Waste sector: Wastewater Treatment Plant Emissions

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1. Introduction

Wastewater is water that has been used for domestic, industrial, or agricultural purposes. In domestic settings, wastewater contains human waste, food scraps and residue, and household chemicals. In industrial settings, wastewater may contain pollutants and industrial byproducts from industries like textile manufacturing, oil and gas extraction, mining, food processing, chemical and pharmaceutical manufacturing (USGS, 2018). Untreated wastewater or raw sewage must be treated before release to the environment, in order to avoid the spread of disease and negative impacts from pollutants (WHO, 2018).

In addition to health and environmental impacts, wastewater is a source of greenhouse gas (GHG) emissions, specifically, methane (CH_4) and nitrous oxide (N_2O) – depending on the treatment method. Wastewater accounted for 5% of global non-CO_2 emissions in 2015, with the highest growth in India, Indonesia, and China. With this projected growth, wastewater emissions are expected to grow by 14% compared to 2015 levels (US EPA, 2019).

The following text describes how four models work together to estimate monthly CH_4 and N_2O emissions from wastewater: two asset-level models and two country-level models, one each for domestic and industrial wastewater. The asset-level model for domestic wastewater relies on asset locations and metadata from HydroWASTE dataset, and the domestic country-level model uses World Health Organization (WHO) / United Nations Children's Fund (UNICEF) sanitation statistics. Meanwhile, the industrial asset-level model uses Climate TRACE asset information from the steel and pulp and paper sectors, and the industrial country-level model combines Climate TRACE industrial data with FAOStat statistics on food production. As both the domestic and the industrial models lean on methodology outlined in Intergovernmental Panel on Climate Change (IPCC) emissions guidelines and both share assumptions, equations, and emissions reduction strategies, this document encompasses both the domestic and industrial wastewater sectors.

Sources of emissions from wastewater treatment

Wastewater is a source of methane, both when treated or untreated. In fact, methane emissions from untreated wastewater may be much higher than treated wastewater (De Foy, 2023). Wastewater is also a source of nitrous oxide and carbon dioxide (CO_2); however, the latter is typically not estimated in GHG inventories since biogenic CO_2 is excluded from national GHG inventories (IPCC, 2019).

When treated, wastewater emissions have many sources that are affected by factors such as (IPCC, 2019):

- The collection of wastewater in open or closed sewers,
- The wastewater treatment pathway, i.e. the process by which wastewater is treated, such as the use of centralized aerobic or anaerobic wastewater treatment systems, lagoons, constructed wetlands, septic tanks, or open latrines,
- Recovery of methane from anaerobic reactors and sludge treatment processes,
- The use of the wastewater treatment plant (WWTP), i.e. for domestic/ municipal usage or industrial processes,
- Total amount of wastewater that is processed at a WWTP.

Current approaches to estimating wastewater emissions

There are three pathways for estimating wastewater emissions (DCEWPC, 2011):

- *Direct measurement approach*: Relies on measured emissions using ground-based emissions monitoring sensors;
- *Mass balance approach*: Emissions are calculated as the difference between input and output of the quantity of substance going in or out of an entire facility. For wastewater, this would be the flowrate and influent/ effluent liquid phase pollutant concentrations.
- *Emission factor method*: Emissions are calculated by multiple activity data (amount of organic waste generated) and an emission factor that characterizes the extent to which this waste generates GHGs.

Each of the above methods has advantages and disadvantages: for instance, while direct measurement provides accurate data that is specific to individual facilities, these data are not widely available globally or at all types of WWTPs. The emission factor approach on the other hand can generate an estimate for any facility or at the country-level, this approach tends to have higher uncertainties due to the use of average emission factors.

In addition, to estimate country or region-wide WWTP emissions, it is necessary to characterize different types of facilities including WWTPs. However, such data are not globally available – in fact, the availability of information such as the percentage of treated and untreated sewage, population served by WWTPs, etc. are not readily available globally (WHO, 2018). As a result, data available on WWTP emissions from many countries are likely to have high uncertainties in estimates due to missing the variation at the facility-level. For example, one study found that there is a lot of variation in fossil CO2 at the facility level – based on whether they are for treating domestic wastewater, oil refineries, or sawmills (Tseng, 2016). Several studies point to the likelihood that emissions from this sector are significantly underestimated (Moore, 2023; Song, 2023; De Foy, 2023).

There are also very few globally comprehensive facility-level WWTP datasets available. While many countries have active GHG Reporting Programs or historical data from such programs (such as the United States of America, Canada and the European Union) that include WWTPs, they tend to be concentrated in high-income, Annex-1 countries. Other datasets include The HydroWASTE database, which is a global database of 58,502 WWTPs and their characteristics (Macedo et al. 2022a). This database was developed by combining national and regional datasets with auxiliary information to derive or complete missing characteristics. However, due to the inherent limitation of underlying datasets and missing attributes, the dataset has uncertainties associated with locations and other characteristics of the WWTPs, and missing WWTPs in countries without any officially published datasets.

Globally comprehensive subnational data on untreated wastewater are even more sparse. The WHO/UNICEF Joint Monitoring Programme's Country-level Water Sanitation and Hygiene (WASH) survey data, which reports the percentages of a country's urban or rural population served by different wastewater pathways, can be used to extrapolate what portion of the country's wastewater is untreated (JMP 2023). In order to address some of the issues with current approaches to estimating emissions from WWTPs, Climate TRACE has developed a novel approach for detecting WWTPs using satellite imagery in order to expand the dataset of known WWTPs and estimate emissions down to individual WWTPs.

For the purposes of this model, a WWTP was defined as a centralized wastewater treatment system for the purpose of treating domestic or industrial wastewater. Wastewater treatment ponds or lagoons are also considered by the model, and an experimental method for detecting them is described in Appendix 8. WWTPs may include any or all treatment processes (primary, secondary, and advanced) that occur onsite between inflow of untreated wastewater and outflow of treated wastewater. WWTPs that conduct primary treatment utilize mechanical processes, such as screening, grit removal, and sedimentation, to remove larger solids from the wastewater and to reduce biochemical oxygen demand (BOD). The removal of organic material available for decomposition mitigates the release of methane. Secondary treatment harnesses biological processes to break down contaminants with the help of microorganisms. Advanced wastewater treatment builds upon the biological processes used in secondary treatment to further purify the water through enhanced biological nutrient removal (nitrification and denitrification) or through advanced physical and chemical processes.

The first step of the approach was to create a new satellite imagery and machine learning-based model to detect WWTPs based on their unique visible characteristics in satellite imagery. Specifically, the machine learning (ML) model was trained to identify a WWTP based on the presence of 'clarifiers', which are circular tanks used to remove solids in wastewater (an example is in Figure 1). Clarifiers also have a characteristic mechanical skimmer to remove surface particles. The model was run in and around a 5km radius of the 125 biggest cities in the world. This dataset was supplemented with additional WWTP locations and data attributes from the HydroWASTE dataset. Emissions were then estimated by applying IPCC guidelines for national greenhouse gas inventories (IPCC 2019). An initial proof of concept for quantifying emissions from untreated wastewater in countries which WHO/UNICEF WASH data identifies as having the world's highest percentage of untreated wastewater has also been conducted and is further detailed in Appendix 8.

Emissions Reductions Strategies (ERS):

For every WWTP in the dataset, one or more Emissions Reduction Strategies (ERS) was assigned, depending on the plant's technology level. The ERS demonstrates how WWTP emissions could be lowered if a different treatment processes were applied. For example, if a WWTP that uses only primary treatment processes were retrofitted to be capable of secondary treatment, and the change in technology level results in emissions with a lower CO_2 Equivalent (CO_2e) for 100-year Global Warming Potential (GWP), the WWTP will be assigned a Primary to Secondary ERS. When more than one ERS is applicable to a WWTP, each ERS is assigned a ranking based on the CO_2 Equivalent for 100-year Global Warming Potential (GWP). There are six different ERS, each of which is described in greater detail in section 2.1.8:

- UP: Untreated to Primary
- CL: Covered Lagoon
- PS: Primary to Secondary
- PA: Primary to Advanced
- 2A: Secondary to Advanced
- IM: Intelligent Management

All six of these strategies apply to domestic WWTPs, while only Intelligent Management applies to industrial WWTPs.

2. Materials and Methods

The following datasets and methods were employed to (a) locate and identify wastewater treatment plants (hereafter, WWTP), (b) estimate wastewater CH_4 and N_2O emissions for individual domestic and industrial WWTPs globally for years 2015 to mid-year 2025, at a monthly time-scale, (c) estimate wastewater emissions at a country-level incorporating both centralized and decentralized treatment, and (d) assign one or more ranked ERS for each WWTP.

Google Maps' satellite imagery was used with known wastewater treatment plant locations to train a binary classification machine learning model to identify unknown WWTPs within and near urban areas. This information was combined with emissions factors (EFs) from the 2019 Refinement to the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* to estimate WWTP emissions (IPCC 2019).

2.1 Datasets employed

2.1.1 Wastewater treatment plants data collection

The HydroWASTE dataset provided by HydroSHED (https://www.hydrosheds.org/products/hydrowaste) was used to source images required for training the binary classification machine learning model. HydroWASTE provides global, spatially explicit locations and estimates for the population served, level of technology used, and outfall location of centralized WWTPs (Macedo et al. 2022a). In addition, the population served and technology level was used to estimate GHG emissions. Figure A3.1 of Appendix 4 contains the distribution of all centralized WWTPs in HydroWASTE that are not labeled "Closed" or "Not Operational". In total, 55,507 WWTPs were used for emissions estimates.

Additionally, the European Environment Agency's Urban Waste Water Treatment Directive reported data was included (EEA 2023). This dataset includes all the urban wastewater treatment plants in Germany as reported by the Member States on the implementation of the directive from the European Commission. This data was used to compare the model results to reported data in the top 80 cities, by population, in Germany (see Section 3.1).

2.1.2 Satellite Imagery

To provide visual imagery for WWTP model training, satellite imagery hosted in The Google Map Statics Application Programming Interface (API). Google map statics API hosts various satellite imagery depending on the zoom level - composite imagery from the Landsat and Copernicus program to finer spatial resolutions consisting of Maxar and Airbus imagery (Figure 1). The API returns an image based on a given coordinate, size, scale, zoom, and map type (satellite); size defines the rectangular dimensions of the image in pixels; scale affects the number of pixels returned and scale = 1 retains the dimensions of defined in size parameter; zoom defined the zoom level of the map which determines the magnification level. Using reported WWTPs, images of the locations were extracted using the Map Static API, then were manually sorted to create the initial training dataset. For this research we have set the input image from Google Map Static API is of the size 400*400 pixels (px) which amounts to 583m by 583m for this location, scale 1, and zoom level 16.

Figure 1. An example of the Google Map Statics API for the Berlin Water Works wastewater treatment plant Waßmannsdorf at 400*400 pixels, scale 1, and zoom level 16 input image. Coordinates: latitude = 52.3886, longitude = 13.47396.

2.1.3 IPCC emission factors

Emissions factors (EFs) from "Chapter 6: Wastewater Treatment and Discharge" in "Volume 5: Waste" of the 2019 Refinement to the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* were used for estimating emissions for WWTPs (IPCC 2019). For each WWTP, both the treatment of influent wastewater and the discharge of treated effluent yield emissions, and these pathways have different emissions factors for CH_4 and N_2O. For both species, Tier 2 approaches are used for estimating the emissions from treatment whereas Tier 1 approaches were used for discharge. Country-specific population behavior and demographics and WWTP specific technology levels were used to estimate the total amount of waste in the influent wastewater treated at a WWTP which denotes Tier 2. No differentiation between discharge receiving water bodies (i.e. rivers, lakes, hypoxic/nutrient-impacted) is made which denotes Tier 1.

2.1.4 Population Data

Population data was used to scale HydroWASTE population estimates in order to be used both prior to 2022 and after and is used for estimating country-level emissions. Year-to-year population estimates are obtained from the United Nations (UN) which covers 237 regions of the 251 that are tracked by Climate TRACE. Population estimates for locations not covered by UN data were either obtained through local administration websites (e.g. Åland Islands), from another online source, or estimated as 0. Monthly temporalization is discussed in the Appendix 7. Additionally, urban / rural population disaggregations from the European Commission's

Global Human Settlement Layer (GHSL) were used to estimate the amount of untreated wastewater at the regional level (Pesaresi et al., 2024).

2.1.5 Other Datasets used for the Country-Level Model

For the new country-level model, UN population estimates are combined with WHO/UNICEF Joint Monitoring Programme WASH data to determine the country-level population treated by different wastewater pathways, as well as the country-level population whose waste is untreated or the result of open defecation (JMP 2023). Industrial wastewater was determined at a country-level by using FAOStat estimates for various food and alcohol production and by using Climate TRACE data for pulp and paper, steel, petroleum, and chemical production.

2.1.6 Gap-filling and forward-filling

Many datasets required gap-filling and forward-filling to model all years estimated by Climate TRACE. For some regions, WASH data was linearly interpolated between years and for all countries WASH data was extended to 2025 by treating 2022 data as constants. Any proportion of a population not covered in WASH data is assumed to have untreated wastewater. Regions missing from WASH were mapped to other regions with similar geographical, historical, or cultural ties. This mapping is in Appendix 9 of this document. Finally, Climate TRACE data for pulp and paper and steel were forward-filled to 2025 by using 2022 and 2023 data, respectively.

2.1.7 Datasets for emissions verification

U.S. and E.U. WWTPs' emissions estimates were verified with the most recent emissions inventory by the Environmental Protection Agency (EPA) (EPA 2023) and national-level emissions estimates for E.U. countries (Parravicini 2022).

2.1.8 ERS context and sourcing

EFs from Table 6.3 of "Chapter 6: Wastewater Treatment and Discharge" in "Volume 5: Waste" of the 2019 Refinement to the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* were used for estimating CH_4 and N_2O emissions for WWTPs to which ERS had been applied (IPCC 2019). Brief descriptions of each ERS, as well as context surrounding the current use of these strategies in practice, are provided below:

UP: Untreated to Primary

This strategy involves constructing one or more centralized WWTPs with at least primary treatment capability in order to manage the currently untreated wastewater within a region.

CL: Covered Lagoon

This strategy is applied to domestic assets and represents an effective, low-cost approach to reducing the large amounts of methane produced in lagoons, also known as waste stabilization ponds, where waste is digested anaerobically. The U.S. Environmental Protection Agency (EPA) recommends covering municipal wastewater treatment lagoons in its 2022 compliance advisory (EPA 2022).

PS: Primary to Secondary

This strategy is applied to domestic assets and involves constructing secondary treatment structures (e.g., trickling filters, aeration tanks, secondary clarifiers) and connecting them with the existing primary treatment effluent.

PA: Primary to Advanced

This strategy is applied to domestic assets and involves constructing advanced treatment structures (e.g., denitrifying filters) and connecting them with the existing primary treatment effluent.

2A: Secondary to Advanced

This strategy is applied to domestic assets and involves constructing secondary treatment structures (e.g., aeration tanks) and advanced treatment structures (e.g., denitrifying filters) and connecting them with the existing primary treatment effluent.

IM: Intelligent Management

Adopting intelligent management technologies which optimize chemical dosing and biological oxygen levels can increase treatment efficiency and reduce emissions (see Appendix 2 for further details). This strategy is applied to both domestic and industrial assets.

2.2 Methods

2.2.1. Machine Learning for Verifying and Detecting Wastewater Treatment

The HydroWASTE dataset was used to produce a facility-level dataset of WWTP emissions for Phase 5 of Climate TRACE; however, not all of the assets were used due to the low-level of confidence of HydroWASTE dataset authors on the location of some assets. In order to resolve this, a vision transformer (ViT) machine learning model was developed to verify HydroWASTE locations and detect unidentified wastewater treatment plants.

This model was trained to detect WWTPs in RGB satellite imagery with a country-based, Swin Tiny classifier (Liu 2021) – this is shown in Figure 2. The initial training set consisted of previously verified HydroWASTE locations as well as non-WWTP images from Open Street Maps sampled by land-use category. When applied to a specific region, human verification was used to identify true positives and false positives from the classifier which were bootstrapped for retraining. This model was first used to verify HydroWASTE locations, and then deployed globally to identify assets previously unaccounted for. Overall, this model verified approximately

58,000 assets and uncovered approximately 16,000 newly identified wastewater facilities. Figure 3.a. shows the HydroWASTE WWTP locations from last year's 2024 release, Figure 3.b. shows the locations of newly identified facilities, and Figure 3.c. shows the combined locations for this year's 2025 release.

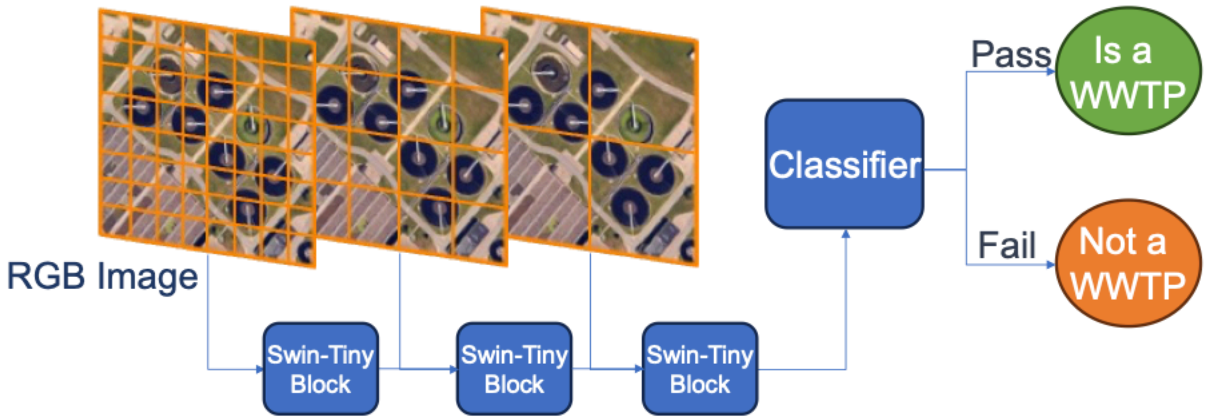
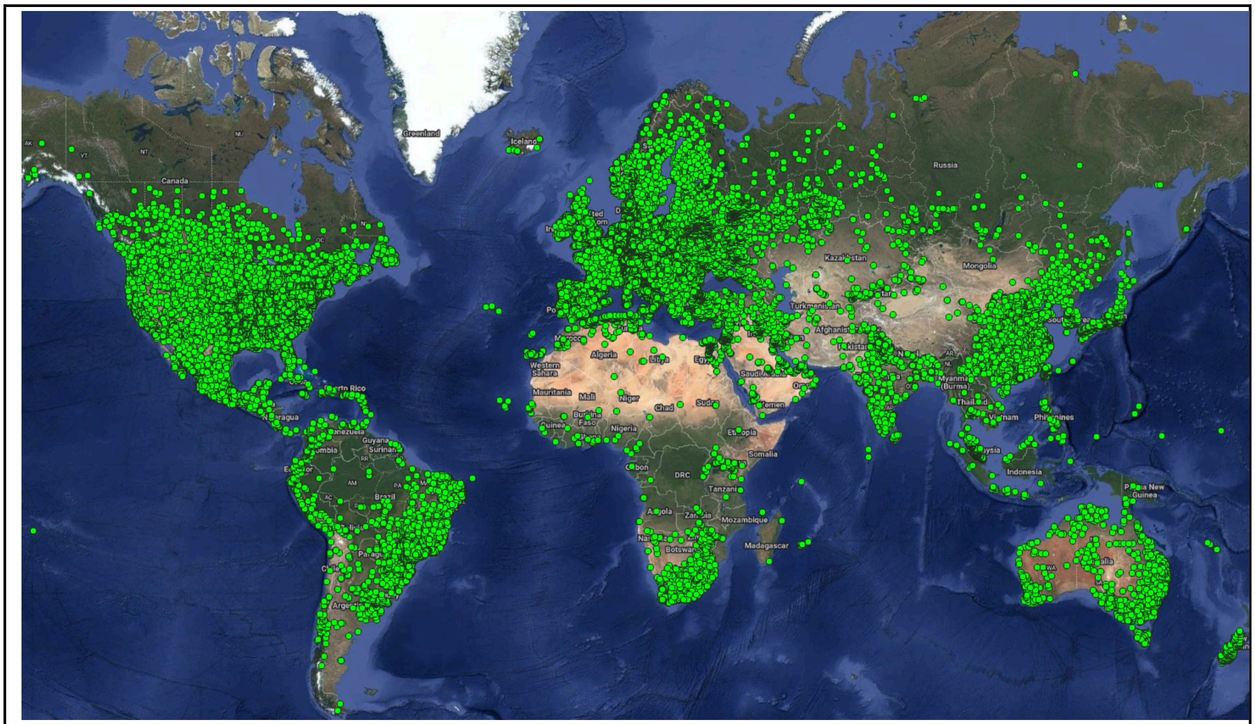
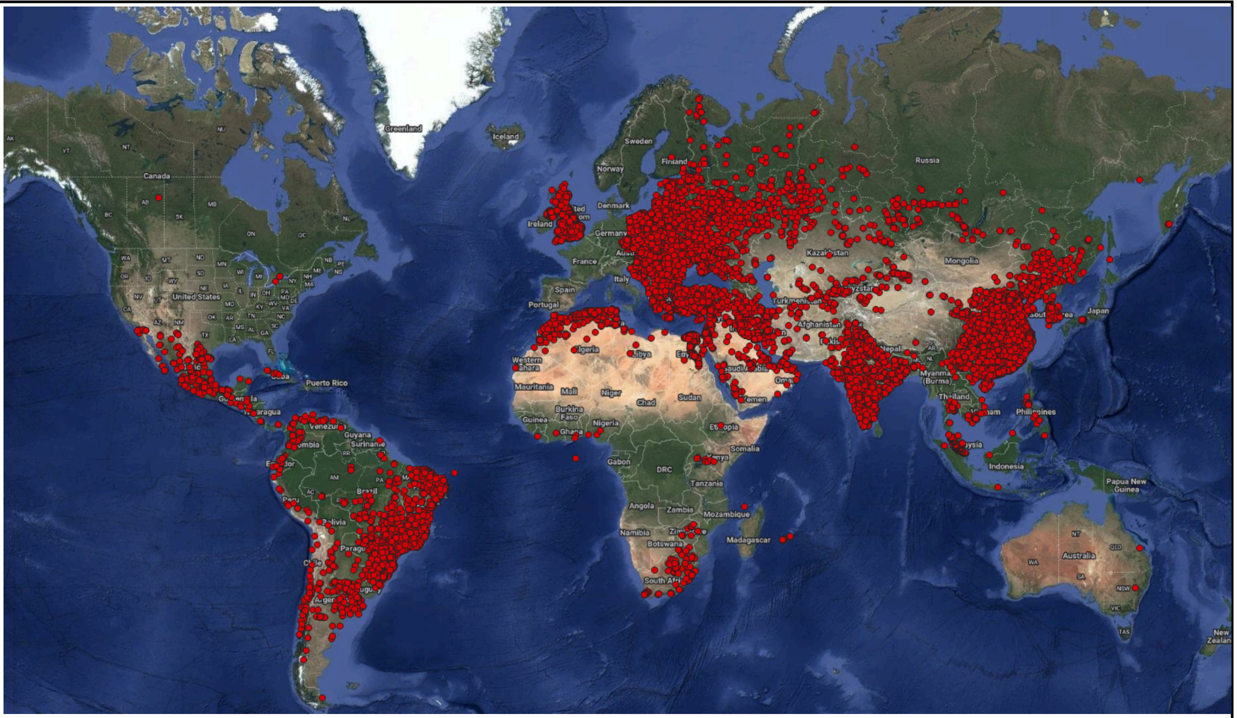


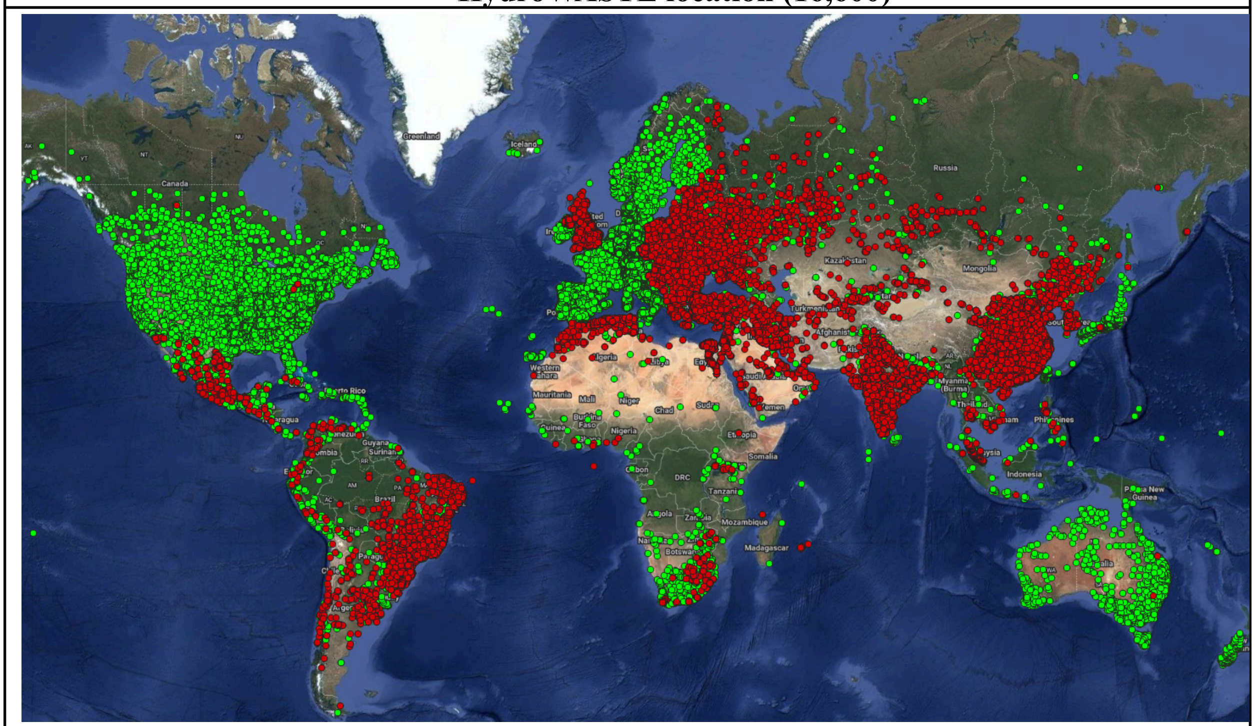
Figure 2: A block diagram of the wastewater facility classifier.



a. HydroWASTE WWTP locations (58,000)



b. **All locations detected by the model to be at more than 50 meters' distance from a HydroWASTE location (16,600)**



c. **Combined HydroWASTE and newly detected WWTP locations**

Figure 3: A comparison between the 2024 and 2025 asset data.

2.2.2 Validating and updating HydroWASTE WWTP characteristics

In order to improve the accuracy of country-level emissions estimates, an analysis was conducted to further validate the characteristics of WWTPs in the HydroWASTE dataset. 87 assets were identified for which the ISO3 value and the country were misaligned. Reasons for this misalignment may include shifting geopolitical borders or inaccurate reporting of the WWTP coordinates in the original dataset. For example, in some regions, the site of the effluent outfall may have been reported as the WWTP location, leading to coordinates in bodies of waters along international boundary lines. For each of the 87 misaligned assets, a visual inspection of the satellite imagery for the asset's coordinates was conducted in order to clarify which country the asset is currently located in as of 2025. The satellite imagery provided sufficient information to correct 60 of these assets, leaving 27 which require further investigation.

2.3 Estimating Asset-level Domestic Emissions

Each WWTP is associated with an estimated population served and technology level within the HydroWASTE dataset. These quantities were used with methodologies described in "Chapter 6: Wastewater Treatment and Discharge" in "Volume 5: Waste" of the 2019 Refinement to the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC 2019), which will be referred to by "IPCC" and the "IPCC guidelines" hereafter, to estimate the monthly CH_4 and N_2O emissions. The IPCC methodologies were derived for estimating country-level emissions based on population and demographics and not for individual WWTPs; however, simple modifications were performed to adapt these methods for this level of granularity. All modifications are summarized in the proceeding text and explicitly described in Appendix 1. Figure 4 contains a flow diagram of the methodology used to obtain source-level emissions estimates for WWTPs in the filtered HydroWASTE dataset. Relevant sections are indicated for each part of the emissions model.

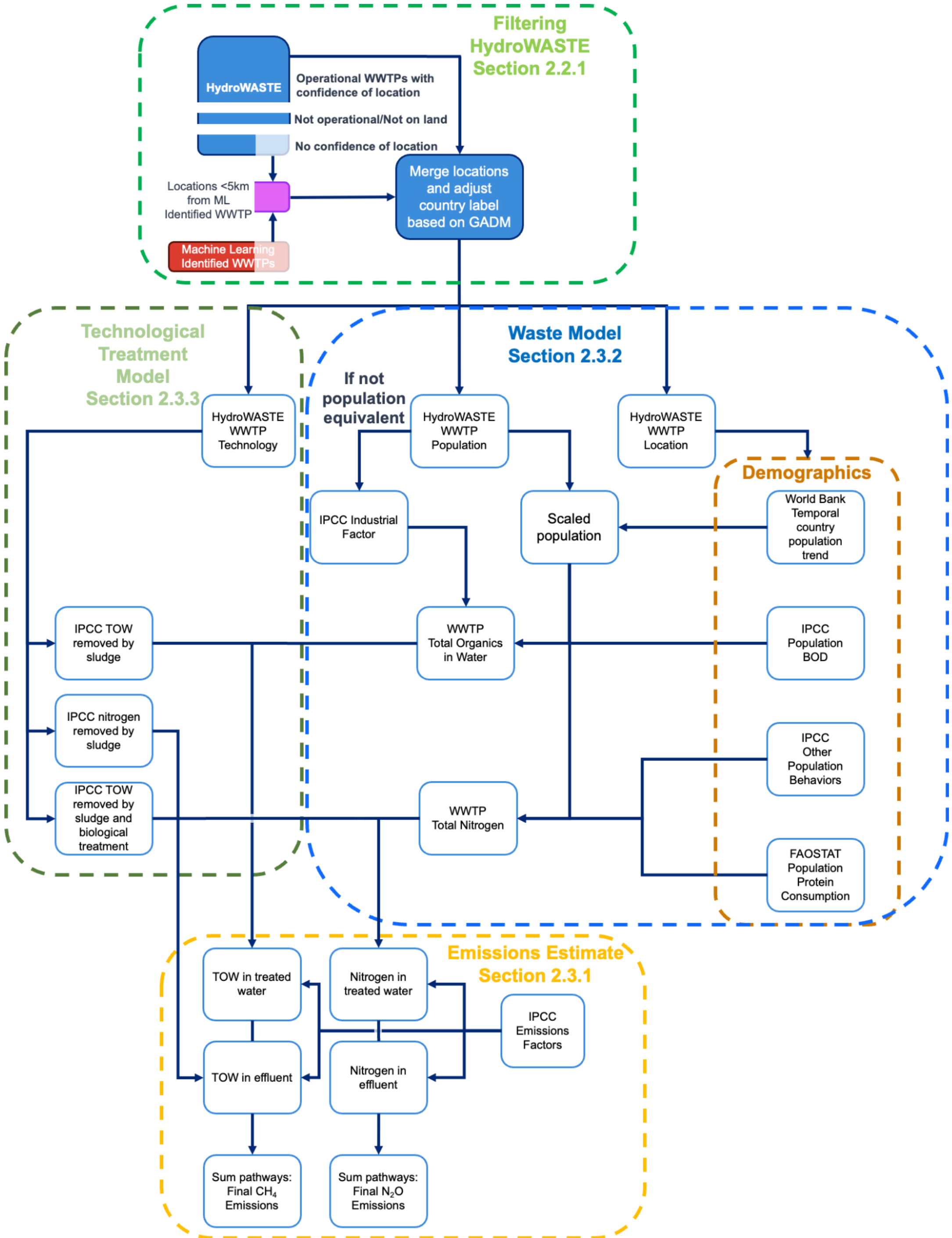


Figure 4. Flow diagram of emissions. HydroWASTE data is filtered based on operationality and location quality. Filtered locations are recovered if identified by machine learning model. Population, technology level, and location are used to develop emissions.

HydroWASTE reports three separate types of "population served" estimations; and since population served affects all calculations, it is important to describe these differences here. Population data that was sourced from authoritative bodies was either labeled as "population served" or "population equivalent" (PE). The first are numbers of people who live in areas where the sewer system connects to the corresponding WWTP. For example, almost all of U.S. data in HydroWASTE comes from the environmental protection agency (EPA) which reports "population served". The second are population estimates arising from (typically) normalization of measurements of the biological oxygen demand (BOD) in untreated wastewater (influent), according to,

$$PE = \frac{g\ BOD}{54\ g\ BOD/\ capita} \text{ (Eq. 1).}$$

As this is a measured quantity, *PE* of a WWTP may include waste from industrial/commercial sources that entered sewer systems and therefore is larger than the population that resides in the region served by the corresponding WWTP. To account for this, all additional scaling factors for industrial waste were treated as a unit value when PE is reported. Finally, HydroWASTE estimated the population served by WWTPs that have no reported population from authoritative bodies. These values were treated like "population served"; however, they have a significantly higher level of uncertainty.

All population data in HydroWASTE were valid for 2022 and thus need to be extended back to 2015 in order to provide emissions over time. This was achieved with linear scaling based on country-level population changes where the WWTP resides. Population data was obtained from UN estimates with gap-filling described in Section 2.1.6.

2.3.1 Emissions Estimates

Generally speaking, there are two sources of emissions from WWTP: the treatment of the water to remove suspended solids and hazardous by-products of waste and industry; and the discharge of treated water (effuse) with some remaining waste into water systems where biochemical reactions occur, releasing emissions. The IPCC guidelines provide methods for estimating the emissions of these individual pathways for both CH_4 and N_2O. See Appendix 1 for a detailed explanation of the methodology and formulae used, including a discussion of uncertainty quantification and confidence (Appendix 1.e.).

2.3.2 Waste Model

Uniting the treatment and discharge pathways are models predicting the amount of organic waste and nitrogen in the influent water treated by centralized WWTPs (the *Waste Model*; Figure 4) and how that treatment influences the emissions based on the technology level of a plant (the *Technological Treatment Model*; Figure 4). See Appendix 1.b. for further details.

2.3.3 Technological Treatment Model

At centralized WWTPs, sludge is the by-product of water treatment and is produced at each level of treatment (primary, secondary, advanced). In addition, different forms of biological treatments are available at plants at different levels of treatment. For a detailed explanation of the Technological Treatment Model, see Appendix 1.c.

2.4 Estimating Asset-level Industrial Emissions

Wastewater emissions are estimated for Climate TRACE pulp and paper and steel assets. Figure 5 shows the locations of the 864 steel assets and 364 pulp and paper assets for which industrial wastewater emissions were estimated.

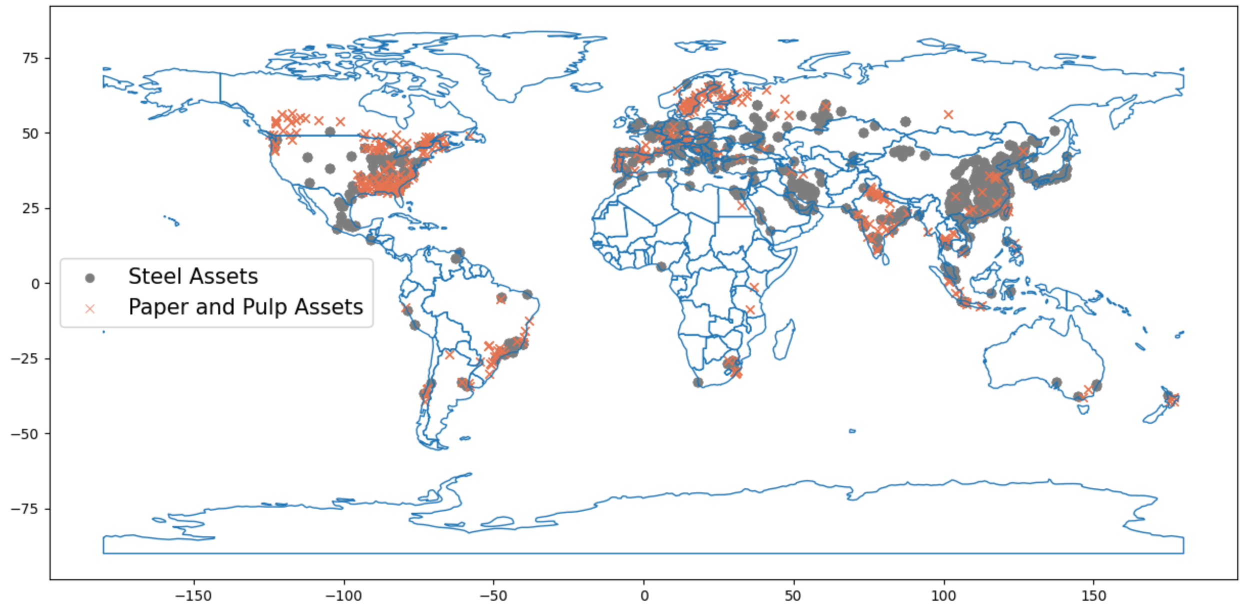


Figure 5. Global distribution of steel (gray dots) and pulp and paper (orange x markers) assets for which wastewater emissions were estimated.

Conveniently, the activity for industrial wastewater emissions – tonnes of product – is the same as that for the emissions from the industrial process. Similarly for domestic wastewater emissions, industrial wastewater produces GHGs during both treatment and in disposal. See Appendix 1.d. for the formulae used in modeling treatment of CH_4 and N_2O emissions.

2.5 Estimating Country-Level Emissions

Decentralized treatment constitutes the majority of wastewater emissions, where precise spatial identification of emissions is difficult. Hence to get a holistic understanding of the total wastewater emissions, a country-level approach which models both centralized and decentralized emissions is needed.

2.5.1. Domestic Wastewater

Like other inventories, e.g. EDGAR and CEDS, Climate TRACE's country-level domestic wastewater emissions were estimated by partitioning country-level populations into separate treatment pathways and applied pathway-specific emissions factors. This is expressed for methane and country c by,

$Em_c = \Sigma_\rho (\alpha_\rho \cdot P_c \cdot BOD_c - S_\rho) \cdot EF_{CH4,\rho} - R_\rho$, (Eq. 2),

where ρ is a specific wastewater pathway, P_c is the population of country c, and BOD_c is the per capita biochemical oxygen demand of the wastewater of country c. For all pathways, $R_\rho = 0$ which is the IPCC Tier 1 default. Nitrous oxide emissions were modeled with,

$Em_c = \Sigma_\rho \alpha_\rho \cdot P_c \cdot N_c \cdot EF_{N2O,\rho} \cdot \frac{44}{28}$, (Eq. 3),

where N_c is the per capita nitrogen content of wastewater, $EF_{N2O,\rho}$ is the nitrous oxide emission factor, and $\frac{44}{28}$ is a nitrogen to nitrous oxide mass-balance factor. The per capita nitrogen content is computed in an identical way as it is for asset-level emissions wherein protein per capita and other country-dependent factors are used. Wastewater effluent emissions were also modeled in the same manner as described earlier.

As diagrammed in Figure 7, the pathways modeled are *Sewer*, *Septic*, *Latrine*, and *No Treatment* and the proportion of each population that is served by each pathway α_ρ was determined by the product of the country-level population and an estimated proportion estimated by WASH.

Two distinguishing features of the Climate TRACE country-level model are that population treated by centralized treatment is appropriately divided into primary, secondary, and advanced treatment categories based on Climate TRACE asset data and that a monthly climatology model is used to determine latrine emissions factors.

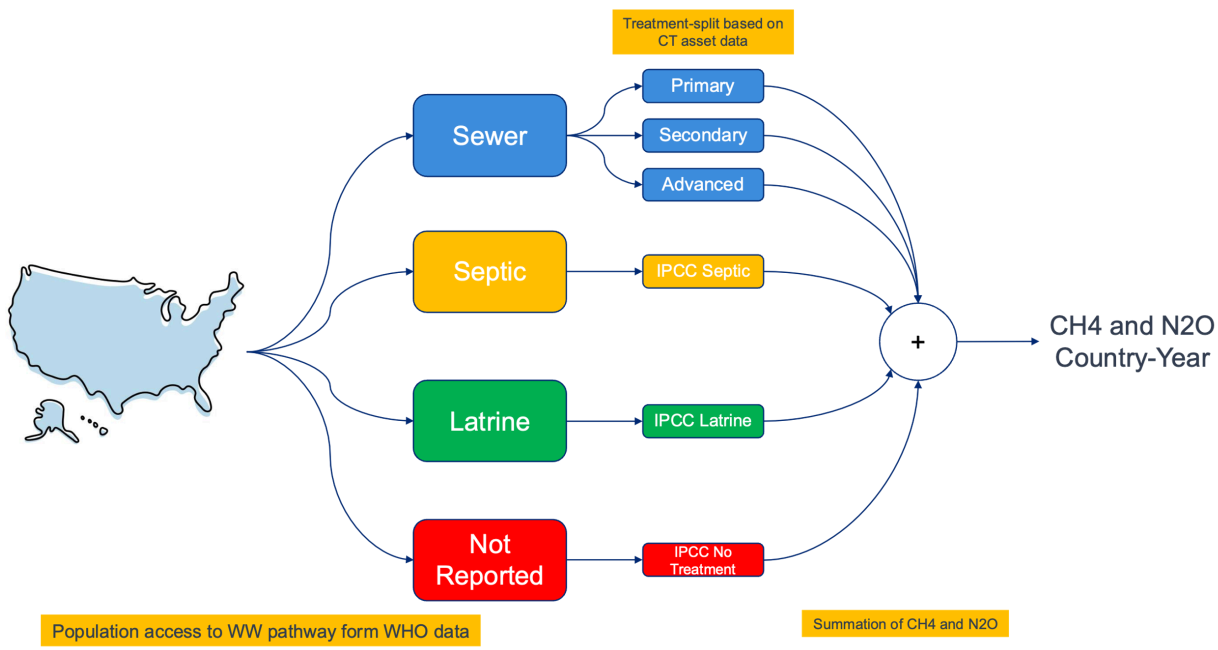


Figure 7. Flow diagram of domestic, country-level emissions model.

The IPCC guidelines differentiate latrines' emissions based on wet versus dry climates. In order to incorporate this difference into the country-level model, IPCC climate zones are determined at a monthly basis and integrated with a global population density grid from the Global Human Settlement Layer (Schiavina 2023). This provides a means of determining the country-level proportion of individuals who live in wet versus dry conditions and thereby the appropriate emissions factors to use. This IPCC climate zone model was also used for determining emissions factors for reservoirs and more detail about the model is contained in the methodology document *Reservoir sector: Emissions from Reservoirs* methodology document. Table 6 shows the partition of the 13 IPCC climate zones into wet and dry climate zones.

Table 6. Aggregated categorization of IPCC Climate Zones for use in estimating latrine emissions.

<table>
<tr><th>IPCC Climate Zones</th><th>Aggregate Climate Zones</th><th>IPCC Climate Zones</th><th>Aggregate Climate Zones</th></tr>
<tr><td>Boreal moist</td><td rowspan="7">Wet</td><td>Boreal dry</td><td rowspan="5">Dry</td></tr>
<tr><td>Polar moist</td><td>Polar dry</td></tr>
<tr><td>Cool temperate moist</td><td>Cool temperate dry</td></tr>
<tr><td>Warm temperate moist</td><td>Warm temperate dry</td></tr>
<tr><td>Tropical montane</td><td>Tropical dry</td></tr>
<tr><td>Tropical Moist</td><td></td><td></td></tr>
<tr><td>Tropical Wet</td><td></td><td></td></tr>
</table>

2.5.2. Industrial Wastewater

Industrial wastewater was estimated at a country-level with Equations 23 and 24 along with effuse disposal emissions for several industries: meat production, pulp and paper, petroleum refinery and petrochemical manufacturing, steel production, fruit and vegetable production, beer production, and ethanol refining. All values are obtained from FAOStat with the exception of steel, pulp and paper, and petroleum refining, which all used Climate TRACE production estimates. It is assumed that aerobic advanced treatment is used, as with the asset-level estimates.

2.3.6 Incorporating ERS into model

This section details the method used to generate emissions for each of the 6 ERS described in section 2.1.8. *Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.*

The methods are based on the theoretical assumption that more advanced wastewater treatment processes lead to lower CO_2e emissions, and – in the case of the Covered Lagoon ERS and Intelligent Management ERS – parameters were calibrated based on real-world examples. For other strategies – the Untreated to Primary ERS, the Primary to Secondary ERS, the Primary to Advanced ERS, and the Secondary to Advanced ERS – Emissions factors relied on IPCC 2019 methodology.

In order for an ERS to be considered appropriate for a particular WWTP, it must assume an initial treatment level corresponding with that of the plant and result in CO2e emissions with reduced 100-yr GWP.

UP: Untreated to Primary

Emissions factors for this ERS were generated by changing the treatment level from *Untreated* to *Primary*, running the model as usual, dividing the output CH_4 and N_2O emissions estimates for these plants at the *Untreated* level from the emissions estimates for these plants at the *Primary* level, and taking the median value.

Importantly, nitrous oxide may be generated during wastewater treatment in centralized, secondary treatment plants through processes such as biological nitrogen removal (BNR), a form of secondary, biological treatment (Law et al., 2012). Thus, this strategy recommends the construction of primary treatment infrastructure, which does not involve secondary, biological treatment.

All assets with a treatment level of *Untreated* are assigned the *UP* ERS for the strategy ID.

CL: Covered Lagoon

The CH_4 emission factor for this ERS was based on the theoretical assumption that recapturing biogas is 100% effective. However, it is important to note that, due to fugitive emissions, it is expected that 10% of the methane produced from covered lagoons will leak (United Nations Framework Convention on Climate Change, n.d.). Nitrous oxide is not considered by this ERS.

All assets with a treatment level of *Lagoon* are assigned the *CL* ERS for the strategy ID.

PS: Primary to Secondary

Emissions factors for this ERS were generated by changing the treatment level from *Primary* to *Secondary*, running the model as usual, dividing the output CH_4 and N_2O emissions estimates for these plants at the *Primary* level from the emissions estimates for these plants at the *Secondary* level, and taking the median value.

All assets with a treatment level of *Primary* are assigned both the *Primary to Secondary* ERS and the *Primary to Advanced* ERS. The priority ranking for each of these two strategies is determined by multiplying the CH_4 and N_2O emissions factor ratios by the asset's CH_4 and N_2O emissions factors, respectively, as well as by the assets' activity value, then converting the results to their CO_2e (100-yr GWP) and summing them together to get the total CO_2e reduction value for each ERS. The ERS with the highest CO_2e reduction value is given a priority of 1, while the ERS with the lower CO_2e reduction value is given a priority of 2.

PA: Primary to Advanced

Emissions factors for this ERS were generated by changing the treatment level from *Primary* to *Advanced*, running the model as usual, dividing the output CH_4 and N_2O emissions estimates for these plants at the *Primary* level from the emissions estimates for these plants at the *Advanced* level, and taking the median value.

2A: Secondary to Advanced

Emissions factors for this ERS were generated by changing the treatment level from *Secondary* to *Advanced*, running the model as usual, dividing the output CH_4 and N_2O emissions estimates for these plants at the *Secondary* level from the emissions estimates for these plants at the *Advanced* level, and taking the median value.

All assets with a treatment level of *Secondary* are assigned the *2A* ERS for the strategy ID.

IM: Intelligent Management

This strategy, based on calculations from a 2024 assessment of GHG mitigation strategies for 3,444 WWTPs in China (Tong et al., 2024), assumes the implementation of both intelligent aeration technology and intelligent dosing technology. This study calculates the mitigation potential of direct GHG emissions when applying intelligent aeration and dosing technology to be 60% (see Table S4 in Tong et al., 2024). The average nitrous oxide reductions for intelligent aeration and intelligent dosing are 62.5% and 60%, respectively, as given by Tong et al., which notes that "over 60% of N_2O productions were determined to be reduced by the controlled supplies of chemicals in some laboratory studies", and as calculated by taking the average of the 35- 90% range provided by Duan et al. for intelligent aeration (Duan et al., 2021; Tong et al., 2024). A CH_4 emissions reduction percentage of 53.72% can then be extrapolated given the average percentage of CO_2e accounted for by CH_4 within our dataset's subset of advanced WWTPs (65%).

All assets with a treatment level of *Advanced* are assigned the *IM* ERS for the strategy ID.

2.6. Summary

In all, there are 4 models that were developed for estimating CH_4 and N_2O emissions from wastewater from 2015 to mid-year 2025 at a monthly time-scale: two asset-level models and two country-level models for domestic and industrial wastewater. The domestic asset-level model used locations and metadata from HydroWASTE along with IPCC emissions estimate guidelines, whereas the industrial asset-level model estimated emissions for Climate TRACE assets using the IPCC guidelines. The domestic country-level model used sanitization statistics from the UN WASH data, whereas the industrial country-level model combined Climate TRACE industrial data along with FAOStat food production statistics. Year-to-year population data were splined to produce population estimates at a monthly scale, which is used to scale WWTP assets.

3. Results

3.1. Domestic WWTPs emissions estimates

The centralized WWTP dataset comprises 55,507 sources for the years 2015 to mid-year 2025, including 1,550 untreated wastewater assets. For the year 2022, it is estimated that these sources account for 149.62 MT of CO_2eq. Figure 8. – which shows the global distribution of centralized WWTPs and their emissions – demonstrates that the dataset lacks Global South coverage. Asia and Africa especially lack the same level of coverage as it has in HydroWASTE prior to filtering (*see Figure A3.1*).

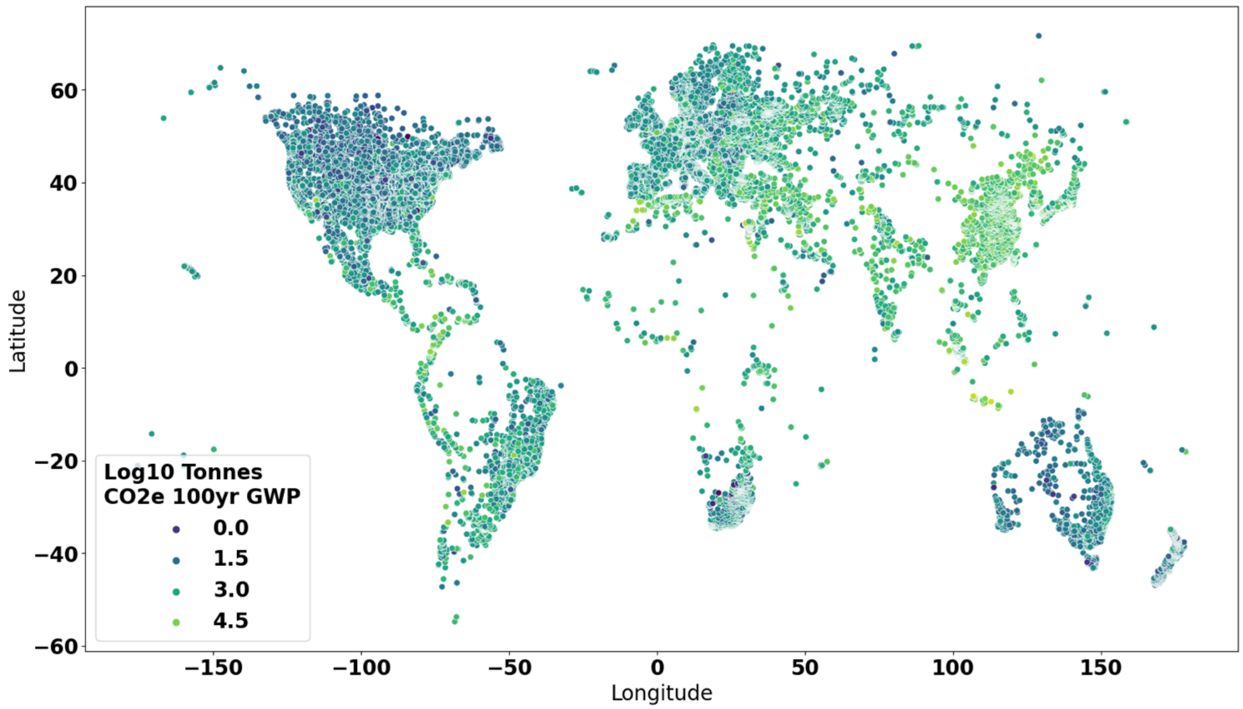


Figure 8. Global distribution of centralized domestic wastewater treatment plants colored based on emissions in 2022. This is not an exhaustive list (*see Section 2.3.6.*).

A majority of WWTPs produce less than one kT of CO_2eq annually as shown by Figure 9; however, almost all emissions come from plants producing more than 1 kT of CO_2eq. As emissions are a function of population, it is expected that the higher emissions plants are also plants that serve larger populations, and hence reduction in emissions by centralized WWTPs will primarily need to come from adoption of cleaner WWTP technology at larger plants.

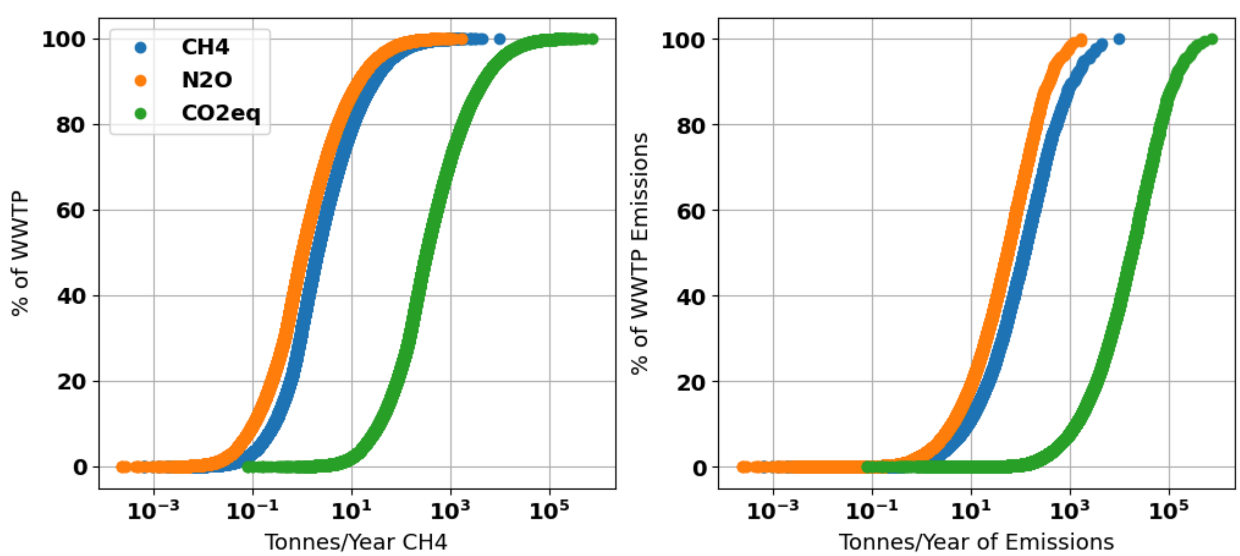


Figure 9. Cumulative distribution of emissions across WWTPs (left) and across WWTP emissions (right) in 2022. The left plot demonstrates that a majority of WWTPs produce less than one kT (10^3 Tonnes/year or 1000 tonnes) of CO_2eq (100 year global warming potential) whereas the plot on the right demonstrates that almost all emissions come from plants that produce more than 1 kT of CO_2eq.

The effect of use of country-level changes in population to extend WWTP emissions estimates to 2015 can be seen in Figure 10. A majority of plants (~80%) saw an increase in their emissions between 2015 and 2022. Twenty-five percent of those saw more than a 5% increase in emissions. Approximately 20% of plants saw a decrease in emissions which reflects decreased population. Further, approximately 80% of plants saw a <5% absolute change in emissions from 2015 to 2022.

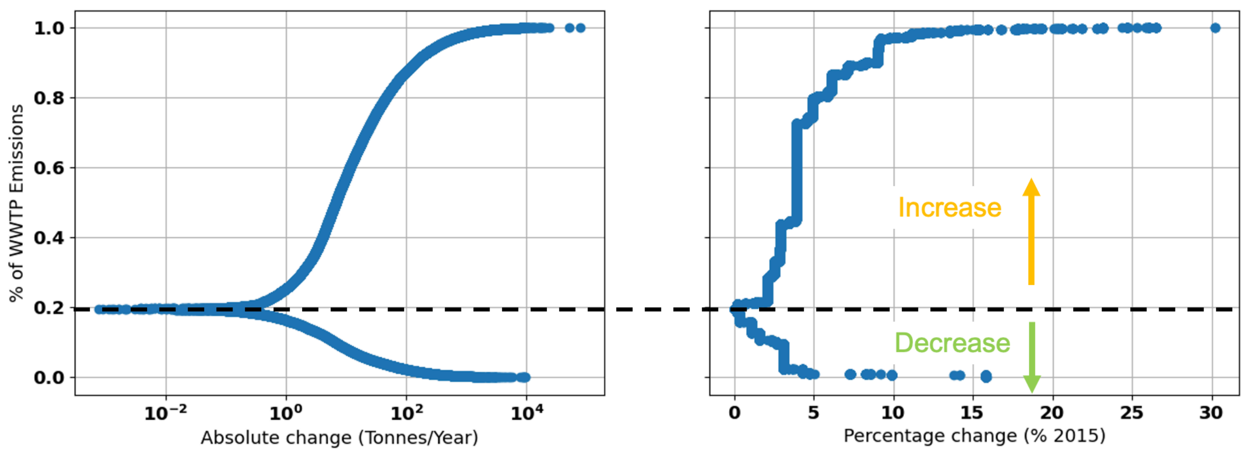


Figure 10. Distribution of change in emissions between 2015 and 2022. Approximately 80% of WWTPs saw an increase in emissions whereas approximately 20% saw a decrease. Approximately 80% of WWTPs had <5% absolute change of emissions.

Uncertainty of emissions estimates is very high. Most plants have one or more orders of magnitude greater standard deviations from the Monte Carlo simulation than their reported emissions estimate as shown by Figure 11. The uncertainty of the emissions from WWTPs whose populations are reported is linearly related to their estimated emissions. For WWTPs where population served is estimated, the standard deviation of the emissions from Monte Carlo is initially constant and becomes aligned with the reported population WWTPs around 10,000 people served as shown in Figure 12.

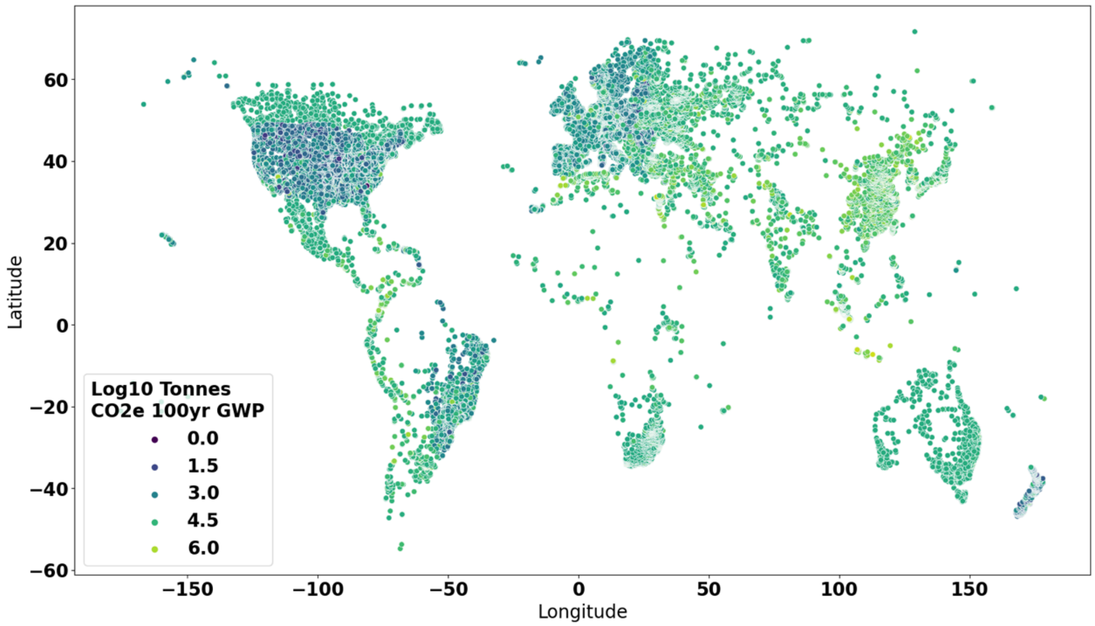


Figure 11. Uncertainty of CO_2eq distributed globally.

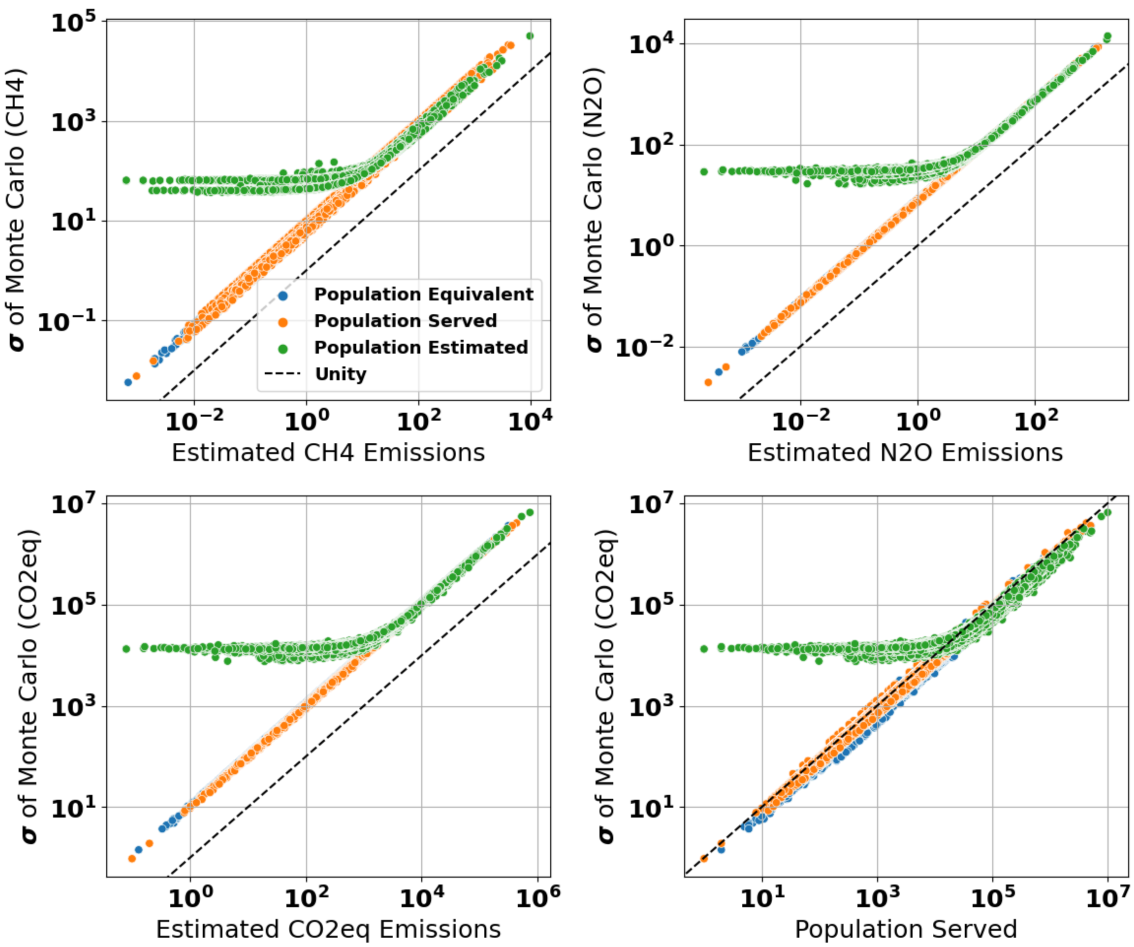


Figure 12. Uncertainty of emissions compared to emissions estimated disaggregated by population type (population served, population equivalent, estimated population) and uncertainty of CO_2eq as a function of population. For lower emissions estimates, uncertainty for emissions of WWTPs with estimated populations is significantly higher than those with reported populations. Overall, uncertainty of emissions is significantly higher than the estimated value.

3.2. Verification of results

The country-level integrations of the GHG emissions from source-level centralized WWTPs was compared to U.S. and E.U. GHG inventories. This allows for the verification of the emissions model for WWTPs where numbers of people are provided and where *PE* is provided as U.S. WWTPs are mostly provided with number of people values and EU WWTPs mostly provided with *PE* values in HydroWASTE. A verification of emissions for WWTPs where estimated population served quantities were provided was not performed as these have very high uncertainties. Overall, Climate TRACE source-level data aligns well with emissions estimates for U.S. and EU in spite of the limitations discussed in 2.3.6.

3.2.1 Comparison of Estimated Emissions to U.S. and EU Inventories

The EPA produces annual emissions estimates for the entirety of the U.S. using IPCC methodology. For verification, a comparison for CH_4 and N_2O emissions from centralized WWTP in 2021 was made using the most current EPA inventory (EPA 2023). The EPA disaggregates domestic wastewater treatment into 4 categories: Septic Systems, Centrally-Treated Aerobic Systems, Centrally-Treated Anaerobic Systems, and Centrally-Treated Wastewater Effluent. For this comparison, the Centrally-Treated Aerobic and Centrally-Treated Anaerobic Systems emissions were combined and compared to treatment emissions from the Climate TRACE sources, and the effluent emissions from the EPA inventory were compared to the effluent emissions from the Climate TRACE sources. The Septic Systems emissions are not used for comparison here. Table 4 has the comparisons for both treatment and effluent emissions as well as the CO_2 equivalent (CO_2eq) 100 year global warming potential in kilotonnes.

Table 4. Comparison between EPA inventory and Climate TRACE (CT) sources of centralized WWTP for the U.S. in 2021 in kilotonnes. CO_2eq is the 100-year global warming potential of the species. EPA treatment values are the aggregation of both Centrally-Treated Aerobic and Centrally-Treated Anaerobic Systems emissions.

		CH_4	**N_2O**	**CO_2eq**
Treatment	*EPA*	193	58	21,084
	CT	134	57	19,287
Effluent	*EPA*	73	16	6,354
	CT	83	6.7	4,076

		CH_4	N_2O	CO_2eq
Total	*EPA*	266	74	27,438
	CT	217	63.4	23,363

Overall, the Climate TRACE source-level estimation for the U.S. aligns well with the EPA for CH_4 effluent and N_2O treatment, decently for CH_4 treatment, and poorly for N_2O effluent. This results in Climate TRACE source-level estimations having a good alignment in CO2eq in treatment emissions and a decent alignment in effluent emissions. N_2O effluent misalignment can be attributed to the use of different methodology tiers. For Climate TRACE sources, the lowest tier emission factor for N_2O from effluent discharged is used. The EPA uses the third tier which has separate emissions factors for hypoxic/nutrient-impaired receiving water systems and for healthy receiving water systems. The emissions factor associated with hypoxic/nutrient-impaired systems are 4 times larger than the emissions factor used here. It is expected that the lack of disaggregation between aerobic and anaerobic systems and the lack of recovered gas estimates plays a significant role in the misalignment of CH_4 emissions from treatment. Further, this lack of disaggregation does not affect the N_2O emissions from treatment estimates as anaerobic treatment does not result in a significant increase in N_2O emissions.

Parravicini *et al.* 2022 utilized IPCC methodologies with chemical-process specific methodologies along with disaggregation of WWTP technologies to produce an estimate of CO2eq emissions for EU countries (Parravicini 2022). Their technological disaggregation was based on the PE of the influent water treated by the plant. Climate TRACE integrated source-level estimates for CO_2eq 100 year global warming potential estimates align very well with Parravicini *et al.* for all countries as shown in Figure 13 with the exception of Croatia (HRV). However, it should be noted that the values from Parravicini *et al.* were obtained using a plot digitizer. The total estimates for the EU also agree with 33.96 MT CO_2eq from Climate TRACE and 34.36 MT CO_2eq from Parravicini *et al.* A labeled country-by-country comparison is shown in Figure A4.1 of Appendix 5.

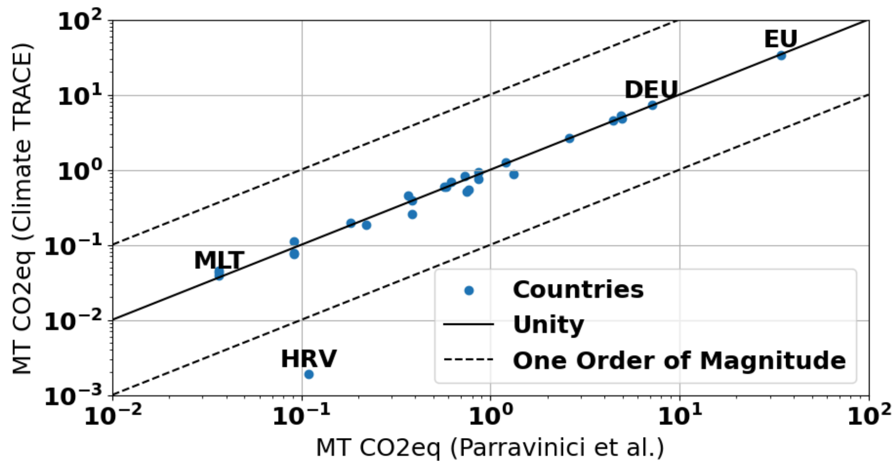


Figure 13. A country by country comparison of emissions from centralized, domestic WWTPs between Parravinici et al. and integrated Climate TRACE sources. The countries with the highest and lowest emissions from WWTPs are labeled, as well as the EU summation and outliers. All countries align very well with the exception of Croatia (HRV).

3.2.2 Satellite verification of ERS implementation

In the future, we may be able to verify the construction of new WWTP facilities or the upgrading of WWTP infrastructure at the asset level using satellite imagery. While this method of verification likely will not allow us to determine whether certain technology, such as intelligent chemical dosing systems, has been implemented, it does grant us the opportunity to check for the existence of new structures, lagoon covers, etc. in accordance with an ERS. Where ERS implementation cannot be verified by satellite, further information may become available at the asset, regional, or national level in the form of reports issued by governments or other institutions. In these cases, caution will need to be taken to disambiguate the terms used by various sources to describe treatment levels and technologies.

3.3 Emissions estimates for Country-level emissions

As shown in Figure 14, combining UN population and WASH estimates reveals that a plurality of the world has their wastewater collected by sewers and presumably treated at a WWTP, followed by septic, latrines, then untreated. The subsequent global emissions are shown in Figure 15 where latrine emissions and septic tank emissions compose a majority of the methane emissions from domestic wastewater emissions and sewer collected wastewater emissions dominate N2O emissions. Although latrines per capita methane emissions are even larger than untreated wastewater, untreated wastewater poses a significant risk to human and agricultural health. In addition, latrine emissions demonstrate the highest seasonality of all pathways due to the impact of shifting climate zones throughout the year.

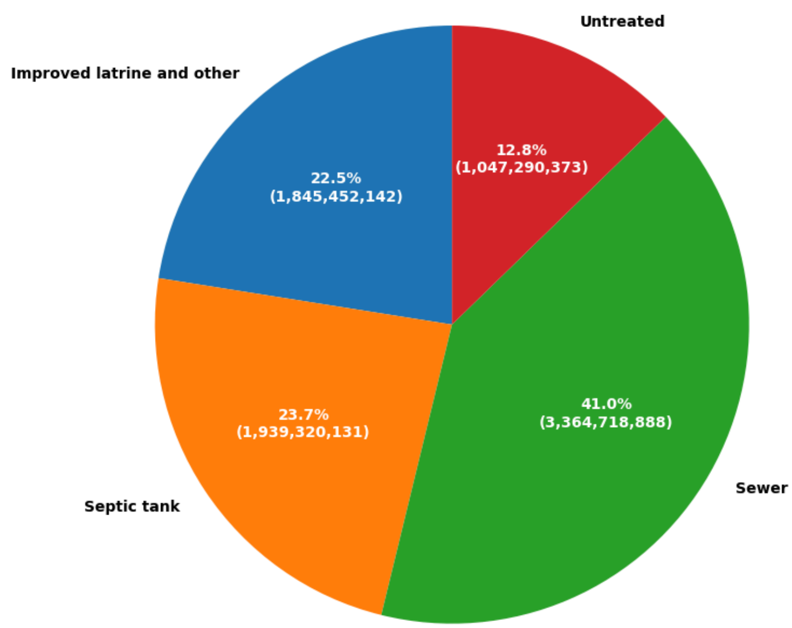


Figure 14. Global breakdown of wastewater pathways as estimated by the WHO. A plurality of the world's population is connected to sewers which leads to reduced emissions and cleaner water systems.

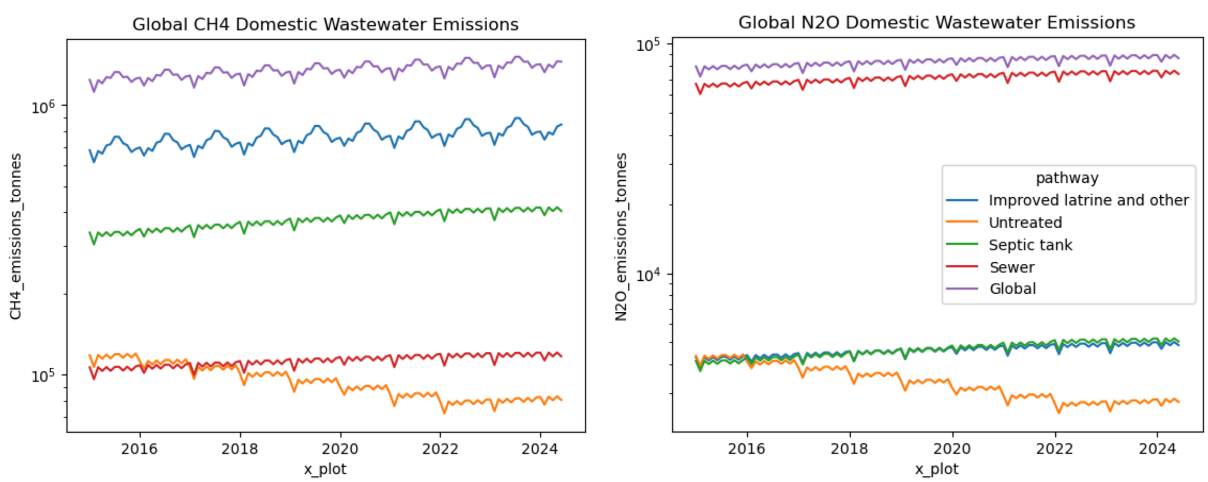


Figure 15. Global domestic wastewater emissions are broken down into different pathways. Latrines contribute significantly to the world's CH_4 emissions (plot above) from wastewater, and also are more highly impacted by seasonality. Sewers comprised the majority of N_2O emissions (figure below). Note, the y-axis in each figure have different ranges.

Table 5 shows validation results for the domestic emissions model compared to the EPA's National Inventory for the U.S. in 2022 where the *Sewer* category for the EPA is a combination of their aerobic treatment, anaerobic treatment, sludge digestion, and effuse categories (EPA 2024). Overall, values for both septic and sewer emissions align well with the EPA; however, the very low utilization of latrines in the U.S. and the difficulty of finding reliable latrine emissions estimates, leaves them currently unvalidated.

Table 5. Validation of a country-level model to the EPA estimates for 2022 (EPA 2024).

Pathway	Climate TRACE CH_4 Emissions (kT)	EPA CH_4 Emissions (kT)	Climate TRACE N_2O Emissions (kT)	EPA N_2O Emissions (kT)
Sewer	245.7	270	89	77
Septic	251	215	2.12	3

Industrial emissions align well to the EPA's National Inventory for most sectors as shown in Figure 16. However, EPA does not estimate the nitrous oxide emissions from steel and ethanol production which Climate TRACE estimates to be large contributors to industrial emissions.

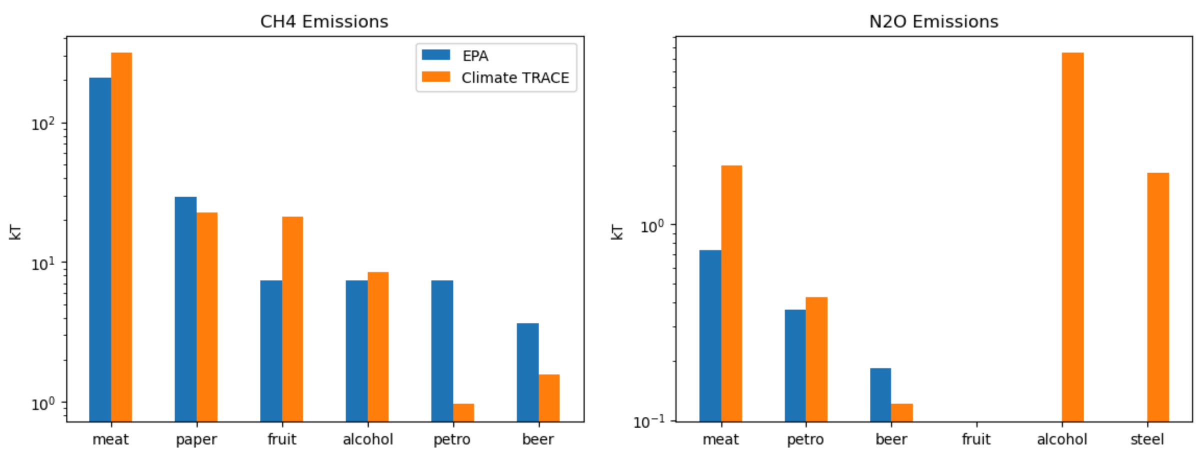


Figure 16. Industrial wastewater comparison with the EPA estimates for 2022 (EPA 2024).

In comparison to EDGAR, while correlated, Climate TRACE country-level emissions are significantly smaller for methane emissions and significantly larger for nitrous oxide emissions as shown in Figure 17. The discrepancy for methane is difficult to assess given that EDGAR does not differentiate domestic from industrial wastewater emissions and their terse methodology description for wastewater make it difficult to recreate (Janssens-Maenhout 2019). However, the nitrous oxide discrepancy is likely due to EDGAR using the 2006 IPCC guidelines (IPCC 2006) which has an order of magnitude smaller emissions factor for domestic emissions (de Haas *et al.* 2022). This is discussed in the Phase 5 methodology document.

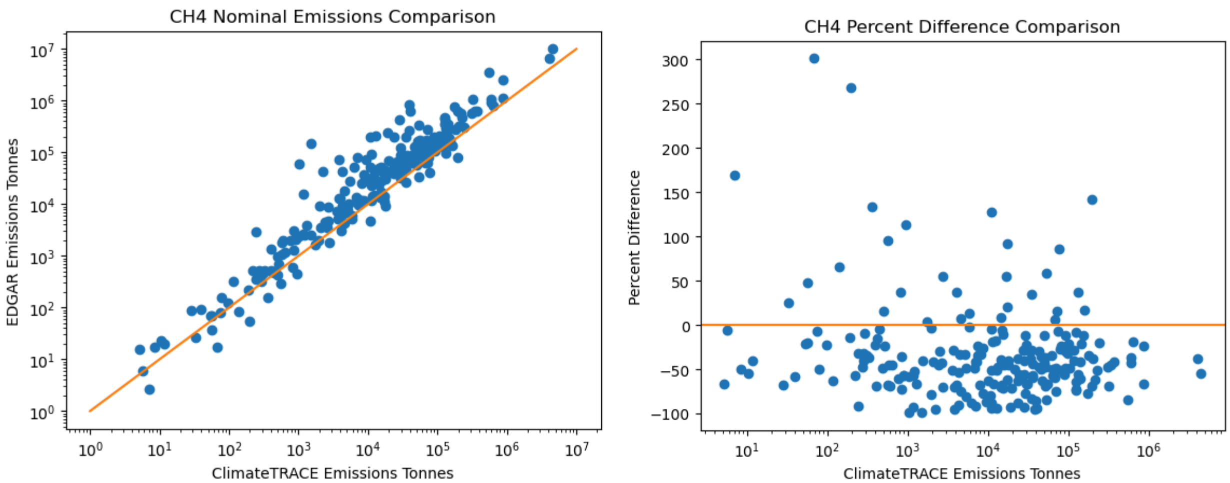


Figure 17. cont.

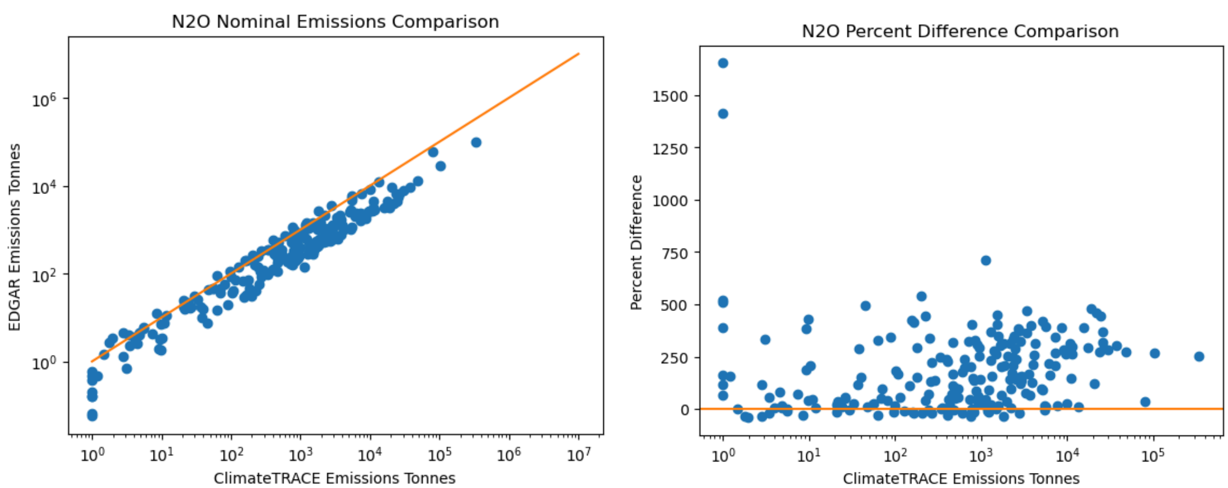


Figure 17. Country-to-country emissions comparison with EDGAR. Overall, the correlation between Climate TRACE and EDGAR is positive, EDGAR estimates a significantly higher methane emissions estimate, whereas Climate TRACE produces larger nitrous oxide estimates. The former difference is difficult to explain as EDGAR's emissions estimates are not reproducible, whereas the latter can be explained by EDGAR using outdated methodologies.

3.3.1 ERS impact on emissions

Comparing the average CH_4 and N_2O emissions reductions for WWTPs before and after the simulated application of ERS can help us understand the impact of the ERS. Table 6 lists the average emissions reduction percentage for methane and nitrous oxide for each ERS for all assets identified for this sector. *Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.*

Table 6. Average emissions reduction percentage for methane and nitrous oxide for each ERS. The percentage is calculated from literature for the CL and IM strategies, and from the climate TRACE dataset of WWTP assets for all other strategies. See section 2.3.6 for details on the methodology used to calculate emissions factors.

ERS	Average CH_4 Emissions Reduction (%)	Average N_2O Emissions Reduction (%)
UP: Untreated to Primary	30.91	2.38
CL: Covered Lagoon	90	0
PS: Primary to Secondary	62.45	7.32
PA: Primary to Advanced	68.77	17.07
2A: Secondary to Advanced	16.83	10.53
IM: Intelligent Management	46.3	62.5

Specific examples of ERS implementation are detailed below for the *Covered Lagoon* and *Intelligent Management* ERS, yet every ERS has been applied in the real world as WWTPs take steps to update their technology and to meet various GHG emissions targets. The construction of centralized WWTPs to manage currently untreated sewage, for example, is encouraged by a number of global initiatives such as the UN's Sustainable Development Goals (United Nations, n.d.) and the World Bank's "Wastewater: From Waste to Resource" initiative (World Bank Group, 2020). While such initiatives often aim to promote the development of wastewater treatment infrastructure capable of at least secondary treatment, the construction of primary treatment infrastructure represents a significant step towards those aims.

As of 2025, the T. E. Maxson Wastewater Treatment Facility (TEMWTF) in Memphis, Tennessee, has been covering facultative lagoons, recapturing the biogas, and flaring the biogas (Shelby County Health Department, 2024). By doing so, TEMWTF anticipates a methane destruction efficiency of at least 98% as well as reductions of other pollutants and odor. Another co-benefit of covering lagoons is the ability to use the captured biogas for facility operations or sale of the fuel.

A July 2024 paper examined the potential benefits of implementing intelligent management strategies for wastewater treatment in China, which possesses the world's largest municipal wastewater treatment infrastructure (Tong et al., 2024). The analysis concludes that WWTPs which adopt intelligent aeration and dosing technology can expect a 60% reduction in direct greenhouse gas (GHG) emissions, specifically N_2O and CH_4.

4. Limitations and Future Directions

The largest limitations in the methane analysis described in Appendix 1 are that the model does not distinguish between aerobic and anaerobic digestion and that Equation 2 does not include flaring/recovery estimates. Anaerobic digestion produces significantly higher CH_4 emissions than aerobic digestion; and although anaerobic digestion is only used at a small percentage of plants, these plants are often treating large volumes of wastewater. In the U.S., only 10% of

WWTPs use anaerobic digestion, yet these plants account for 55% of all centralized treated wastewater (Song et al. 2023). Further, there is no approach for estimating flaring/recovery of collected CH_4 which is expected to be substantial at larger plants.

For N_2O emissions, our approach currently lacks a distinction between effuse discharge into healthy receiving water systems and into hypoxic/nutrient-impaired receiving water systems (Tier 3 approach); instead, all receiving bodies are treated as healthy (Tier 1 approach). Discharge into hypoxic/nutrient-impaired water systems is expected to result in significantly higher N_2O emissions due to the higher rates of nitrification, and hence our N_2O emissions from effuse is likely an underestimate.

WWTP population scaling based on country-level changes does not account for changes in population distribution throughout a country; therefore, emissions estimates decrease in accuracy for years further away from 2022.

As the approach described here uses WWTP information from HydroWASTE, the final set of sources do not include WWTPs used for industrial waste treated on-site and do not include WWTPs that are not in HydroWASTE.

Practical challenges to the implementation of all ERS include the upfront cost associated with the construction of more advanced treatment structures or the implementation of new technology such as intelligent chemical dosing systems. In the case of the *Untreated to Primary* ERS, although the upfront cost is likely to be significant, centralizing wastewater treatment carries economic benefits (e.g., through the reuse of wastewater in agriculture, industry, or even as drinking water, depending on the sanitation level ultimately achieved), which may help offset this cost.

4. Conclusion

The methodology used to create source-level emissions estimates for centralized domestic wastewater treatment plants was presented. HydroWASTE – a global dataset of WWTPs – was filtered and used to obtain population served estimates, technologies used, and locations of WWTPs. These values were then used with modified IPCC methodologies in order to derive emissions estimates. Country-level population trends were used to create emissions estimates from 2022 back to 2015 and extend forward to mid-year 2025. Overall, emissions estimates align well with country-level estimates for the U.S. and the E.U. However, the uncertainty in emissions estimates is very high. A Monte Carlo approach was used to estimate the uncertainty of emissions estimates, and for most WWTPs the standard deviation of the Monte Carlo samples was an order of magnitude higher than the actual emissions estimate.

Despite the high uncertainty, the emissions estimate presented here is an initial attempt to create a source-level dataset of emissions from centralized, domestic wastewater treatment plants. Future improvements should focus on the limitations listed in Section 2.3.6; primarily the identification of technology used at WWTPs (aerobic/anaerobic) and estimations of flaring and recovery would improve CH_4 emissions estimates, whereas determination of hypoxic/nutrient-impaired receiving bodies will improve N_2O emissions estimates. Further, using more fine-grain population changes to extend emissions estimates in time would improve overall emissions estimates. Inclusion of wastewater treatment in industrial facilities outside the paper and steel sectors will improve overall coverage, as well as inclusion of WWTPs not reported by HydroWASTE.

The Emissions Reduction Strategies described in this document represent a data-driven attempt to estimate the impact of system and process advancements in WWTPs around the globe, regardless of their current technology level. Adoption of intelligent management strategies may be accelerated by national policies aimed at decreasing GHG emissions, as in China (Tong et al., 2024).

Supplementary materials

Table S2 describes the source-level data for WWTPs. These data are in the form of comma separated values files with names "source-climate-trace_waste-water-treatment_MMDDYY.csv" where MMDDYY is the month-day-year of the starting date of the annual emissions estimate for centralized WWTPs. For example, "010122" is the annual emissions estimate for centralized WWTPs for 2022. Table S3 describes how confidence and uncertainty data is provided. Section 2.3.5 describes the methodology used to produce uncertainty and confidence values. These files are named "confidence/uncertainty-climate-trace_waste-water-treatment_MMDDYY.csv" where MMDDYY is the date when the files were created.

Table S1 General dataset information for domestic wastewater treatment plants**.**

General Description	Definition
Sector definition	*Emissions from the processing of wastewater in domestic, centralized wastewater treatment plants*
UNFCCC Sector Equivalent	*5.D Wastewater treatment and handling*
Temporal Coverage	*2015 – June 2025*
Temporal Resolution	*Monthly*
Data format(s)	YYYY-MM-DD
Coordinate Reference System	*WKT_Point*
Total emissions for 2022	*976.70kT CH_4, 450.74 kT N_2O, 149.62 MT CO_2e 100yr GWP*

General Description	Definition
Ownership	*No ownership data available*
What emission factors were used?	*Tier 2 emissions factors for influent treatment and Tier 1 emissions factor for effluent discharge from* (IPCC 2019)
What is the difference between a "NULL / none / nan" versus "0" data field?	*"0" values are for true non-existent emissions. If we know that the sector has emissions for that specific gas, but the gas was not modeled, this is represented by "NULL/none/nan"*
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	*Climate TRACE uses IPCC AR6 CO_2e GWPs. CO_2e conversion guidelines are here:* *https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FullReport_small.pdf*

Table S2 Source-level metadata description for "asset-climate-trace_domestic-wastewater-treatment_MMDDYY.csv"**.**

Data attribute	Definition
sector	Waste
source_sub-sector_name	5.D Wastewater Treatment and Discharge
source definition	Emissions from domestic, centralized, wastewater treatment plants
start_date	YYYY-MM-DD
end_date	YYYY-MM-DD
source_identifier	Internal identifier id of the WWTP.
source_name	Name of WasteWater Plant (if available)
iso3_country	ISO 3166-1 alpha-3 code of the region the WWTP resides in based on GADM boundaries
location	WKT_point_location
type	"domestic centralized aerobic [[Technology Level]]"
capacity_description	Population served/Population Equivalent
capacity_units	Capita
capacity_factor_description	Unit quantity
capacity_factor_units	Unitless
activity_description	Population served/Population Equivalent
activity_units	Capita

Data attribute	Definition
CO2_emissions_factor	0, CO_2 emissions are not significant
CH4_emissions_factor	CH_4 per Capita, driven by population and technology factors
N2O_emissions_factor	N_2O per Capita, driven by population and technology factors
other_gas_emissions_factor	NaN
CO2_emissions	0, CO_2 emissions are not significant
CH4_emissions	Annual CH_4 emissions in Tonnes
N2O_emissions	Annual N_2O emissions in Tonnes
other_gas_emissions	NaN
total_CO2e_100yrGWP	CO_2 Equivalent for 100 year Global Warming Potential (Tonnes)
total_CO2e_20yrGWP	CO_2 Equivalent for 20 year Global Warming Potential (Tonnes)
other1_description	HydroWASTE reported Dilution Factor of Effluent Water
other1_units	(Q of Effluent + Q of Discharging Body)/(Q of Effluent) where Q is volumetric flow rate
other2_description	Population Served value from HydroWASTE
other2_units	Capita
other3_description	Population Equivalent – same as other 2 if HydroWASTE reports PE, different otherwise
other3_units	Capita

Table S3 Source level metadata description confidence and uncertainty for confidence/uncertainty-climate-trace_domestic-wastewater-treatment_MMDDYY.csv.

Data attribute	Confidence Definition	Uncertainty Definition
type	Medium if reported, low if estimated	Not provided
capacity_description	Medium if reported Low if estimated for 2022. Then reduced by 1 level at 2020, and another at 2018	Standard deviation from Monte Carlo
capacity_factor_description	Very high confidence as it is a chosen unitless value	0, as it is a chosen unitless value
capacity_factor_units	Unitless	Unitless

Data attribute	Confidence Definition	Uncertainty Definition
activity_description	Same confidence as capacity	Standard deviation from Monte Carlo
CO2_emissions_factor	Very high	0, negligible CO_2 emissions
CH4_emissions_factor	Medium as it comes from IPCC	Standard deviation from Monte Carlo
N2O_emissions_factor	Medium as it comes from IPCC defaults	Standard deviation from Monte Carlo
other_gas_emissions_factor	NaN	NaN
CO2_emissions	Very high	0, negligible CO_2 emissions
CH4_emissions	Medium for 2021-2022, and Low prior	Standard deviation from Monte Carlo
N2O_emissions	Medium	Standard deviation from Monte Carlo
other_gas_emissions	NaN	NaN
total_CO2e_100yrGWP	Low	Standard deviation from Monte Carlo
total_CO2e_20yrGWP	Low	Standard deviation from Monte Carlo

Table S4 General dataset information for industrial wastewater treatment plants**.**

General Description	Definition
Sector definition	*Emissions from the processing of wastewater in industrial, centralized wastewater treatment plants*
UNFCCC Sector Equivalent	*5.D Wastewater treatment and handling*
Temporal Coverage	*2015 – June 2025*
Temporal Resolution	*Monthly*
Data format(s)	YYYY-MM-DD
Coordinate Reference System	*WKT_Point*
Total emissions for 2022	*68.27kT CH_4, 29.32kT N_2O, 9.86 MT CO_2e 100yr GWP*
Ownership	*No ownership data available*
What emission factors were used?	*Tier 2 emissions factors for influent treatment and Tier 1 emissions factor for effluent discharge from* (IPCC 2019)

General Description	Definition
What is the difference between a "NULL / none / nan" versus "0" data field?	*"0" values are for true non-existent emissions. If we know that the sector has emissions for that specific gas, but the gas was not modeled, this is represented by "NULL/none/nan"*
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	Climate TRACE uses IPCC AR6 CO_2e GWPs. CO_2e conversion guidelines are here: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FullReport_small.pdf

Table S5 Source level metadata description for "source-climate-trace_industrial-wastewater-treatment_MMDDYY.csv"**.**

Data attribute	Definition
sector	Waste
source_sub-sector_name	5.D Wastewater Treatment and Discharge
source definition	Emissions from industrial, centralized, wastewater treatment plants
start_date	YYYY-MM-DD
end_date	YYYY-MM-DD
source_identifier	Internal identifier id of the WWTP.
source_name	Name of WasteWater Plant (if available)
iso3_country	ISO 3166-1 alpha-3 code of the region the WWTP resides in based on GADM boundaries
location	WKT_point_location
type	"[[INDUSTRY]], industrial centralized aerobic [[Technology Level]]"
capacity_description	Tonnage of product
capacity_units	Tonnage
capacity_factor_description	Chosen to be 1 i.e. unitless
capacity_factor_units	Unitless
activity_description	Tonnage of product
activity_units	Tonnage
CO2_emissions_factor	0, CO_2 emissions are not significant
CH4_emissions_factor	CH_4 per Capita, driven by population and technology factors
N2O_emissions_factor	N_2O per Capita, driven by population and technology factors

Data attribute	Definition
other_gas_emissions_factor	NaN
CO2_emissions	0, CO_2 emissions are not significant
CH4_emissions	Annual CH_4 emissions in Tonnes
N2O_emissions	Annual N_2O emissions in Tonnes
other_gas_emissions	NaN
total_CO2e_100yrGWP	CO_2 Equivalent for 100 year Global Warming Potential (Tonnes)
total_CO2e_20yrGWP	CO_2 Equivalent for 20 year Global Warming Potential (Tonnes)

Table S6 Source level metadata description confidence and uncertainty for "confidence/uncertainty-climate-trace_industrial-wastewater-treatment_MMDDYY.csv".

Data attribute	Confidence Definition	Uncertainty Definition
type	high	Not provided
capacity_description	medium	Standard deviation from Monte Carlo
capacity_factor_description	Very high confidence as it is a chosen unitless value	0, as it is a chosen unitless value
capacity_factor_units	Unitless	Unitless
activity_description	Same confidence as capacity	Standard deviation from Monte Carlo
CO2_emissions_factor	Very high	0, negligible CO_2 emissions
CH4_emissions_factor	Medium as it comes from IPCC	Standard deviation from Monte Carlo
N2O_emissions_factor	Medium as it comes from IPCC defaults	Standard deviation from Monte Carlo
other_gas_emissions_factor	NaN	NaN
CO2_emissions	Very high	0, negligible CO_2 emissions
CH4_emissions	Low	Standard deviation from Monte Carlo
N2O_emissions	Low	Standard deviation from Monte Carlo
other_gas_emissions	NaN	NaN

Data attribute	Confidence Definition	Uncertainty Definition
total_CO2e_100yrGWP	Low	Standard deviation from Monte Carlo
total_CO2e_20yrGWP	Low	Standard deviation from Monte Carlo

Table S7 Strategy ERS Table employed for domestic and industrial wastewater treatment plants. Native strategy ids (i.e. CL, 2A, PS etc.) occur before "strategy_name". *Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.*

CL	**Definitions**
strategy_name	Covered Lagoon
strategy_description	Covering the Lagoon and Capturing Methane Emissions in the Form of Biogas
mechanism	retrofit
asset_type_new	centralized, secondary treatment
max_activity_affected_ratio	1
ch4_emissions_factor_new_to_old_ratio	0.1
n2o_emissions_factor_new_to_old_ratio	1
confidence	medium
2A	**Definitions**
strategy_name	Secondary Treatment to Advanced Treatment
strategy_description	Construction of Advanced Treatment Structures and Connection with Existing Secondary Treatment Effluent
mechanism	retrofit
asset_type_new	centralized, advanced treatment
max_activity_affected_ratio	1
ch4_emissions_factor_new_to_old_ratio	0.831683
n2o_emissions_factor_new_to_old_ratio	0.894737
confidence	low
PS	**Definitions**
strategy_name	Primary Treatment to Secondary Treatment
strategy_description	Construction of Secondary Treatment Structures and Connection with Existing Primary Treatment Effluent

mechanism	retrofit
asset_type_new	centralized, secondary treatment
max_activity_affected_ratio	1
ch4_emissions_factor_new_to_old_ratio	0.375465
n2o_emissions_factor_new_to_old_ratio	0.926829
confidence	low
PA	**Definitions**
strategy_name	Primary Treatment to Advanced Treatment
strategy_description	Construction of Secondary and Advanced Treatment Structures and Connection with Existing Primary Treatment Effluent
mechanism	retrofit
asset_type_new	centralized, advanced treatment
max_activity_affected_ratio	1
ch4_emissions_factor_new_to_old_ratio	0.312268
n2o_emissions_factor_new_to_old_ratio	0.829268
confidence	low
IM	**Definitions**
strategy_name	Intelligent Management
strategy_description	Utilization of Intelligent Aeration and Intelligent Dosing Technology for WWTP Management
mechanism	retrofit
asset_type_new	centralized, advanced treatment
max_activity_affected_ratio	1
ch4_emissions_factor_new_to_old_ratio	0.537154159
n2o_emissions_factor_new_to_old_ratio	0.375
confidence	low
UP	**Definitions**
strategy_name	Untreated to Primary Treatment
strategy_description	Construction of Primary Treatment Structures to Manage Previously Untreated Wastewater
mechanism	retrofit

asset_type_new	centralized, primary treatment
max_activity_affected_ratio	1
ch4_emissions_factor_new_to_old_ratio	0.690876
n2o_emissions_factor_new_to_old_ratio	0.97619
confidence	low

Acknowledgements:
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Data citation format: Anderson, S., Collins, G., Tulloch, P., Chen, A., Peña, A., Katz, C., Sridhar, L., Piatko, C., Reilly, E., (2025). *Waste sector: Wastewater Emissions and Emissions Reduction Strategies*. Johns Hopkins Applied Physics Laboratory, USA, Climate TRACE Emissions Inventory. https://climatetrace.org [Accessed date]

Geographic boundaries and names (iso3_country data attribute): The depiction and use of boundaries, geographic names and related data shown on maps and included in lists, tables, documents, and databases on Climate TRACE are generated from the Global Administrative Areas (GADM) project (Version 4.1 released on 16 July 2022) along with their corresponding ISO3 codes, and with the following adaptations:

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

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

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

Appendix 1: Detailed Explanation of Emissions Estimation Methodology

Appendix 1.a.: Estimating the Effect of Treatment and Effluent Emissions:
Aerobic and anaerobic treatment all result in CH_4 emissions as natural and induced biochemical processes consumes organics in the wastewater, resulting in emissions. Hence, the total organics in the influent wastewater TOW and how it is treated are the main drivers of CH_4 emissions. The effect of treatment on methane emissions is represented by the amount of organic waste removed in the form of sludge from the wastewater S, the amount of emissions removed from flaring or recovered R, and the treatment emission factor $EF_{CH4,\,Treat}$, based on Equation 6.1 from the IPCC guidelines:

$$CH_4Emissions_{Treat} = [(TOW - S)\cdot EF_{CH4,Treat} - R]\cdot 0.001 \text{ (Eq. A1.1),}$$

where 0.001 is a conversion from kg to T.

An emission factor of $EF_{CH4,\,Treat} = 0.018\ (kg\ CH_4/kg\ BOD)$ was used which is the Tier 2 method from Table 6.3 in the IPCC guidelines. Flaring and recovery amounts were not estimated, and there is no differentiation between aerobic and anaerobic treatment.

When discharged into a body of water, remaining organics in the wastewater are consumed by microorganisms, resulting in further emissions. The methane emissions from the discharge of treated wastewater is primarily a function of the remaining organic waste in the effluent water TOW_{Eff} after sludge removal and biological treatment, and is defined by,

$$CH_4Emissions_{Eff} = TOW_{Eff}\,EF_{CH4,Eff}\cdot 0.001 \text{ (Eq. A1.2),}$$

where the Tier 1 estimate of $EF_{CH4,Eff} = 0.068\ (kg\ CH_4/kg\ BOD)$ from Table 6.3 of the IPCC guidelines is used and 0.001 is the conversion factor for kg to T.

The total emissions from CH_4 for each WWTP is the summation of treatment and effluent emissions, according to,

$$CH_4 Emissions_{WWTP} = CH_4 Emissions_{Treat} + CH_4 Emissions_{Eff} \quad \text{(Eq. A1.3).}$$

Likewise, N_2O emissions from a WWTP can be disaggregated into treatment and discharge pathways. In treatment, nitrification and denitrification processes both result in the production of N_2O. The total nitrogen content in influent wastewater $TN_{inf}(kg)$ is the primary quantity that drives N_2O emissions at centralized WWTPs, defined in the IPCC guidelines by,

$$N_2O\ Emissions_{Treat} = TN_{inf}\, EF_{N2O,Treat} \frac{44}{28} \cdot 0.001 \quad \text{(Eq. A1.4),}$$

where $EF_{N2O,Treat} = 0.016\ (kg\ N_2O\ N/kg\ N)$ is the emission factor, $\frac{44}{28}\ (kg\ N_2O/kg\ N_2ON)$ is the mass-balance factor for atomic N and N_2O, and 0.001 is the conversion from kg to T.

The nitrogen in the treated effluent N_{Eff} produces N_2O from biochemical nitrification in the receiving body of water that it is discharged into. This pathway was modeled with,

$$N_2O\ Emissions_{Eff} = N_{Eff}\, EF_{N2O,\, Eff} \frac{44}{28} \cdot 0.001 \quad \text{(Eq. A1.5),}$$

where $EF_{N2O,\, Eff} = 0.005\ (kg\ N_2O\ N/kg\ N)$ was used (Tier 1).

As with CH_4, the total N_2O emissions for each WWTP is the summation of treatment and effluent emissions, according to

$$N_2O\ Emissions_{WWTP} = N_2O\ Emissions_{Treat} + N_2O\ Emissions_{Eff} \quad \text{(Eq. A1.6)}$$

Appendix 1.b.: Waste Model

Using the IPCC methodology, the amount of waste (organics and nitrogen) in the influent water entering a centralized WWTP is primarily a function of population served and demographics (i.e. diet, behaviors, and local laws). The total organics in the influent wastewater TOW drives the CH_4 emissions as these organics are readily consumable by microorganisms whose resulting methane can be released in settling basins, anaerobic pockets, and when wastewater is aerated in upstream sewer lines.

In the IPCC guidelines, the $TOW\ (kg/year)$ in Eq. A1.1 is a function of the number of people served P by the WWTP and the amount of BOD they generate, defined by,

$TOW = P \cdot BOD_c \cdot I \cdot 0.001 \cdot days$ (Eq. A1.7),

where BOD_c is the production ($g/day/capita$) of BOD of a person living in country c, $I = 1.25$ is a factor that accounts for industrial wastewater that enters the sewer system linked to the WWTP, and $days$ is the corresponding data per month. Population-served is estimated at the half-month of a given month with splines described in Appendix 7. As mentioned earlier, HydroWASTE provides three separated definitions for "population served": number of people, population equivalent (PE), and an estimated population served. For WWTPs where the number of people or estimated population served is provided, BOD_c is obtained from Table 6.4 in the IPCC guidelines. For WWTPs where a PE quantity is given, $BOD_c = 54\ g/day/capita$ is used. Further, since PE is obtained from sampling of the influent wastewater, the influence of industrial run-off is already accounted for in the reported PE, and thereby $I = 1.0$ is used.

In the IPCC guidelines, population P in Eq. A1.7 is a country/region-level population and TOW is disaggregated into separated pathways for each wastewater treatment technology (e.g. septic tanks, latrines, centralized treatment, etc.) based on regional economic demographics; however, this disaggregation was not needed here as we are only examining populations served by centralized WWTPs.

The total nitrogen in the influent wastewater TN_{inf} (see Eq. A1.4) drives N_2O emissions and typically comes in the form of urea, proteins, and ammonia which can be attributed to human diet and waste, disposal of food waste and cleaning products into sewers, and industrial run-off. The IPCC guidelines estimate this quantity with the population served and their protein consumption and behavioral characteristics, according to,

$TN_{inf} = P \cdot Protein \cdot F_{NR} \cdot N_{HH} \cdot F_{NON-CON} \cdot F_{IND-COM} \cdot 0.001$ (Eq. A1.8),

where $Protein$ is the protein consumption rate in $grams/capita/day$, $F_{NR} = 0.16$ is the fraction of protein that is nitrogen, N_{HH} is a factor for nitrogen in wastewater from the disposal of household products into sewers, $F_{NON-CON}$ is a factor for nitrogen in wastewater from the disposal of non-consumed food waste into sewers, $F_{IND-COM}$ is a factor for industrial run-off, and 0.001 is a conversion for g to kg.

The amount of protein consumed is estimated from the region/national supply of protein obtained from FAOSTAT (FAO n.d.) and regional estimates of the fraction of supplied protein consumed FPC in Table 6.10A of the IPCC:

$Protein = Protein_{supply} \cdot FPC$ (Eq. A1.9).

The remaining quantities in Eq. A1.2 were obtained using Table 6.10A.

Appendix 1.c.: Technological Treatment Model

At centralized WWTPs, sludge and biological treatment affect emissions via two mechanisms: removing waste quantities (TOW and TN) from the water that will become effluent discharge downstream and inherently releasing emissions from their own processes. For CH_4, the collection of solid sludge directly removes BOD from influent water, and the biological treatment of influent water also removes TOW prior to discharge.

The total mass of dry sludge S_{mass} produced at a WWTP is estimated to be $30\ g/day/capita$ (Turovskiy et al. 2006), and the total BOD removed by the WWTP is defined in the IPCC with

$S = S_{mass} \cdot K_{rem}$ (Eq. A1.10),

where K_{rem} is the *sludge factor* – a quantity that reflects the amount of $kg\ BOD$ removed per kg of sludge. K_{rem} is dependent on technology level and is given by Table 6.6A in the IPCC guidelines. This is used in Eq. A1.1.

Accounting for both sludge and biological treatment, the TOW carried by effluent water in Eq. A1.2 is determined with

$TOW_{Eff} = TOW \cdot (1 - TOW_{rem})$ (Eq. A1.11),

where TOW_{rem} $(kg\ BOD)$ is the amount of organic waste removed by the WWTP and is determined with Table 6.6B based on technology level.

The remaining Nitrogen in effluent discharged N_{Eff} (kg) in Eq. A1.5 was derived from TN_{inf}, according to

$N_{Eff} = TN_{inf}(1 - N_{rem})$ (Eq. A1.12),

where N_{rem} is the fraction of protein removed from the treatment of wastewater and is obtained from Table 6.10C based on the technology level of the WWTP.

Appendix 1.d.: Modified Capacity and Emissions Factors

Climate TRACE sources are reported in terms of capacity, capacity factor (CF), activity, and emissions factor (EF), wherein

$Activity = Capacity \cdot CF$ (Eq. A1.13),
$Emissions = Activity \cdot EF$ (Eq. A1.14),

and where the CH_4 and N_2O emissions share the same capacity, CF, and activity but differing EF s. However, the approaches for CH_4 and N_2O emissions are not immediately amenable to this formulation as they are each composed of two separate capacities and activities. Hence, the capacity is chosen to be the "Population Served" quantity P, the CF is a constant unit value, and the revised emissions factors are,

$EF_{CH4} = \frac{CH_4\ Emissions_{WWTP}}{P}$ (Eq. A1.15),
$EF_{N2O} = \frac{N_2O\ Emissions_{WWTP}}{P}$ (Eq. A1.16).

Appendix 1.e.: Uncertainty Quantification & Confidence
A Monte Carlo approach was used for estimating the uncertainty of the emissions wherein each variable was sampled stochastically, and the standard deviation of the distribution of the capacity, CF, activity, EF, emissions, and CO_2 equivalents (20 year and 100 year) were reported. Each variable in the above formulations are assumed to have normal distributions whose mean is the value used in the analysis. To obtain the variance of the distribution of each variable, a conversion from reported confidence intervals (assumed to be 95%) to standard deviation is made, according to,

$\sigma = \sqrt{N}\ \frac{upper\ limit - lower\ limit}{3.92}$ (Eq. A1.17),

where N is the number of sources used to obtain the reported value. An assumed sample size of 30 is used across the board to simplify analysis.

All quantities in the IPCC guidelines have an associated confidence interval. For HydroWASTE population values, an assumed $\pm 5\%$ confidence interval was used if the population served is reported by an authoritative body (i.e., numbers of people and PE values). There is no associated confidence interval for the estimated population served values. Instead, the error (whose mean and standard deviation is derived from information in the HydroWASTE supplemental (Macedo et al. 2022b) is sampled and used to adjust estimated population served in the Monte Carlo analysis. Here the error e_P in the estimated population served is defined by,

$e_P = \widetilde{P} - P$ (Eq. A1.18),

where $\widetilde{P}$ is the estimated population served (i.e. HydroWASTE estimated value) and P is the true but unknown population served. The mean error $\bar{e}_P$ and variance σ^2_P of the estimated populations are

$\bar{e}_P = -\frac{PBIAS \cdot \bar{P}}{100}$ (Eq. A1.19),

$\sigma^2_{e_P} = RMSE^2 - \bar{e}^2_P$ (Eq. A1.20),

where $PBIAS$ and RMSE are the percent bias and root mean square error of the the estimation approach when applied to the set of known population served and $\bar{P}$ is the mean population served of that set. $PBIAS$ and the normalized RMSE are provided in the HydroWASTE supplemental (Macedo et al. 2022b) and $\bar{P}$ was recreated.

The adjusted population served used in Monte Carlo for HydroWASTE facility i with estimated population served $\widetilde{P}_i$ is,

$P_{i, adj} = \max(\widetilde{P}_i - \epsilon, 0)$ (Eq. A1.21),

where $\epsilon \sim N(\bar{e}_P, \sigma^2_{e_P})$.

The mean (Equation A1.19) and variance (Equation A1.20) of the error estimated population values are used to sample the error of the estimated population using Equation A1.21. In the accompanying HydroWASTE manuscript and supplemental, the approach for estimating missing population served values is applied to all of the WWTPs with reported population served/PE. The performance of the estimation technique is reported and shown in Figure A2.1.

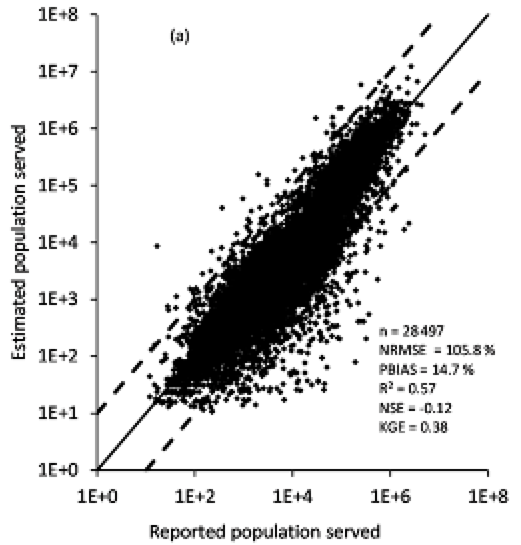

Figure A2.1. Figure 4.a in Macedo et al. (2022a). The performance of the population served estimation approach when applied to WWTPs with known population served/PE. The solid line is the unit line (i.e. no error), and the dashed lines represent an order of magnitude difference between the estimated and known populations. n is the total number of WWTPs analyzed, $NRMSE$ is the normalized root mean square error, $PBIAS$ is the percent bias, R^2 is the coefficient of determination, NSE is the Nash-Sutcliffe Efficiency, and KGE is the Kling-Gupta efficiency.

Using Equation A1.18 as the definition of estimated population error, the mean of the error is easily determined by the percent bias, according to,

$$PBIAS = 100 \cdot \frac{\Sigma (P_i - \tilde{P}_i)}{\Sigma P_i} \text{ (Eq. A2.1)},$$

$$\bar{e}_p = - \frac{PBIAS \cdot \bar{P}}{100} \text{ (Eq. A2.2)}.$$

The mean known population served/PE ($\bar{P}$) was recalculated for this analysis. The variance of the error is defined by

$$\sigma^2_{e_P} = \frac{\Sigma (e_i - \bar{e})^2}{N} \text{ (Eq. A2.3)},$$

where N is the number of WWTPs with known population served/PE. Expansion of the additive quantities in Equation A2.3 yields

$$\sigma^2_{e_P} = \frac{\Sigma e_i^2 - 2 e_i \bar{e} + \bar{e}^2}{N} \text{ (Eq. A2.4)}.$$

Separate integration of each term shows that the first term is the square of the root mean square error and the second and third terms combine, yielding,

$\sigma^2_{e_P} = RMSE^2 - \bar{e}^2$ (Eq. A2.5),

where $RMSE = NRMSE \cdot \bar{P}$.

A convergence study of the Monte Carlo simulation was performed where multiple Monte Carlo simulations were computed with varying sample sizes: 125, 250, 500, 1000, 2000, 4000, 8000, 16000, 32000, 64000, 128000. Figure A1 shows that the Monte Carlo simulation convergences around a sample size of $O(10^4)$. The results of the largest sized Monte Carlo simulation are provided.

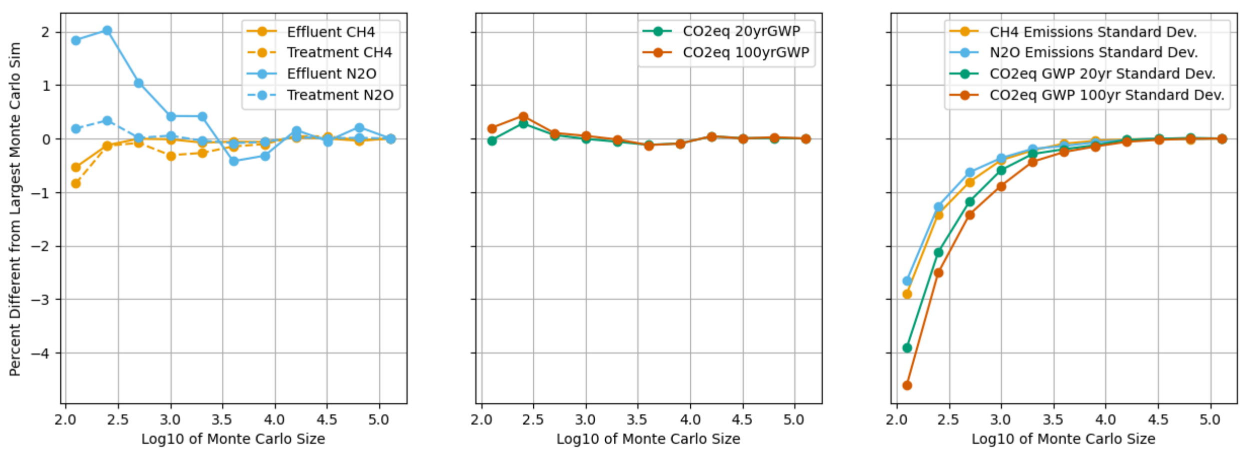

Figure A1. The percent difference of the treatment, effluent, and CO2eq emissions between the largest Monte Carlo simulation and the other Monte Carlo simulations. Convergence occurs around a sample size of $O(10^4)$.

Confidence of reported emissions is determined by the methodology that was used to obtain inputs and how inputs are combined. As mentioned repeatedly, HydroWASTE has both reported and estimated population served values. As reported population served values are obtained from authoritative bodies, they are assigned a high confidence whereas estimated populations served are given a medium confidence. Linear scaling degrades confidence as population served values are extended before 2022. These confidences reduce by one level for the years 2021 to 2019, then another for years prior to 2018 – i.e. reported population served goes from high to medium to low and estimated population served goes from medium to low to very low. HydroWASTE obtains technology levels from either authoritative sources or by estimation with regional economic development level. Hence, confidence in reported technology levels is considered high, whereas confidence in estimated technology levels is considered medium. A medium confidence is assigned to emissions factors and table quantities found in the IPCC. Finally, as flaring/recovery is not estimated in Equation 2, it is assigned a very low confidence.

As emissions estimates are derived from the combination of several values, the multiplication or addition of two variables is assigned the confidence of the floored average of the numerical equivalents of the confidence levels (1 for very low and 5 for very high). This results in a medium confidence for N_2O emissions for all years, and a medium confidence for CH_4 emissions for the years 2019 to 2022 while the years prior to 2019 have a split between medium confidence and low confidence for CH_4 emissions.

Appendix 1.d.: Detailed Methodology for the Estimation of Asset-level Industrial Emissions

Treatment of CH_4 emissions were modeled by,

$Em_I = (T_I \cdot W_I \cdot COD_I - S) \cdot EF_{CH4} - R$, (Eq. A.1.1),

where T_I is the tonnes of product I produced in a given month, W_I is the wastewater produced by the industrial process, COD_I is the chemical oxygen demand of the wastewater, S is the organics removed from the wastewater in the form of sludge, EF_{CH4} is the emission factor, and R is methane emissions removed by flaring. By default, $R = 0$ for IPCC Tier 1 estimates. Similarly, nitrous oxide emissions were modeled by,

$Em_I = T_I \cdot W_I \cdot N_I \cdot EF_{N2O} \cdot \frac{44}{28}$, (Eq. 24),

where N_I is the per capita nitrogen content of wastewater for product I, EF_{N2O} is the nitrous oxide emission factor, and $\frac{44}{28}$ is a nitrogen to nitrous oxide mass-balance factor. The emissions from the disposal of effluent wastewater are similar to those for domestic wastewater and is described in the Phase 5 methodology document.

For all assets, it is assumed that aerobic treatment was used, which is IPCC's Tier 1 default. In addition, it was assumed that advanced treatment was used to process and remove sludge. This is done in order to produce conservative estimates of emissions, as this metadata is not available to the same level as it is for domestic assets. The IPCC values for W_I, COD_I, and N_I were used dependent on the industry.

Appendix 2: Intelligent Management Strategies for Advanced Wastewater Treatment Systems

During treatment, wastewater is often aerated to provide oxygen to microorganisms that digest organic compounds in the water. Oxygen levels that are too low may inhibit treatment efficiency by hampering the growth and reproduction of microorganisms; on the other hand, over-aerating wastes energy. Intelligent aeration systems optimize the oxygen supply in biochemical pools, lowering direct and indirect GHG emissions by reducing energy consumption and nitrous oxide emissions.

Certain chemicals are sometimes also added to wastewater during treatment to remove nitrogen and phosphorous. The manual adjustment of these chemicals typically leads to overdosing. Automating the dosing process reduces waste and can lead to significantly lowered nitrous oxide emissions.

Intelligent management processes become especially important in the context of industrial wastewater treatment, where highly variable wastewater loads make it more difficult to manually balance oxygen and chemical levels (Huber Technology, n.d.). The composition of industrial wastewater varies widely depending on the industry which generates it (e.g., pulp and paper, steel production, food processing) and may contain toxic compounds, extreme pH, or organic loads higher than those in domestic wastewater. In order to account for higher concentrations of pollutants, as well as other factors such as increased effluent corresponding to production cycles, industrial wastewater treatment often requires more specialized equipment and processes than domestic wastewater treatment.

Appendix 3: Grid search method deployed in test region South Africa (SA).

There were 155 total WWTP in SA, out of which 27 were of the particular type of wastewater treatment plants that are of interest, and 20 of them were in the bounds in which the model was running over. A combination of offset, batch_size, and epochs uniquely identifies a model. Each row is a unique model. The current best model got 80% of the WWTP [16/20]. Out of the four missed, two were not clear due to the color and resolution, one due to alignment.

Table A3.1 Hyperparameter tuning of Inception v3

Offset	Batch_Size	Epochs	Total Positives [Out of 34000]	Total Matches [Out of 20]	True Positives [%]	False Positives [%]	Average Accuracy [%]
F	32	80	129	12	60	0.34	79.83
F	32	100	32	8	40	0.07	69.96
F	32	120	66	9	45	0.17	72.42
F	64	80	61	11	55	0.15	77.43
F	64	100	60	11	55	0.14	77.43

Offset	Batch_Size	Epochs	Total Positives [Out of 34000]	Total Matches [Out of 20]	True Positives [%]	False Positives [%]	Average Accuracy [%]
P	32	80	135	16	80	0.35	89.83
P	32	100	50	12	60	0.11	79.94
P	32	120	84	13	65	0.21	82.40
P	64	80	72	16	80	0.16	89.92
P	64	100	74	16	80	0.17	89.91

Appendix 4: HydroWASTE Dataset Statistics

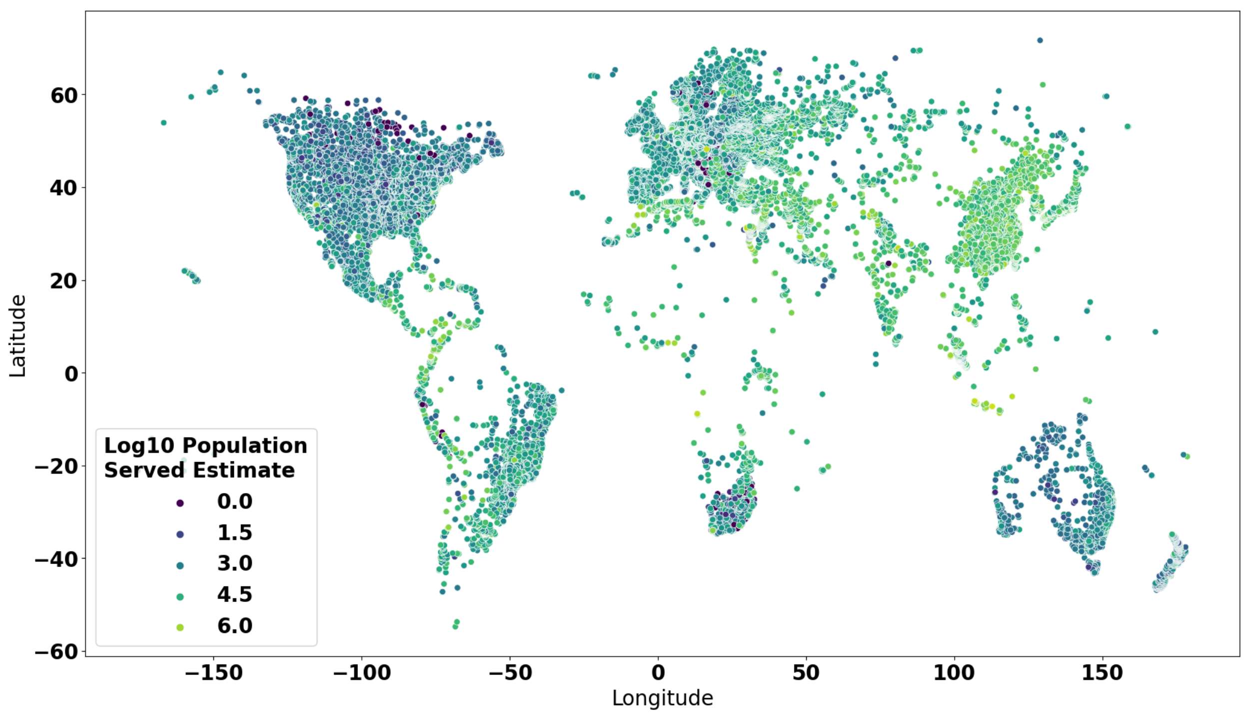

Figure A4.1. HydroWASTE global distribution of centralized WWTPs identified as not "Closed" or "Not Operational". Further filtering occurs prior to emissions estimates to remove plants whose locations are of low confidence (i.e., those that have some likelihood of being incorrectly labeled).

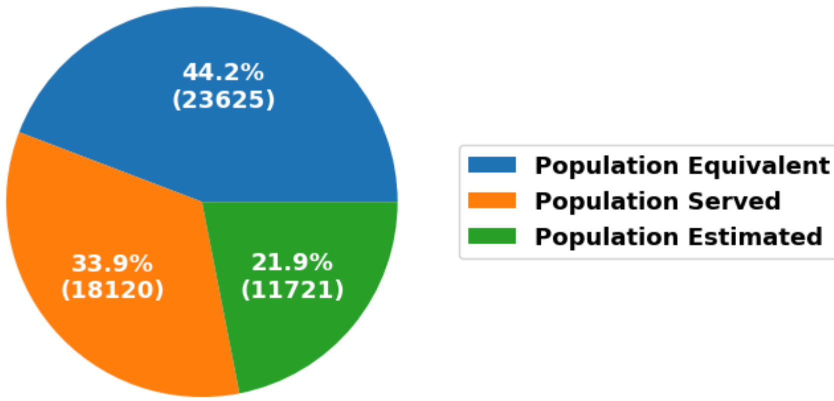

Figure A4.2. Proportion of WWTPs based on computed population served.

Appendix 5: Country-by-country comparison of E.U. emissions estimates

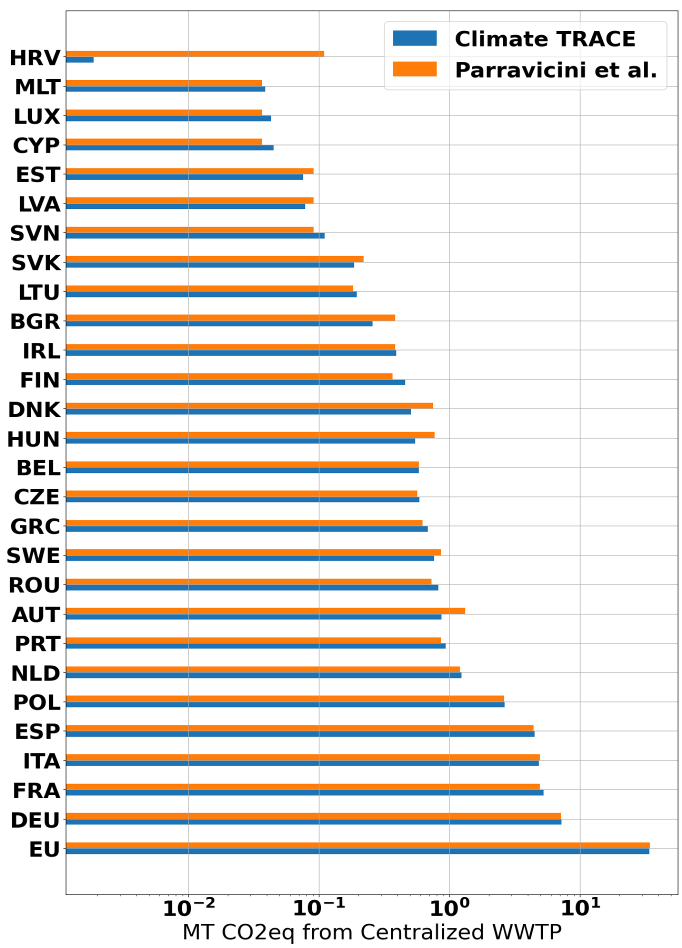

Figure A5.1. A comparison of CO_2eq between Parravicini *et al.* emissions estimates (CO_2eq 100 year global warming potential) and Climate TRACE. Countries are labeled with their ISO 3166-1 alpha-3 codes. Overall, Climate TRACE and Parravicini *et al.* align well for most countries.

Appendix 6: Hyperparameters used to train the WWTP identification network

Table A6.1

Hyperparameter	Value
Activation Function	Sigmoid
Loss function	Sparse categorical cross entropy
Learning rate optimizer function	Adam (learning rate=0.0001)
Batch size	64
Epochs	100

Appendix 7. Month seasonality

Unlike Phase 5, wastewater emissions for Phase 6 of Climate TRACE are provided at a monthly scale. Seasonal variation based on temperature has been studied (Masuda 2015, Demir 2019, Asadi 2021, Gruber 2021, Daelman 2015) and generally there is correlation between ambient temperature and methane emissions and a general lagging anticorrelation of ambient temperature and nitrous oxide emissions. However, modeling these trends is difficult, as often they are dependent on specific WWTP technologies. Papers disagree on the level of correlation between ambient temperature and emissions, as well as on emissions per influent volume rate at the same temperature. Also, there is a greater dependence on influent water temperature, which is influenced by many latent factors other than ambient temperature. Hence, for Phase 6, only population trends are used for modeling monthly changes in wastewater emissions.

A cubic spline of UN annual mid-year population data is used to estimate month-to-month populations of each country. As UN population data is currently only available up until 2023, mid-year population data is estimated assuming a geometric growth rate, expressed by,

$$P_{2024} = P_{2023} \cdot \frac{P_{2023}}{P_{2022}}. \quad \text{Eq. A7.1}$$

An example of this splining for Puerto Rico is shown in Figure A7.1.

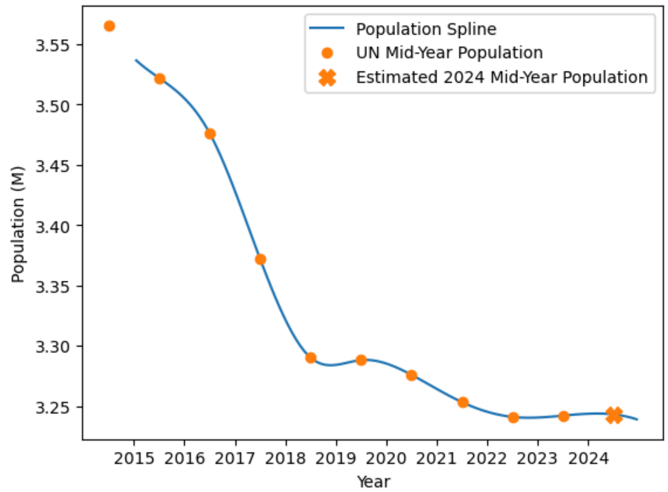

Figure A7.1 Spline of Puerto Rico's population from 2015 to mid-year 2024 which is used to model monthly emissions.

Appendix 8. Emissions Estimation for Untreated Wastewater

A proof of concept was conducted to estimate CH_4 and N_2O emissions from untreated wastewater at the GADM2 level, beginning with a subset of 19 countries in the WHO/UNICEF WASH data for which over 50% of wastewater is untreated and which have sufficient population and sanitation data to support interpolation (see Table A8.1) (JMP 2023). The Holy See was removed from consideration since detailed sanitation data is unavailable. Sanitation data is unavailable for Eritrea since 2017 and for Comoros since 2019. The most recent available data for these countries was forward filled.

Table A8.1 Countries with the highest percentage of untreated wastewater, where "Coverage" indicates the percentage of the total population (both urban and rural) producing wastewater that is listed as "unimproved" or "open defecation".

ISO3	Country	Coverage	ISO3	Country	Coverage
VAT	Holy See	100.00000	UGA	Uganda	61.84697
ETH	Ethiopia	82.17602	BEN	Benin	60.53957
TCD	Chad	81.61313	SLB	Solomon Islands	59.05193
ERI	Eritrea	78.29609	MOZ	Mozambique	57.57056
PNG	Papua New Guinea	76.40736	SDN	Sudan	54.73926
SSD	South Sudan	75.13118	GNB	Guinea-Bissau	54.41239
NER	Niger	73.56099	TGO	Togo	53.25339
CAF	Central African Republic	69.83976	NAM	Namibia	51.03046
COD	Democratic Republic of the Congo	66.25322	LBR	Liberia	51.01541
MDG	Madagascar	63.33157	COM	Comoros	50.89899

For the purposes of this analysis, each GADM2 region in the set of 20 countries in Table A8.1 (minus the Holy See) is considered an untreated wastewater "asset". Global Human Settlement Layer (GHSL) gridded population data (Pesaresi et al., 2024) was mapped to GADM2 boundaries to create a map of GADM2 regions containing detailed urban-rural population classifications. Some regions, including many of the GADM2 regions in the Solomon Islands, do not have GHSL urban-rural percentage calculations. Population served estimates for these regions were preserved in the data for the sake of completeness with a value of 0.0. The Republic of Congo has two regions (both densely forested) with missing population data: there is no population data for COD.21.10_1 (Tshumbe) and COD.21.1_1 (Bena-Dibele) and no 2020 or 2025 population data for COD.21.10_1 (Tshumbe).

Meanwhile, WASH data provides the percentage of the urban and rural population for each country. In order to align these GHSL and WASH urban-rural classification, the model considers regions with a GHSL classification of "30: Urban Centre Grid Cell", "23: Dense Urban Cluster Grid Cell", "22: Semi-Dense Urban Cluster Grid Cell", and "21: Suburban or Peri-Urban Grid Cell" to be "Urban", while "13: Rural Cluster Grid Cell", "12: Low Density Rural Grid Cell", "11: Very Low Density Rural Grid Cell", and "10: Water Grid Cell" to be "Rural." Urban and rural population percentages are then calculated for each GADM2 region. Population data, available only for 2015, 2020, and 2025, was forward filled in order to enable historical emissions estimates. For every GADM2 region (i.e., untreated wastewater "asset"), the percentage of the urban and rural populations producing untreated wastewater (from WASH) was multiplied with the urban and rural population values per region (from GHSL) to calculate the total number of people producing untreated wastewater in each region. These values were used as the "Population Served" for the untreated wastewater "assets."

Assets with a treatment level of "Untreated" were assigned a value of zero for the following model parameters: wastewater treatment nitrogen removal fraction and fraction of total wastewater organics removed during wastewater treatment. These untreated assets were then combined with the set of domestic assets for emissions calculation. For countries where the sum of asset-level emissions exceeds the country-level emissions (Democratic Republic of the Congo, Ethiopia, Liberia, Madagascar, Mozambique, Namibia, Niger, Papua New Guinea, Sudan, South Sudan, Chad, Togo, Uganda), the difference was taken between the sum of the asset emissions and the country emissions, then scaled by the ratio between this difference. The difference between the sum of asset-level emissions and country-level emissions for these countries is likely due to differences between the population datasets used (GHSL and UN population data) and will be further investigated in the coming months.

Appendix 9. Mapping of Unlisted Countries to Proxy Country in WASH Data

Table A9.1. Missing country mapping. Each of the ISO3 country code is mapped to another proxy country for gap-filling of WASH data. *zero* implies that the population of the particular country is zero or no mapping is needed.

Country	Proxy Country
ALA	FIN
ATA	zero
ATF	SXM
BES	SXM
BVT	zero
CCK	LKA
COK	ASM
CXR	LKA
ESH	MAR
GGY	GBR
HMD	zero
IOT	GBR
JEY	GBR

Country	Proxy Country
XKX	zero
NCL	PYF
NFK	AUS
PCN	AUS
SGS	GBR
SJM	NOR
SPM	CAN
TKL	ASM
TWN	CHN
UMI	ASM
UNK	zero
VAT	full

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