries like Turkey and Poland demonstrate unique reporting dynamics that distinguish them from the rest.

This visualization is instrumental in identifying both systematic and sector-specific divergence in emissions reporting and highlights which countries may require further methodological harmonization between TRACE and UNFCCC frameworks.

6. SECTOR FREQUENCY ANALYSIS

This heatmap (figure 18)illustrates the distribution of relative percentage differences between TRACE and UNFCCC emission estimates across various agricultural and waste-related subcategories. Each row corresponds to a specific sector (e.g., Solid Waste Disposal, Manure Management, Rice Cultivation), while each column represents a defined range of percentage differences "-10% to 10%" considered the most consistent range. Each cell contains a count of how many country–sector combinations fall within that discrepancy range. For instance, the value 41 in the "Solid Waste Disposal" row and "-10% to 10%" column indicates that this category contains 41 data points with a relative difference between TRACE and UNFCCC within ±10%, suggesting strong consistency.

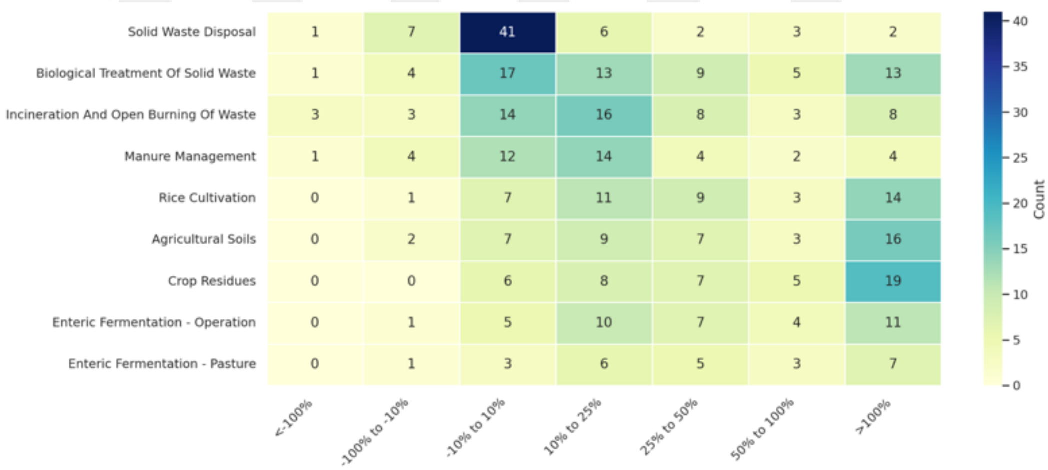

Figure 6.1. Heatmap showing the count of TRACE–UNFCCC percentage differences across sectors and deviation ranges. Higher counts in the -10% to 10% range indicate stronger consistency between datasets.

Solid Waste Disposal shows remarkable agreement between TRACE and UNFCCC, with the majority (41 entries) falling in the ±10% range. Manure Management and Enteric Fermentation – Operation also show moderate consistency, with a visible number of entries in the 10–25% and -10% to 10% ranges. Hence it has a high consistency.

Agricultural Soils and Crop Residues exhibit a high number of entries in the ¿100% range (16 and 19 entries respectively), indicating substantial disagreement in reported emissions. Similarly, Biological Treatment of Solid Waste and Rice Cultivation contain multiple entries in both extremes, suggesting possible methodological or data quality divergences. Hence it has low consistency.

Several sectors such as Incineration and Open Burning of Waste display a wide spread of differences, with no particular concentration in the central range, which might reflect sector-specific estimation challenges or definitional mismatches between TRACE and UNFCCC protocols. Hence it can be called as asymmetry of distribution.

Overall, this visualization serves as a powerful diagnostic tool to identify sectors with high or low alignment between datasets, offering clues for where methodological harmonization or further investigation is needed. The color gradient-ranging from light yellow (low count) to dark blue (high count)-provides a visual cue of density, reinforcing which ranges dominate each category.

7. RESULTS

Satellite-based and AI-integrated next-generation inventories are emerging as promising alternatives to traditional greenhouse gas (GHG) measurement and reporting methods. In addition to the currently available data, the ability of these systems to provide both missing and forward-looking emission estimates holds great potential for identifying emission sources more precisely. However, a closer look at Climate TRACE-a technology-driven inventory-reveals significant percentage differences compared to the traditional inventory maintained by the UNFCCC, both at the main sector and subsector levels.

There are various reasons behind these discrepancies. In this study, comparisons between Climate TRACE and UNFCCC GHG inventories were conducted for selected countries-Australia (AUS), Belgium (BEL), Germany (DEU), Japan (JPN), Poland (POL), Turkey (TUR), the United States of America (USA), and Brazil (BRA)-with a focus on the most notable subsectoral differences for each country.

Due to differing categorization systems, a comparison structure was established based on the methodologies of both inventories, as presented in Table 3. Initially, main sector emissions for the year 2021 were compared across both inventories. Subsequently, sectoral discrepancies were explored in detail at the subsector level. Using average difference charts generated in association with Figure 4.2, Figure 4.4, Figure 4.6, Figure 4.8, Figure 4.10, Figure 4.12, Figure 4.13, Figure 4.14, the subsectors for each country were ranked from most to least aligned between the two inventories, and selected categories were analyzed accordingly.

For Belgium, for instance, the largest inconsistency in 2021 was observed in the agriculture sector, particularly in the "manure management" subsector, with a discrepancy reaching 770%. In contrast, highly aligned subsectors showed differences as low as 0.27% to 1.94%. From a methodological standpoint, Climate TRACE does not utilize satellite data or AI for every subsector. In the agricultural domain, while Climate TRACE integrates AI, the UNFCCC relies on Tier 1 and Tier 2 methods, which are more default-data-based.

One of the areas where country-specific advantages of Climate TRACE became evident was the comparison of "enteric fermentation" for Belgium. The remarkably close alignment between the two inventories in this category is primarily due to the fact that Climate TRACE applies AI and remote sensing only in selected countries-Belgium not being one of them. Consequently, for Belgium, Climate TRACE follows methodologies more closely aligned with the IPCC guidelines, resulting in higher methodological consistency with the UNFCCC inventory.

In Germany, the most prominent discrepancy was observed in the waste sector, which also reflects a country-specific condition. When examining the subsectors under waste, the largest difference was identified in the "wastewater treatment" category, where a striking 900% difference was recorded. One plausible explanation for this substantial discrepancy lies in Climate TRACE's technological approach: using its own wastewater treatment plant (WWTP) detection model, Climate TRACE reports 373 WWTPs in Germany-154 more than the 219 facilities officially reported by the European Environment Agency (EEA) (Collins *et al.*, 2024). This suggests that the large discrepancy may stem directly from differences in source identification and facility detection methodologies.

Japan stands out among the countries analyzed in this study due to the overall consistency between the Climate TRACE and UNFCCC datasets. Unlike other countries, where differences exceeding 100% were observed in several categories, Japan exhibited its highest sectoral discrepancy in the LULUCF category for the year 2021. However, when examining the 2015–2021 period, the most significant difference was found in the fossil fuel operations category, reaching up to 1900%. This extreme discrepancy may be largely attributed to the satellite-based observations used by Climate TRACE, particularly in accounting for flaring inefficiencies and the detection of ultra-emitters. While it has been suggested that the UNFCCC may underestimate emissions in the oil sector (Lu *et al.*, 2022; Scarpelli *et al.*, 2022), the factors of flaring efficiency and ultra-emitters could play a substantial role in driving such a large divergence in reported emissions.

For Poland, the most pronounced discrepancy between the two inventories during the 2015–2021 period was observed in the crop residues subcategory, where the difference reached up to 5000%. This divergence can be attributed to methodological inconsistencies: while Climate TRACE relies on satellite-based detection systems, the UNFCCC inventory often excludes fires resulting from biogenic materials, which contributes significantly to the gap between the two datasets.

In the case of Turkey, the two subcategories that exhibited the highest discrepancies between Climate TRACE and UNFCCC during the 2015–2021 period both belong to the waste sector. Interestingly, the most consistent subcategory also falls within this sector-namely, the biological treatment of solid waste. Notably, Climate TRACE has acknowledged an overestimation in its own data for the solid waste disposal subcategory when comparing its 2024 version (v3) to earlier versions (v1), especially in relation to satellite-based inputs and Bayesian regression updates (Raniga, 2023). This self-critique highlights Climate TRACE's recognition of the potential inflation of its emission estimates relative to the UNFCCC reports.

The United States, similar to Poland, exhibited one of the highest discrepancies between the two inventories in the crop residues subcategory, with percentage differences reaching up to 1700%. Unlike Poland, however, Climate TRACE incorporates BSA (Burned Area Satellite) estimates into its methodology for the U.S. Notably, when compared to other inventories, BSA estimates have been found to align reasonably well for the U.S. (Kochhar, Ahmed, and Luong, 2023), which not only strengthens the confidence in TRACE's technological approach but also invites a more critical perspective toward self-reported national inventories such as those submitted to the UNFCCC.

For both Australia and Brazil, the largest differences between Climate TRACE and UNFCCC inventories were observed in the Forest Land subcategory of the LULUCF sector. In Australia, the discrepancy during the 2015–2020 period reached as high as 2342%, while for Brazil-based on data available for 2015–2016-it approached 708%. A key feature of this subcategory is its reliance on a wide array of technological tools and datasets. In addition, discrepancies in forest definitions between UNFCCC guidelines and TRACE's detection algorithms contribute further to this divergence. In the case of Brazil, a recent study (da Costa *et al.*, 2025) highlighted that TRACE's use of seasonal satellite observations leads to fluctuating annual classifications of the LULUCF sector as either a net sink or a net emitter, diverging significantly from more static traditional inventories. The substantial technological differences and the variation in included parameters have likely driven the large discrepancies in Forest Land estimates for both countries.

The analysis of emission discrepancies between Climate TRACE and UNFCCC data utilized both country profile detection and sectoral consistency assessment. Country profile detection, employing Principal Component Analysis (PCA) and K-means clustering (Figure 17), revealed three distinct country clusters based on their sectoral percentage differences. Turkey was identified as an outlier (Cluster 0), demonstrating significantly higher TRACE-UNFCCC discrepancies, indicative of a systematic overestimation in TRACE data across most sectors. Conversely, Germany, Belgium, Brazil, Japan, the United States, and Australia formed Cluster 1, exhibiting generally similar and moderate levels of discrepancy, suggesting more consistent methodological profiles. Poland, forming Cluster 2, stood apart due to exceptionally high positive or negative differences in a few specific sectors, indicating a distinct deviation pattern rather than a systematic bias. This PCA-based clustering effectively highlights systematic and sector-specific divergences in emission reporting.

For sectoral consistency assessment, a heatmap (Figure 18) was constructed to visualize the distribution of relative percentage differences across agricultural and waste-related subcategories. The Solid Waste Disposal sub-sector showed remarkable agreement between the two inventories, with the majority (41 entries) falling within the ±10% difference range, interpreted as consistent. Manure Management and Enteric Fermentation – Operation also displayed moderate consistency. In contrast, Agricultural Soils and Crop Residues exhibited substantial disagreement, with 16 and 19 entries, respectively, showing over 100% difference. Similarly, Biological Treatment of Solid Waste and Rice Cultivation contained multiple entries in both extremes, suggesting possible methodological or data quality divergences. Furthermore, sectors such as Incineration and Open Burning of Waste showed a wide spread of differences with no particular concentration in the central range, reflecting potential sector-specific estimation challenges or definitional mismatches. This heatmap served as a valuable diagnostic tool for identifying sectors with high or low alignment between datasets, indicating areas requiring further methodological harmonization or investigation

The Climate TRACE dataset evolves across different versions as new methodologies and technologies are incorporated. Moreover, the methodologies themselves differ from one country to another, making direct comparisons with other inventories more complex-for instance, the discrepancies observed in Germany and the United States illustrate this challenge. Climate TRACE itself acknowledges that the availability and quality of data vary significantly across countries (Schmeisser *et al.*, 2023). Therefore, examining a sector solely within the scope of Climate TRACE is quite challenging, as the technologies it employs vary across countries. Consequently, in addition to sector-based analyses, investigating sectoral differences on a country-by-country basis has been of great importance in understanding the underlying causes of these discrepancies.

While analyzing sectoral differences across the 2015–2021 period at the subsector level, another important observation emerged: for some countries, specific TRACE micro-sectors aligned more closely with UNFCCC data than others. For example, the UNFCCC transportation sector does not provide detailed subsectoral breakdowns, yet the category generally includes emissions from domestic aviation, shipping, and road transport. In highly developed countries, both domestic and international aviation represent major emission sources, whereas in lower-income countries, rail transportation can account for up to 67% of transport-related emissions (Zhang *et al.*, 2024). Among these, road transportation remains a common and significant emission source across all countries (McDuffie *et al.*, 2020). This divergence in subsectoral relevance, which is also supported by findings in the literature, highlights a promising area for future research when comparing sectoral consistency between UNFCCC and TRACE inventories. On the other hand, another noteworthy finding throughout the study was the significant year-to-year variability observed within Climate TRACE data for the same sector and country. For instance, in the comparison of incineration and open burning for Belgium, UNFCCC estimates decreased from 291.6 MtCO_2e in 2015 to 257.0 MtCO_2e in 2016. In contrast, TRACE estimates for the same subsector increased substantially from 321.7 MtCO_2e to 415 MtCO_2e within just one year-causing the percentage difference between the two inventories to rise from 10% to 62%. As previously discussed, TRACE frequently updates its methodologies, and the shift in values across versions has occasionally resulted in overestimations, as acknowledged in its own documentation (Raniga, 2024). This intra-dataset inconsistency suggests that, beyond cross-inventory comparisons, the temporal consistency of Climate TRACE data itself may warrant further independent investigation.

The significant percentage differences observed across countries and sectors, often with Climate TRACE reporting higher emissions, highlight inherent methodological divergences. Climate TRACE, with its integration of satellite imagery, AI, and remote sensing, offers granular, high-resolution estimates that can capture emissions potentially overlooked by traditional national inventories, such as additional wastewater treatment plants in Germany or specific flaring inefficiencies and ultra-emitters in fossil fuel operations. However, these advanced methods also introduce complexities and, at times, self-acknowledged overestimations, or categorical gaps (e.g., liming and organic fertilizers in Brazil). The variability in Climate TRACE's methodology across different sub-categories and countries (e.g., Belgium's enteric fermentation versus other countries' AI-driven estimates) further complicates direct comparisons and suggests that its data consistency can fluctuate.

Conversely, the UNFCCC relies on country - contributed national inventories, which, while providing a standardized reporting framework, can suffer from underreporting due to data unavailability (e.g., historical waste data, open burning statistics) or specific reporting guidelines that exclude certain biogenic emissions. The noted underestimation of fugitive emissions in the oil sector by UNFCCC inventories further exemplifies these limitations.

Therefore, the observed discrepancies underscore that both inventories have strengths and weaknesses rooted in their distinct data sources, methodologies, and reporting scopes. Rather than favoring one over the other, the findings emphasize the need for critical assessment and a complementary approach, leveraging the strengths of both systems to achieve a more comprehensive and robust understanding of global GHG emissions. Further methodological harmonization and transparent definitions are crucial to enhance the reliability and comparability of emission data for international climate accountability.

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