Waste sector: Emissions from Wastewater Treatment Plants

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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).

Sources of emissions from wastewater treatment
Wastewater is a source of methane, both when treated and 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 GHG Reporting 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 of the WWTPs, and missing WWTPs in countries without any officially published datasets.

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 wastewater. The WWTP was assumed to include all treatment processes (primary and secondary) that occur onsite between inflow of untreated wastewater and outflow of treated wastewater. 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 the IPCC guidelines for national greenhouse gas inventories.

Since the source-level database is not comprehensive (i.e., does not account for every single WWTP in all countries and does not account for emissions from untreated water), country-level emissions estimates were taken from Emissions Database for Global Atmospheric Research (EDGAR) dataset (EDGAR, 2023). In instances where the total emissions of all sources in a country exceeded the EDGAR estimate, the facility level totals were used instead to avoid instances where the facility totals (mainly for N_2O values) exceeded country totals. It should be noted that this difference in N_2O estimates is likely because the EDGAR methodology has not considered the 2019 refinement to the IPCC National Greenhouse Gas Inventory Guidelines. See Appendix 6 to see the full list of countries where this approach was used.

2. Materials and Methods

The following datasets and methods were employed to (a) locate and identify wastewater treatment plants (hereafter, WWTP) and (b) estimate wastewater CH_4 and N_2O emissions for individual WWTPs globally for years 2015 to 2021.

Satellite imagery from Google Maps 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 the Intergovernmental Panel on Climate Change (IPCC) emissions factors (EFs) to estimate WWTP emissions.

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 contains the distribution of all centralized WWTPs in HydroWASTE that are not labeled “Closed” or “Not Operational”. In total, 53,466 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 Non-wastewater treatment plant data

To train a model to identify WWTPs, we also needed non-WWTP locations and their images. A feature set was built which corresponds to non-WWTP images from latlong.net, a data repository of coordinates of different places (https://www.latlong.net/). This feature set helped train the model to differentiate between WWTP and non-WWTP images. These images belonged to various categories as shown in Table 1.

Table 1. Non-WWTP data collection, totaling 10,000 images. Row S.No-1 was sourced from HydroWASTE, row Sample Number (S.No)-2 was sourced from the false positive data collected from test model runs, and rows categories S.No-3 to S.No-18 were sourced latlong.net.

S No.	Total Images	Image Category	S No.	Total Images	Image Category
1	3,999	HydroWASTE [False Positives]	11	200	Gas Plants
2	1,000	Farms	12	188	Geothermal Plants
3	161	Stadiums	13	200	Hydro Plants
4	1,000	Cities	14	195	Nuclear Plants
5	1,842	Dams	15	200	Oil Plants
6	111	Ponds	16	200	Solar Plants
7	22	Rivers	17	10	Wind and Tidal Plants
8	200	Biomass Plants	18	200	Wind Plants
9	200	Coal Plants	19	31	False Positives
10	41	Cogeneration Plants	**Total images = 10,000**		

2.1.3 Satellite Imagery

To provide visual imagery for WWTP model training, satellite imagery hosted in The Google Map Statics Application Programming Interface (API) was accessed to identify WWTP in the top 125 global cities by population. 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 and non-WWTP from Table 1, images of the locations were extracted using the Map Static API, then they 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.

2.1.4 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 are used for discharge. Country-specific population behavior and demographics and WWTP specific technology levels are 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.

2.1.5 Population Data Prior to 2022

The population served estimates from HydroWASTE are valid for 2022, and an extension to 2015 was made using linear scaling based on the country-level population changes. Most annual country-level population data were obtained from the World Bank (World Bank Group n.d.). Taiwan population history was obtained from a Republic of China government database (Republic of China n.d.). For some regions no population scaling was applied as reliable and accurate population data for these regions are difficult to identify: Åland Islands, North Cyprus, Martinique, Réunion, Guadeloupe, French Guiana, Saint Barthélemy, Cook Islands, Mayotte, and Montserrat.

2.1.6 Datasets for emissions verification

Emissions estimates for WWTPs in the U.S. and E.U. are 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)

2.2 Methods

2.2.1 WWTP Identification Model Development

The model development was undertaken using a 7-step process, shown in Figure 2, outlining the steps required in the decision making pipeline. Figure 3 provides sample images corresponding to each of the steps in the decision making pipeline. Each step is described in detail below.

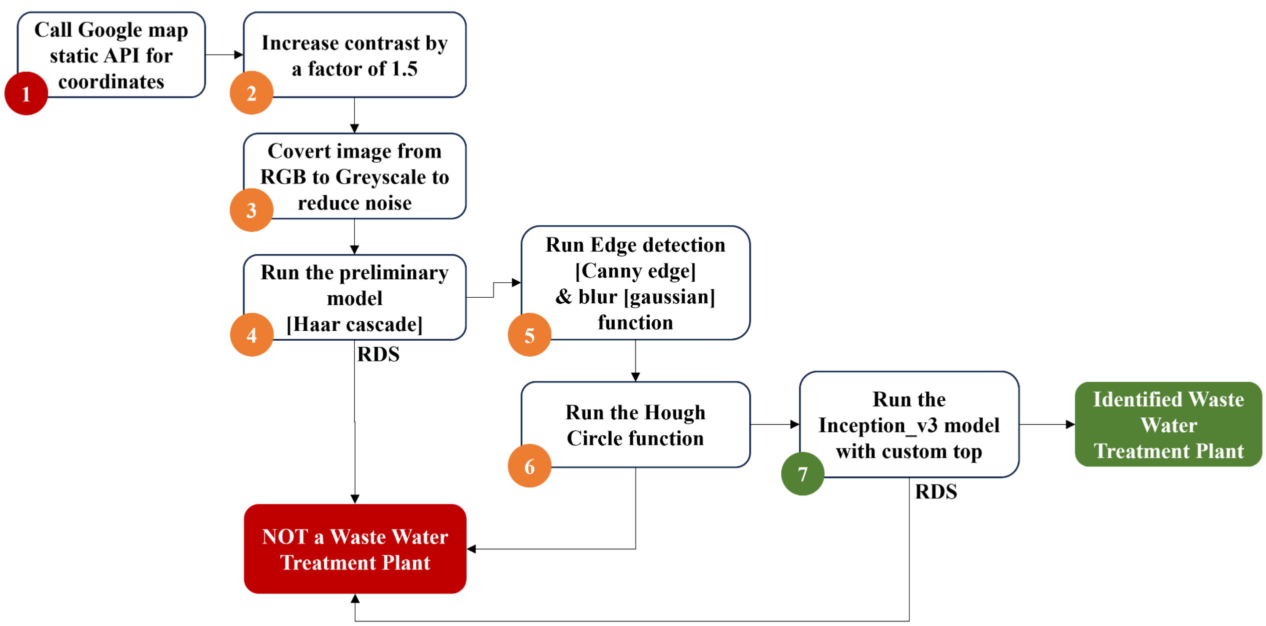


Figure 2. Flowchart highlighting the model development process for detecting WWTPs using satellite imagery. Each step is described in the text below.

Step 1: Call Google Map API, and Steps 2 and 3: Pre-processing data

The satellite imagery from Google Map Static API was accessed and went through multiple stages of preprocessing. First, the image contrast was increased by a factor of 1.5. This helped to make the features of the image more prominent and led to the most optimum balance between the false positives and false negatives while identifying the clarifiers – a feature that is a present in the particular type of WWTP that are of interest. The image was then converted from color (RGB) to grayscale to reduce noise which might be caused due to color variation.

Steps 4 to 6: Detecting WWTP candidates

After pre-processing, WWTP candidates were detected using a two-step process. First, a preliminary model was used to identify objects which look like clarifiers. The preliminary model was a Haar Cascade Classifier trained on 3000 clarifier images and 6000 negative, non-clarifier, images. A Haar Cascade model was used due to its speed and accuracy when trained on small amounts of data, and the optimum values for general purpose application of this model were used**:** Min hit rate, 0.99; Max false alarm, 0.25; Weight trim rate-0.95; and Epochs, 10.

Other parameters were selected through a grid search method. The image goes through a Canny edge detection function and a Gaussian blur function with a 5x5 matrix. This is done to reduce the noise in the image and makes it easier to identify the circular clarifier-like objects.

Lastly, the OpenCV's Hough Circles function was used to confirm the presence of clarifier-like objects. The hough circles function uses gradient information from edges to identify a circle. The minimum radius for the HoughCircles function was set to 2px and the maximum radius was 30px. This meant that the minimum radius of a circle which the function could identify is 2px and the maximum radius is 30 px.

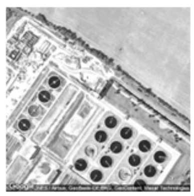
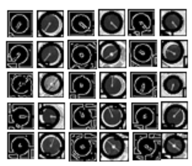
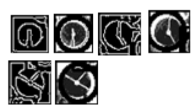
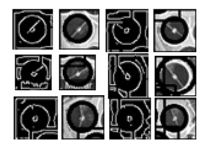
	Sample Image 1	Sample Image 2	Sample Image 3
[STEP 1] Call Google map static API for coordinates			
[STEP 2] Increase contrast by a factor of 1.5			
[STEP 3] Covert image from RGB to Greyscale to reduce noise			
[STEP 4] Run the preliminary model [Haar cascade]			
[STEP 5 and 6] Run Edge detection [Canny edge], blur [gaussian] and Hough Circle function			

Figure 3. Examples of the sample outputs for the steps 1 to 6.

Step 7: Confirming wastewater treatment plant candidates

Images that passed the preliminary check were passed to the second model to confirm the presence of a WWTP at a specific location. The second model applied was a Convolutional Neural Network (CNN)- viz Inception v3, published by Google (Google, 2023) . ImageNet weights were used for feature transformation with a custom top for classification. The top of the CNN contains 2 dense layers with 2048 units and ReLU (rectified linear unit) activation function, followed by a final dense layer with 2 units and sigmoid activation function. In the top of the CNN there is a dropout layer (0.6) between each dense layer to prevent overfitting of the model. During the model training each batch of the images went through data augmentation to prevent overfitting of the model. The model was trained with 10,000 wastewater treatment images and 10,000 non-wastewater treatment plant images with a 70-30 split for training and testing images. We tried several models - VGG-16, VGG-19, ResNet, MobileNet, Xception, and Inception v3 - before deciding on Inception v3 as this model produced more accurate results relative to the other models. The specifications for the second model and the hyperparameters for which were decided through a grid search method are shown in Table A5.1.

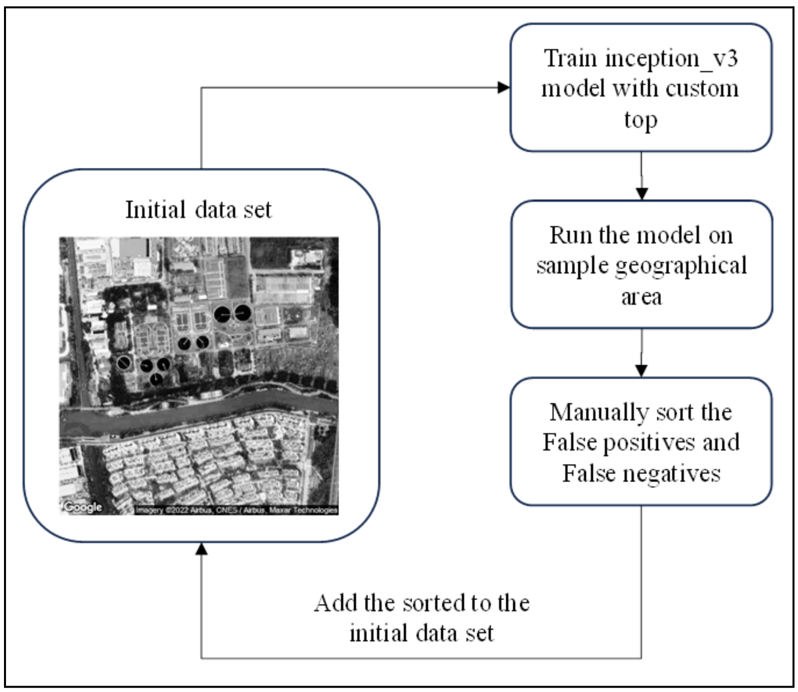


Figure 4. Flowchart describing the wastewater treatment plant data collection process for model training.

To create the data set for the second model, data augmentation was done to increase the number of True WWTP images for the training of the model. There were 2,000 unique images, which were scaled to 10,000 due to attributes changed, like vertical/horizontal flip, blur/sharpen, and stretch/shift, to generate the batch of images (Table 2).

Table 2. Augmentation attributes for preparing the training data

S No.	Number	Attribute changed
1	2,000	Original base dataset
2	2,000	Gaussian Blur + Vertical Flip
3	2,000	Sharpen + Horizontal Flip
4	500	Parallel Shift [Threshold: 10%]
5	500	Stretch [Threshold: 10%]
6	2,000	Horizontal Flip + Vertical Flip
7	1,000	Rotate [Threshold: 30 Degrees]
Total = 10,000		

While training the second model, there was another stage of post-data augmentation done to prevent overfitting of the model. There were various aspects of the image which were set to change randomly on each batch of the image. These included rotation of the image about its center, ±20 degrees of freedom; vertical/horizontal/shear shift of the image, up to 10% of original dimensions; zoom level, up to 20% of original dimensions; and horizontal/vertical flip.

The second model was then tested on 6,000 test images which comprised data from HydroWASTE for the following regions: Abruzzo, Italy; Basque, Spain; Delhi, India; and Western Cape, South Africa (Table 3). The results of the second model then went through a manual cleanup process to eliminate the false positives. The manual cleanup process involves visually inspecting each image to remove false positives.

Table 3. Confusion Matrix for the test run on the 6,000 images describing true and predicted labels for non-WWTP and WWTP.

		Predicted Label	
		Non-WWTP	**WWTP**
True Label	**Non-WWTP**	**2,933**	**67**
	WWTP	**62**	**2,938**

2.2.2 Model deployment - Executing the model over a geographical area.

The model was executed over a city in a grid like fashion. The city's geographical bounding box (yellow box in Figure 5) and polygon data were collected from OpenStreetMap and the bounding box was extended on each side by an increment proportional to the size of the city (orange box in Figure 5), this is done to ensure no geographical area, part of the city, was missed out. After this, the model scanned square plots of land of size ranging from 600m ~ 800m depending on the location on Earth. For each coordinate the model checked whether the point was either inside the polygon (red dots show the original city polygon, Figure 5) or within a certain distance from the polygon (blue dots show the extended city polygon, Figure 5). This distance was proportional to the area of the polygon. The model scans a city twice, once starting from the top left corner of the bounding box, then through a slightly offset grid. This was done to capture the WWTPs present on the intersection of the gridlines (Figure 6).

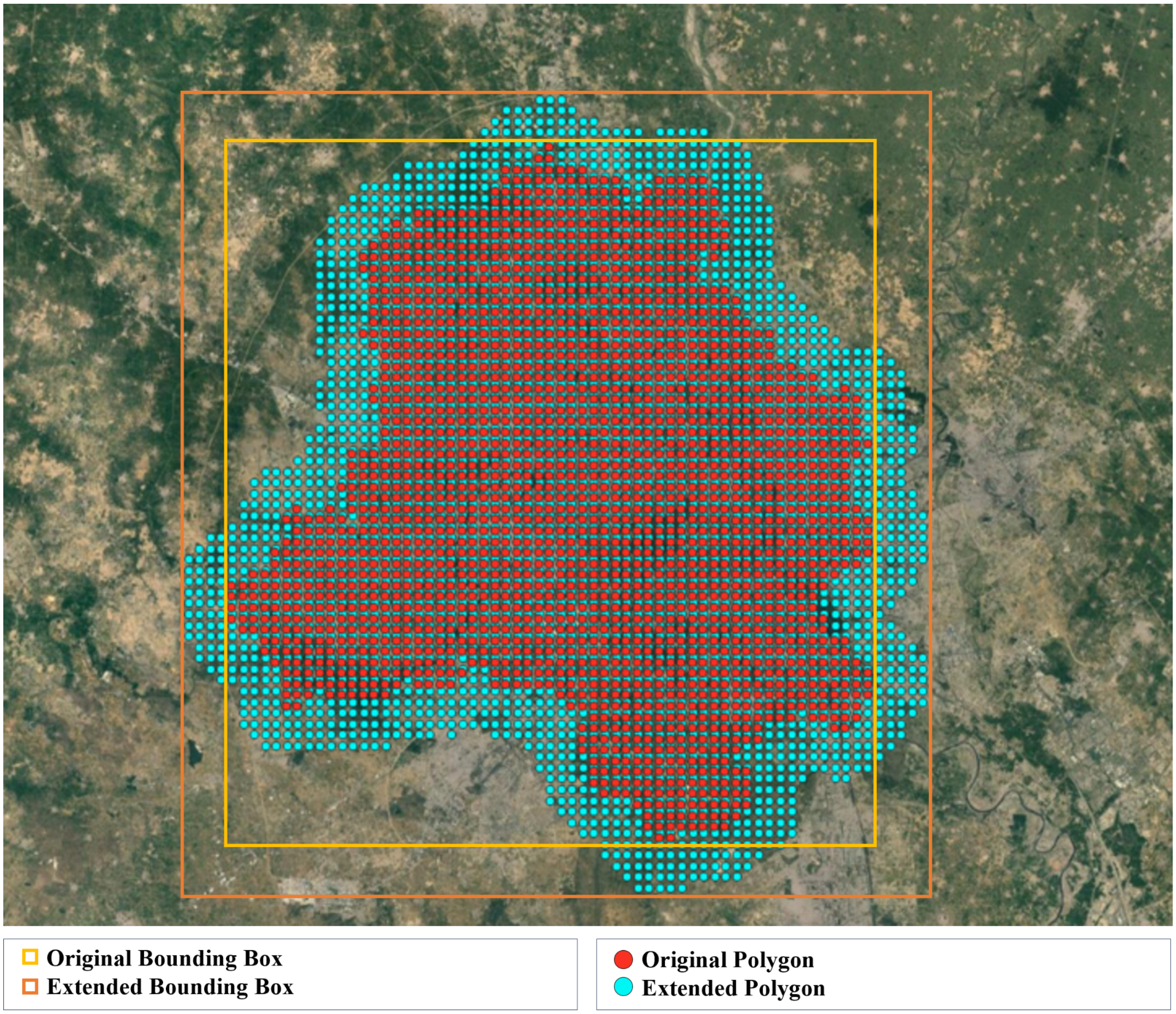


Figure 5. An example of the deployment of a city's geographical bounding box and the incremental bounding box for comprehensive coverage.

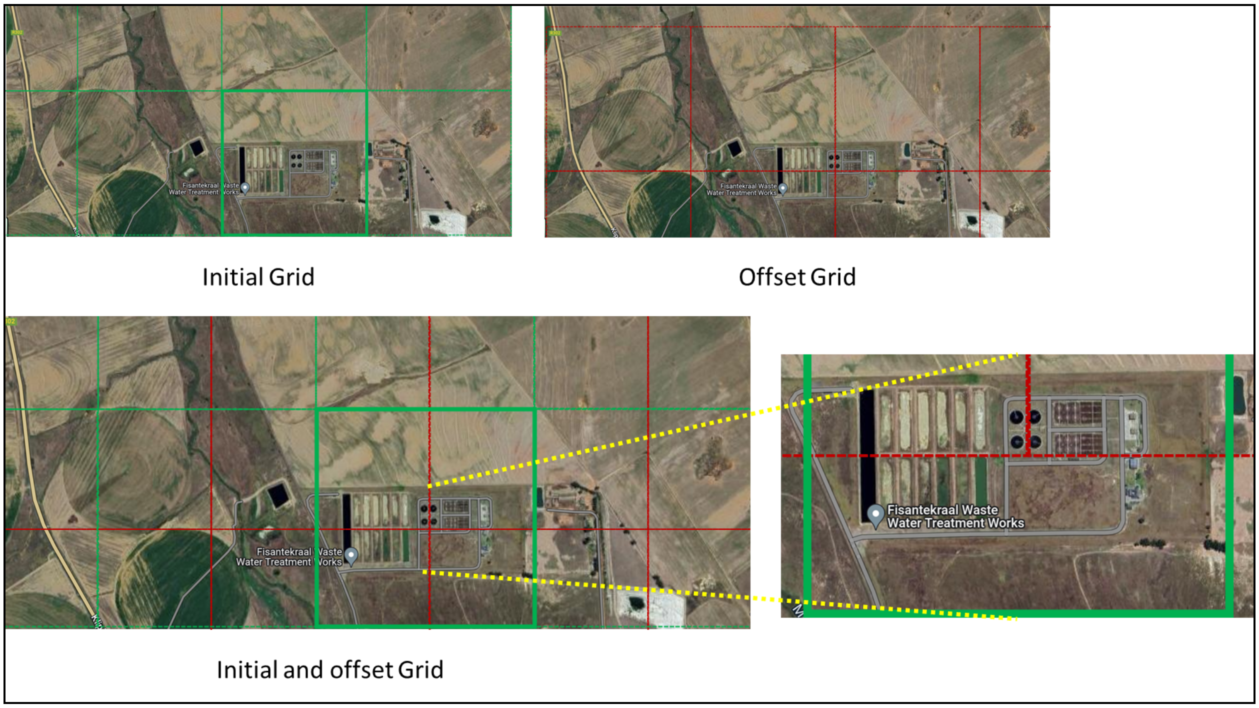


Figure 6. An example of the initial (green squares) and off-setting (red squares) grid search used to capture the WWTP at the intersection of grids.

After the model scanning, each output goes through a clean-up process which removes duplicate WWTPs due to overlapping geographical areas of the city bounding boxes, the off-setting images, or large wastewater treatment plants spanning over more than one image. For the clean-up process we assumed that there were no two WWTPs within 1,500m of each other, a self-defined distance threshold.

2.2.3 Filtering HydroWASTE WWTPs and merging with model identified WWTPS

To create a comprehensive as possible WWTP for emissions estimation, a three-step filtering of the HydroWASTE locations was performed. The first filter removed non-operating plants. Plants labeled as “Closed”, “Construction Completed”, “Decommissioned”', “Non-Operational”, “Projected”, “Proposed”, “Under Construction” under the “STATUS” column in HydroWASTE were removed. A total of 1,702 plants were removed.

Then the second filter removed plants that have both low location confidence and were not identified by the machine learning approach. HydroWASTE provides WWTP locations derived from national sources and from OpenStreetMap. HydroWASTE also provides a “location quality” ranking which indicates how reliable the location data are. These ratings go from 1 (highest) - 4 (lowest), which denote location testing accuracy. Locations with a quality of 4 are those that have not been tested and may be inaccurate. These locations were cross-referenced with WWTPs identified by the machine learning technique described above. Locations with a minimum distance greater than 5km from the identified WWTPs using the ML technique were removed. In total, 379 location quality 4 plants were retained and 3,019 were removed.

The third filter identified the countries where the WWTPs reside in then using their Global Administrative Areas (GADM). Overall, 283 HydroWASTE locations were in the boundaries of a different country than the one that was reported and three were removed as they were not located on land. In total 53,466 WWTPs remain out of the original 58,502 WWTPs in HydroWASTE.

2.3 Methods for Emissions Estimation

Each WWTP had their estimated population served and technology level described by the HydroWASTE dataset was used to estimate the annual CH_4 and N_2O emissions. These quantities are 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. These 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 explicitly described in the proceeding text. Figure 7 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.

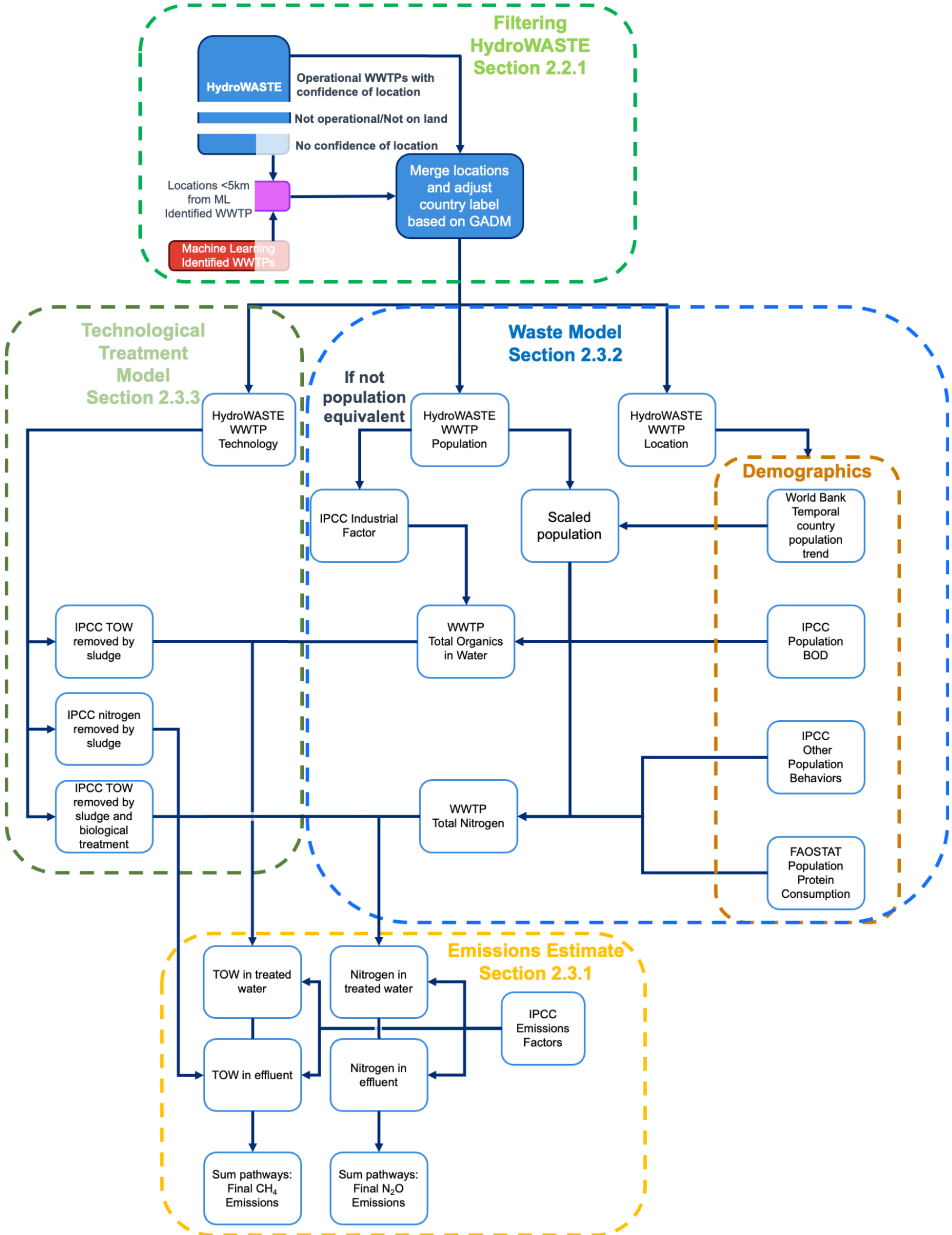


Figure 7. Flow diagram of emissions. HydroWASTE data is filtered based on operationality and location quality. Filtered locations are recovered if identified by machine learning model. Population, technology level, and location are used to develop emissions.

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 of most regions were obtained from World Bank (World Bank Group n.d.); Taiwan population history was obtained from a Republic of China government database (Republic of China n.d.); and a population scale of 1.0 was used for the remaining regions: Åland Islands, North Cyprus, Martinique, Réunion, Guadeloupe, French Guiana, Saint Barthélemy, Cook Islands, Mayotte, and Montserrat.These regions were set to 1 because most of these regions have small population changes to begin with, and hunting down accurate population estimates for each of these regions is difficult.

2.3.1 Emissions Estimates

Generally, 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.

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 emissions factor $EF_{CH4,\,Treat}$, based on Equation 6.1 from the IPCC guidelines:

$$CH_4Emissions_{Treat} = [(TOW - S) \cdot EF_{CH4,Treat} - R] \cdot 0.001 \text{ (Eq. 2)},$$

where 0.001 is a conversion from kg to T.

An emissions 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,

$$CH_4Emissions_{Eff} = TOW_{Eff}\, EF_{CH4,Eff} \cdot 0.001 \text{ (Eq. 3)},$$

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,

$$CH_4Emissions_{WWTP} = CH_4Emissions_{Treat} + CH_4Emissions_{Eff} \text{ (Eq. 4)}.$$

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,

$$N_2O\ Emissions_{Treat} = TN_{inf}\, EF_{N2O,Treat} \frac{44}{28} \cdot 0.001 \text{ (Eq. 5)},$$

where $EF_{N2O,Treat} = 0.016\ (kg\ N_2O\ N/kg\ N)$ is the emissions 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,

$N_2O\ Emissions_{Eff} = N_{Eff}\, EF_{N2O,\,Eff}\, \frac{44}{28} \cdot 0.001$ (Eq. 6),

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

$N_2O\ Emissions_{WWTP} = N_2O\ Emissions_{Treat} + N_2O\ Emissions_{Eff}$ (Eq. 7)

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 7) and how that treatment influences the emissions based on the technology level of a plant (the *Technological Treatment Model*; Figure 7). A discussion of these models follows.

2.3.2 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. 2 is a function of the number of people served P by the WWTP and the amount of BOD they generate, defined by,

$TOW = P \cdot BOD_c \cdot I \cdot 0.001 \cdot 365$ (Eq. 8),

where BOD_c is the production $(g/day/capita)$ of BOD of a person living in country c and $I = 1.25$ is a factor that accounts for industrial wastewater that enters the sewer system linked to the WWTP. 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. 8 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. 5) 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 estimates 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. 9),

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. 10).

The remaining quantities in Eq. 3 were obtained using Table 6.10A.

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, tertiary). In addition, different forms of biological treatments are available at plants at different levels of treatment. 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. 11),

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. 2.

Accounting for both sludge and biological treatment, the TOW carried by effluent water in Eq. 3 is determined with

$TOW_{Eff} = TOW \cdot (1 - TOW_{rem})$ (Eq. 12),

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. 6 was derived from TN_{inf}, according to

$N_{Eff} = TN_{inf}(1 - N_{rem})$ (Eq. 13),

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.

2.3.4 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. 14),

$Emissions \ = \ Activity \cdot EF$ (Eq. 15),

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,

$$EF_{CH4} = \frac{CH_4 \ Emissions_{WWTP}}{P} \text{ (Eq. 16)},$$

$$EF_{N2O} = \frac{N_2O \ Emissions_{WWTP}}{P} \text{ (Eq. 17)}.$$

2.3.5 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 is 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,

$$\sigma \ = \ \sqrt{N} \ \frac{upper\ limit - lower\ limit}{3.92} \text{ (Eq. 18)},$$

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 a $\pm$ 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,

$$e_P = \widetilde{P} - P \text{ (Eq. 19)},$$

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. 20),

$\sigma^2_{e_P} = RMSE^2 - \bar{e}^2_P$ (Eq. 21),

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 derivations of Equations 20 and 21 are in the Appendix. 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. 22),

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

A convergence study of the Monte Carlo simulation was performed where multiple Monte Carlo simulations were computed with varying sample sizes: 125, 250, 500, 1,000, 2,000, 4,000, 8,000, 16,000, 32,000, 64,000, 128,000. Figure 8 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.

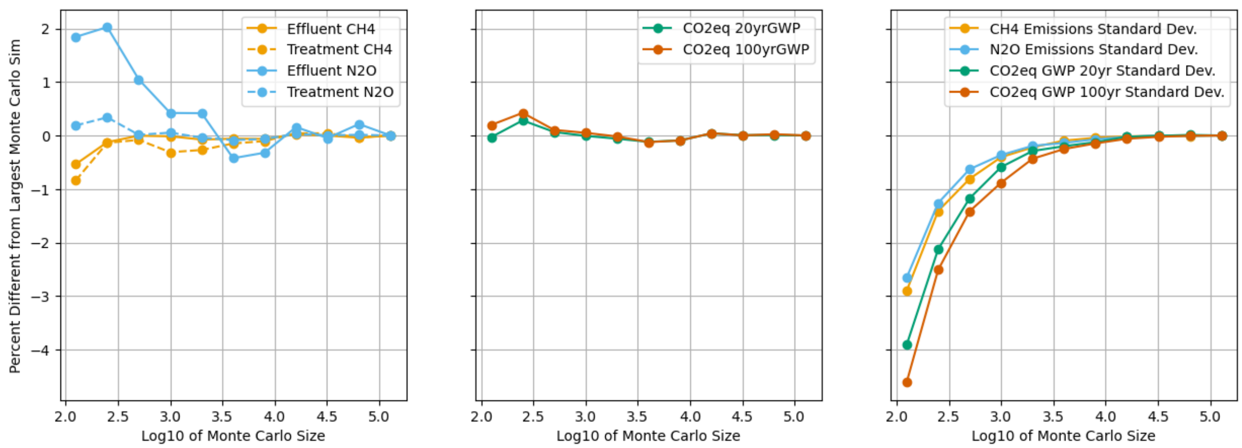


Figure 8. The percent difference of the treatment, effluent, and CO2eq emissions between the largest Monte Carlo simulation and the other Monte Carlo simulations. Convergence occurs around a sample size of $O(10^4)$.

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.

2.3.6 Limitations

The largest limitations in the methane analysis described in Section 2.3.1. are the lack of disparate treatment of plants that use anaerobic digestion and the lack of flaring/recovery estimates in Equation 2. 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 US, 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.

Lastly, 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.

3. Results

3.1 Machine learning model for identifying WWTPs

The ML model scanned 125 of the biggest cities (based on population), where 2237 WWTPs were identified.

In order to test the model performance against reported data, the model was also run on the largest 80 cities in Germany (by population) and was compared to reported data from the European Environment Agency (EEA). There were a total of 338 officially reported WWTPs (All types) in the scanned 80 cities (purple dots in the left image of Figure 9). Of these, 219 were centralized WWTP (red dots in the right image of Figure 9) with more than one clarifier, a unique visible characteristic in the form of a structure that is present in centralized WWTP. Our model detected 373 centralized WWTPs (yellow dots in Figure 9) in these 80 cities, i.e., 154 more unique WWTPs than the 219 reported centralized WWTPs. Note: There could be a difference in the number of WWTPs in the scanned area versus reported due to differences in administrative polygon definition and due to only certain industries being required to report WWTP information to the European Commission.

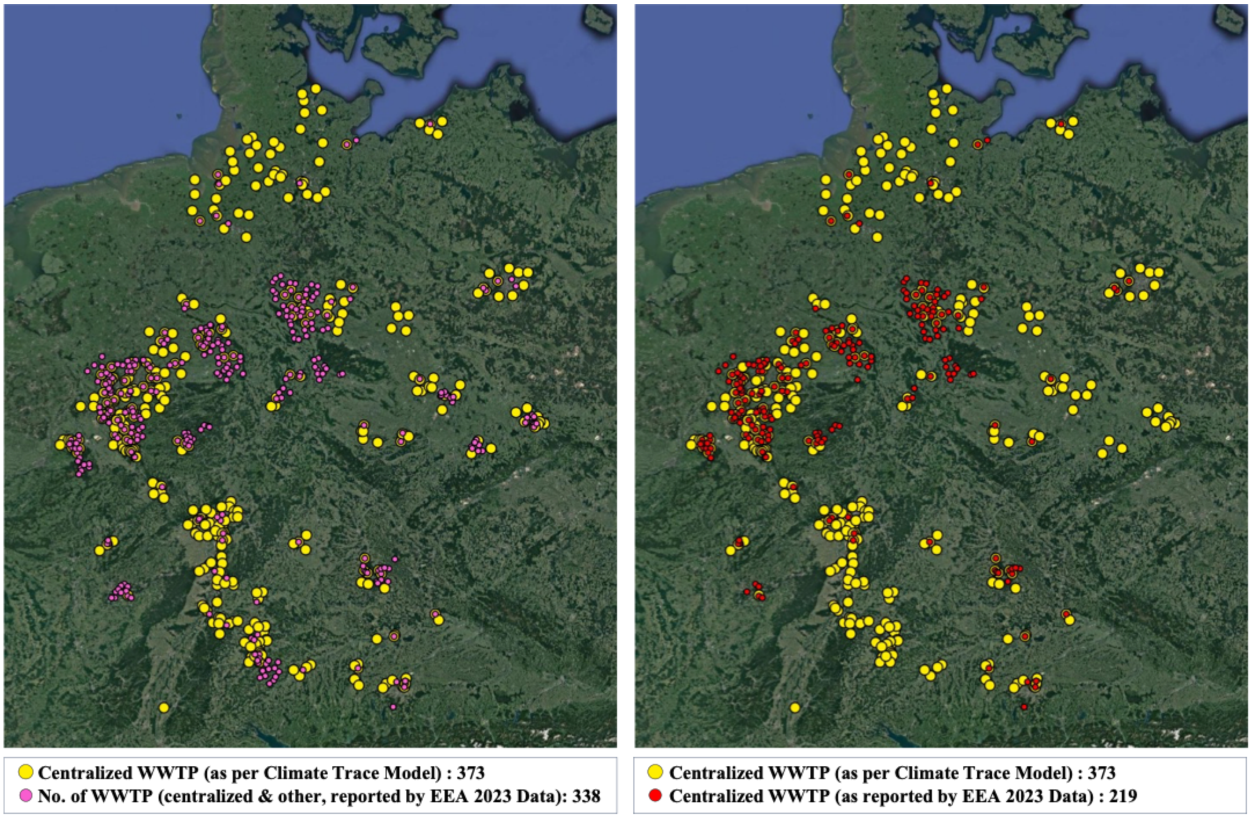


Figure 9. compares the WWTP found by the model to the WWTP reported by the government

3.2. Emissions estimates for WWTPs

The centralized WWTP dataset comprises 53,466 sources for the years 2015 to 2022. For the year 2022, it is estimated that these sources account for 130.7 MT of CO2eq. Figure 10. – 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*).

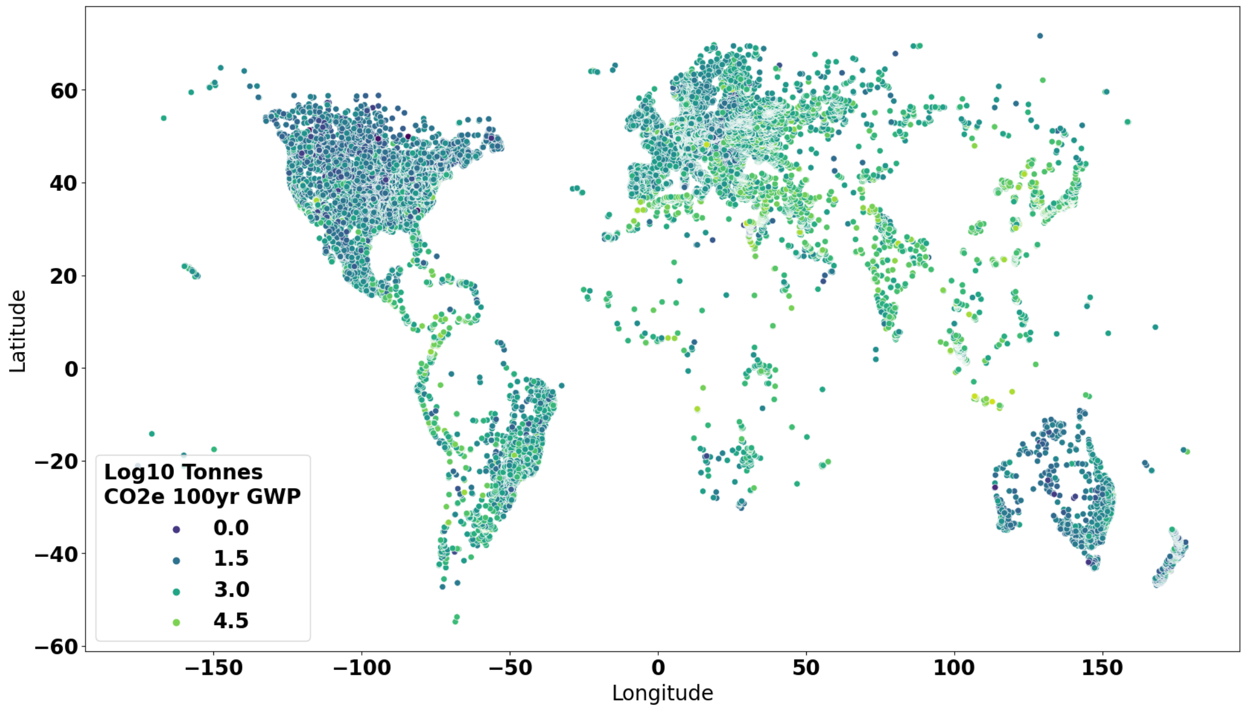


Figure 10. Global distribution of centralized domestic wastewater treatment plants colored based on emissions in 2022. This is not an exhaustive list (*see Section 2.3.6.*).

A majority of WWTPs produce less than one kT of CO_2eq annually as shown by Figure 11; 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.

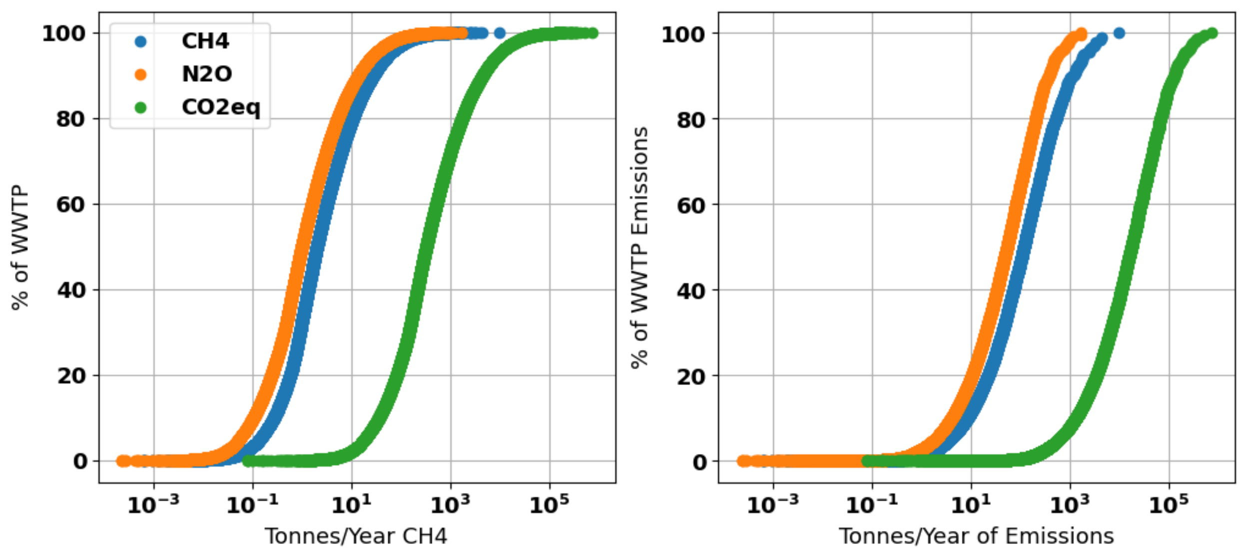


Figure 11. Cumulative distribution of emissions across WWTPs (left) and across WWTP emissions (right) in 2022. The left plot demonstrates that a majority of WWTPs produce less than one kT (10^3 Tonnes/year or 1000 tonnes) of CO2eq (100 year global warming potential) whereas the plot on the right demonstrates that almost all emissions come from plants that produce more than 1 kT of CO2eq.

The effect of use of country-level changes in population to extend WWTP emissions estimates to 2015 can be seen in Figure 12. 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.

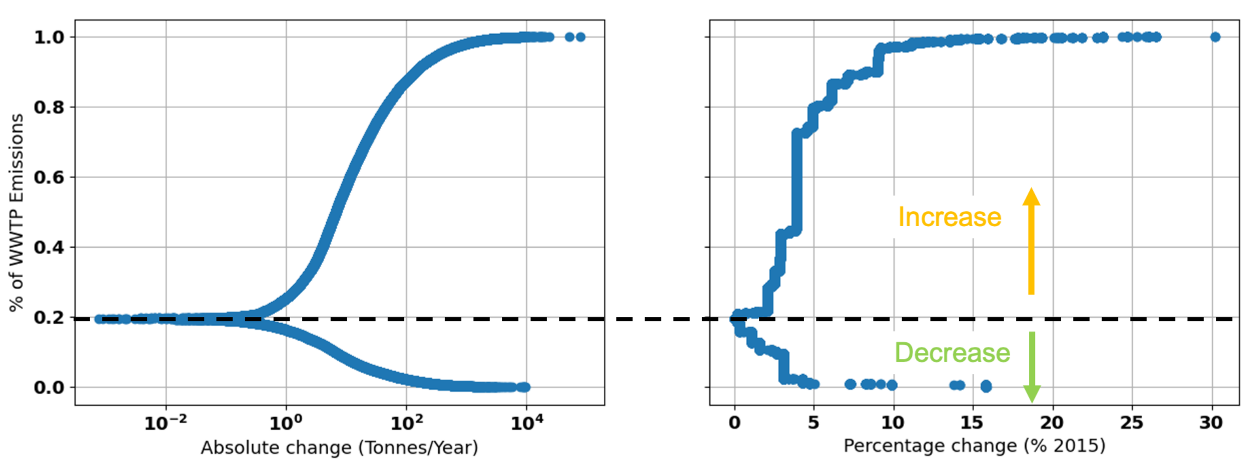


Figure 12. Distribution of change in emissions between 2015 and 2022. Approximately 80% of WWTPs saw an increase in emissions whereas approximately 20% saw a decrease. Approximately 80% of WWTPs had <5% absolute change of emissions.

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 13. 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 14.

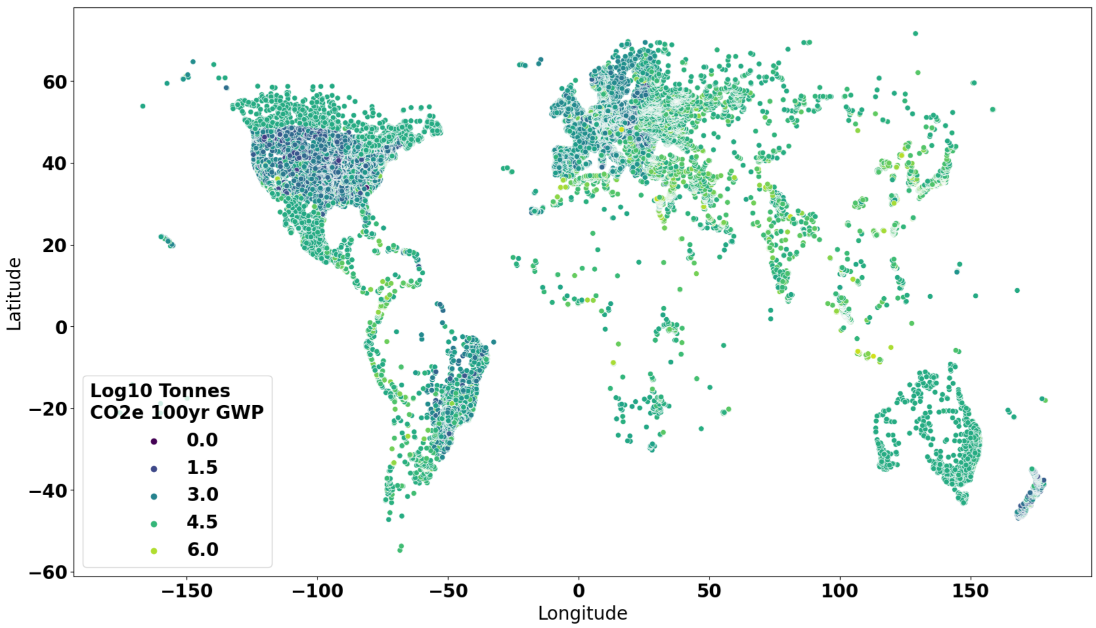


Figure 13. Uncertainty of CO_2eq distributed globally.

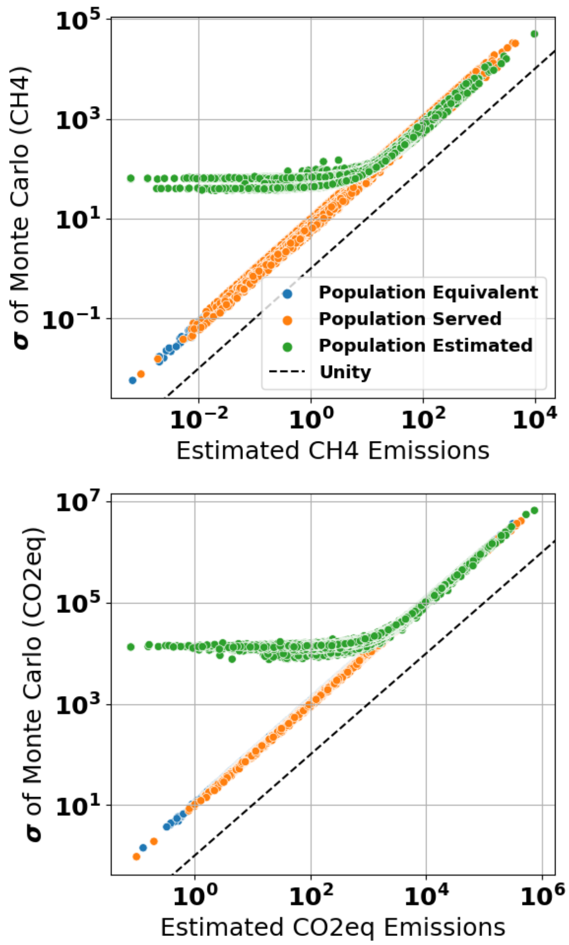


Figure 14. Uncertainty of emissions compared to emissions estimated disaggregated by population type (population served, population equivalent, estimated population) and uncertainty of CO_2eq as a function of population. For lower emissions estimates, uncertainty for emissions of WWTPs with estimated populations is significantly higher than those with reported populations. Overall, uncertainty of emissions is significantly higher than the estimated value.

3.3. 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 US and EU in spite of the limitations discussed in 2.3.6.

3.3.1 Comparison of Estimated Emissions to US 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 US 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
Total	*EPA*	266	74	27,438
	CT	217	89.5	23,363

Overall, the Climate TRACE source-level estimation for the US 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 emissions 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 CO2eq 100 year global warming potential estimates align very well with Parravicini *et al.* for all countries as shown in Figure 15 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 CO2eq from Climate TRACE and 34.36 MT CO2eq from Parravicini *et al.* A labeled country-by-country comparison is shown in Figure A4.1.

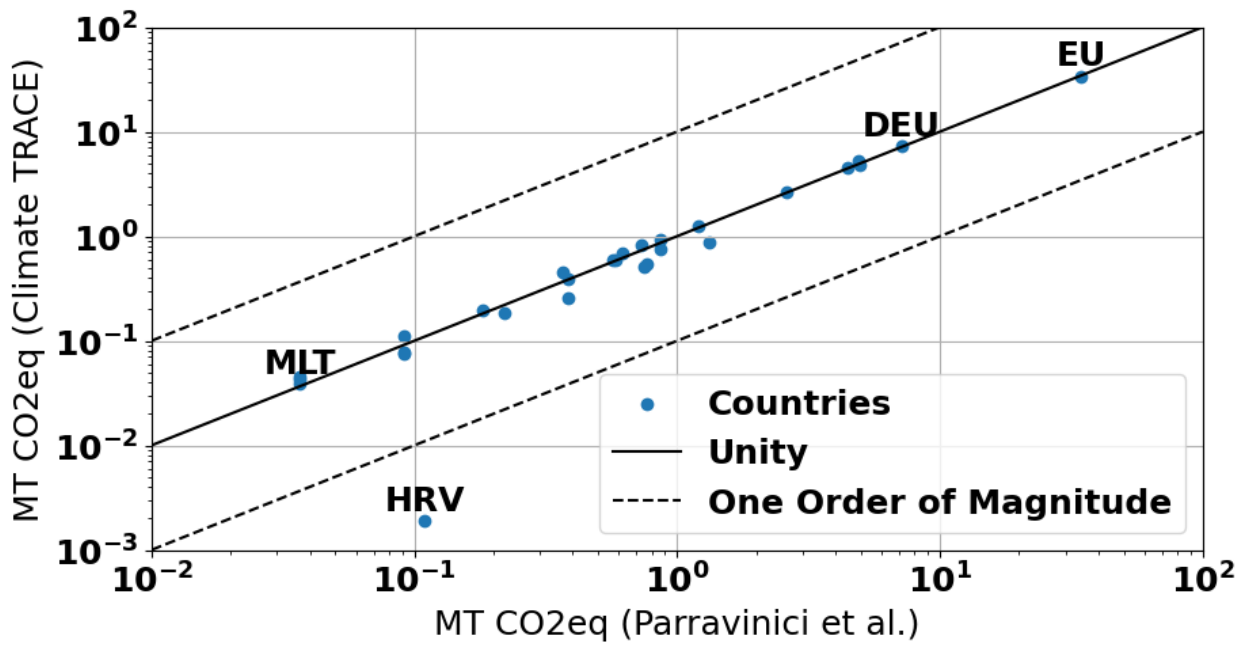


Figure 15. A country by country comparison of emissions from centralized, domestic WWTPs between Parravinici et al. and integrated Climate TRACE sources. The countries with the highest and lowest emissions from WWTPs are labeled, as well as the EU summation and outliers. All countries align very well with the exception of Croatia (HRV).

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 extend emissions estimates from 2022 back to 2015. 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 a good 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 will improve overall coverage as well as inclusion of WWTPs not reported by HydroWASTE.

5. Supplementary materials metadata

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 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 – 2022*
Temporal Resolution	*Yearly*
Data format(s)	YYYY-MM-DD
Coordinate Reference System	*WKT_Point*
Total emissions for 2022	*832.05kT CH4, 395.76 kT N2O, 130.67 MT CO2e 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)
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 confidence and uncertainty for confidence/uncertainty-climate-trace_waste-water-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 in 2020, and another in 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
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

Data citation format: Collins, G., Jain, A., Sridhar, L., Reilly, E., (2023). *Wastewater sector - Emissions from Wastewater treatment plants*. 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: 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 best model right now got 80% off the WWTP [16/20]. Out of the 4 missed, 2 were not clear due to the color and resolution, 1 due to alignment, and it outright missed 1.

Table A1.1 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
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 2: Derivation of Mean and Variance of Estimated Population Error

In Section 2.3.5, the mean (Equation 20) and variance (Equation 21) of the error estimated population values are used to sample the error of the estimated population using Equation 22. 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.

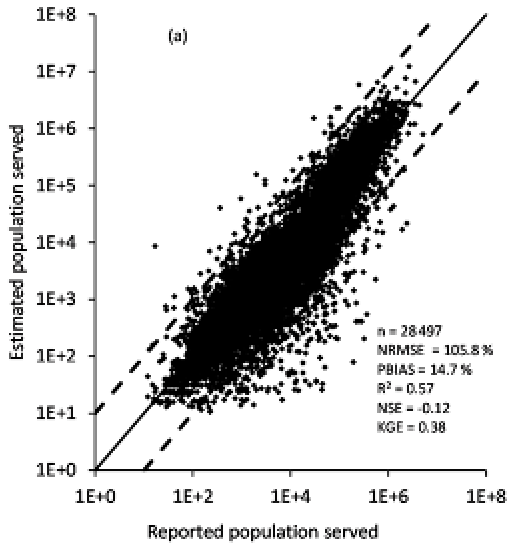


Figure A2.1. Figure 4.a in Macedo et al. (2022a). The performance of the population served estimation approach when applied to WWTPs with known population served/PE. The solid line is the unit line (i.e. no error), and the dashed lines represent an order of magnitude difference between the estimated 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 19 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

$$\sigma^2_{e_P} = \frac{\Sigma e_i^2 - 2e_i\bar{e} + \bar{e}^2}{N}$$ (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 $RMSE = NRMSE \cdot \bar{P}$.

Appendix 3: HydroWASTE Dataset Statistics

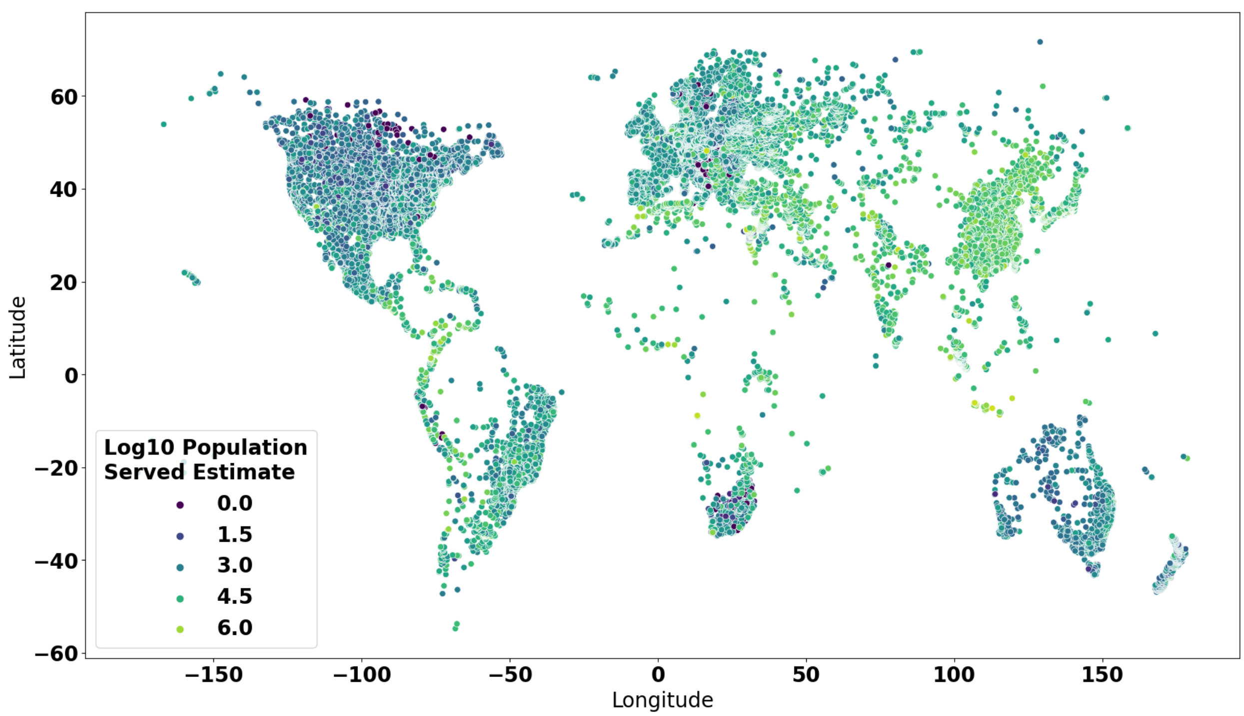


Figure A3.1. HydroWASTE global distribution of centralized WWTPs identified as not “Closed” or “Not Operational”. Further filtering occurs prior to emissions estimates to remove plants whose locations are of low confidence (i.e., those that have some likelihood of being incorrectly labeled).

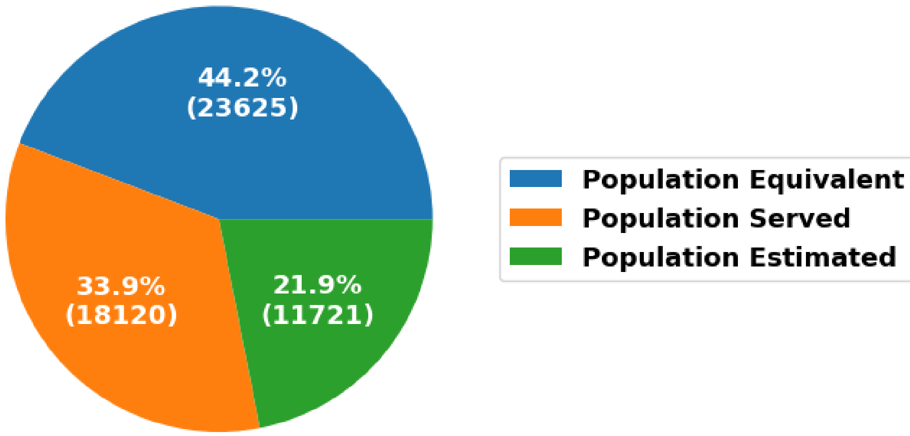


Figure A3.2. Proportion of WWTPs based on computed population served.

Appendix 4: Country-by-country comparison of E.U. emissions estimates

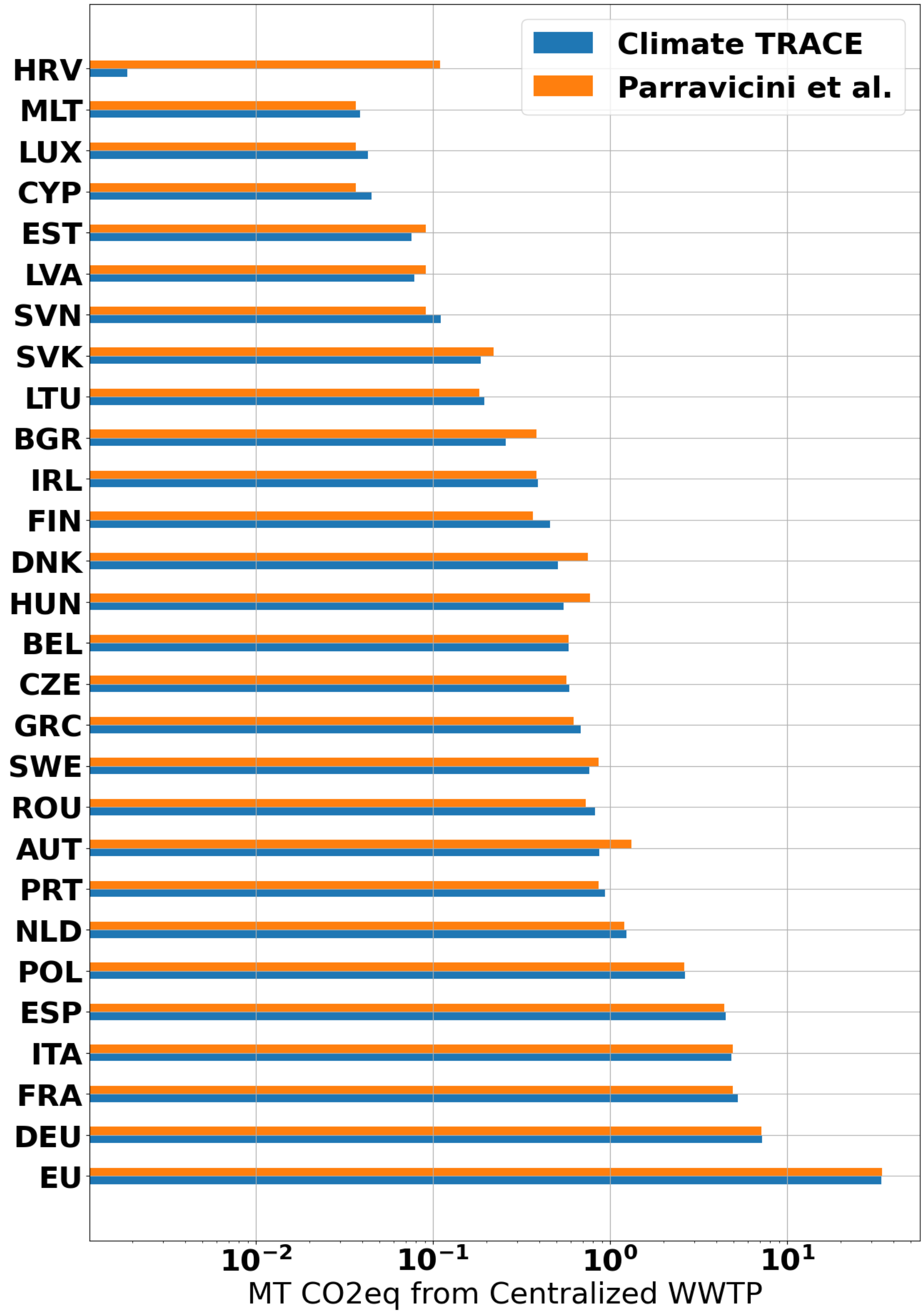


Figure A4.1. A comparison of CO_2eq between Parravicini *et al.* emissions estimates (CO_2eq 100 year global warming potential) and Climate TRACE. Countries are labeled with their ISO 3166-1 alpha-3 codes. Overall, Climate TRACE and Parravicini *et al.* align well for most countries.

Appendix 5: Hyperparameters used to train the WWTP identification network

Table A5.1

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 6: List of countries where the EDGAR country-level estimate (EDGAR, 2023) was replaced with estimates from the sum of Climate TRACE source-level estimates

Since the source-level dataset presented in this document is not globally comprehensive, wastewater treatment emissions at the country-level have been taken from the EDGAR dataset (EDGAR, 2023). In some instances, the sum of all WWTPs modeled using the methodology presented here exceeded the country level estimate from EDGAR. In those instances, the source-level sum was replaced. The list of countries where the source-level sum was used are listed in Table A6.1.

Table A6.1. Countries and years where integrated source emission values are used instead of EDGAR country-level data for reported country-level emissions from wastewater treatment.

Country	Years	Replacement
ALB	2015-2022	N_2O
ARE	2015-2022	N_2O
ARG	2015-2022	N_2O
ASM	2015-2022	N_2O
AUS	2015-2022	N_2O
AUT	2015-2022	N_2O
BEL	2015-2022	N_2O
BGR	2015-2022	N_2O
BHR	2015-2022	N_2O
BLM	2015-2022	CH_4
BLR	2015-2022	N_2O
BOL	2015-2022	N_2O
BRA	2015-2022	N_2O
BRN	2015-2022	N_2O
CAN	2015-2022	N_2O
CHE	2015-2022	N_2O
COK	2015-2022	N_2O
COL	2015-2022	N_2O
CUB	2019-2022	N_2O
CUW	2015-2022	CH_4
CYP	2015-2022	N_2O
CZE	2015-2022	N_2O
DEU	2015-2022	N_2O
DNK	2015-2022	N_2O
DZA	2015-2022	N_2O
EGY	2015-2022	N_2O
ESP	2015-2022	N_2O
EST	2015-2022	N_2O
FIN	2015-2022	N_2O
FJI	2015-2019	N_2O
FRA	2015-2022	N_2O
FSM	2015-2022	N_2O
GBR	2015-2022	N_2O
GLP	2015-2022	N_2O
GRC	2015-2022	N_2O
GUM	2015-2022	N_2O
HKG	2015-2022	N_2O
HUN	2015-2022	N_2O
IRL	2015-2022	N_2O
ISL	2015-2022	N_2O
ISR	2015-2022	N_2O
ITA	2015-2022	N_2O
JOR	2018-2022	N_2O
JPN	2015-2022	N_2O
KNA	2015-2021	N_2O
KOR	2015-2022	N_2O
XKX	2015-2022	CH_4
KWT	2015-2022	N_2O
LTU	2015-2022	N_2O
LUX	2015-2022	N_2O
LVA	2015-2022	N_2O
MAC	2015-2022	N_2O
MAF	2015-2022	CH_4
MCO	2015-2022	CH_4
MEX	2015-2022	N_2O
MHL	2015-2022	N_2O
MLT	2015-2022	N_2O
MNE	2015-2022	CH_4
MNP	2015-2022	N_2O
MSR	2015-2022	N_2O
MTQ	2015-2022	N_2O
MYS	2015-2022	N_2O
MYT	2015-2022	N_2O
NLD	2015-2022	N_2O
NOR	2015-2022	N_2O
NZL	2015-2022	N_2O
PAN	2015-2020	N_2O
PER	2015-2022	N_2O
PLW	2015-2022	N_2O
POL	2015-2022	N_2O
PRI	2015-2022	N_2O
PRT	2015-2022	N_2O
PSE	2015-2022	CH_4
QAT	2015-2022	N_2O
REU	2015-2022	N_2O
ROU	2015-2022	N_2O
RUS	2015-2022	N_2O
SGP	2015-2022	N_2O
SLV	2015-2022	N_2O
SRB	2015-2022	CH_4
SSD	2015-2022	CH_4
SVK	2015-2022	N_2O
SVN	2015-2022	N_2O
SWE	2015-2022	N_2O
SXM	2015-2022	CH_4
SYC	2020-2022	N_2O
TUN	2015-2022	N_2O
TUR	2015-2022	N_2O
TWN	2015-2022	N_2O
UKR	2015-2022	N_2O
URY	2015-2022	N_2O
USA	2015-2022	N_2O
VIR	2015-2022	N_2O

References

1. IPCC, Bartram, D., Short, M., Ebie, Y., Farkaš, J., Gueguen, C., Peters, G., Zanzottera, N., Karthik, M., Masuda, S., 2019. *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Chapter 6: Wastewater Treatment and Discharge. UN.
2. de Foy, Benjamin, Schauer, James J, Lorente, Alba, and Borsdorff, Tobias, 2023. Investigating high methane emissions from urban areas detected by TROPOMI and their association with untreated wastewater, Environ. Res. Lett. 18 044004.
3. EDGAR (Emissions Database for Global Atmospheric Research) Community GHG Database, a collaboration between the European Commission, Joint Research Centre (JRC), the International Energy Agency (IEA), and comprising IEA-EDGAR CO2,

EDGAR CH4, EDGAR N2O, EDGAR F-GASES version 8.0, (2023) European Commission, JRC (Datasets): https://edgar.jrc.ec.europa.eu/

4. European Environment Agency (EEA) 2023. Urban Waste Water Treatment Directive, Waterbase reported under UWWTD: https://www.eea.europa.eu/en/datahub/datahubitem-view/6244937d-1c2c-47f5-bdf1-33ca01ff1715
5. EPA. 2023. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2021. U.S. Environmental Protection Agency, EPA 430-R-23-002. https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2021.
6. FAO. FAOSTAT-Food Balances. License: CC BY-NC-SA 3.0 IGO. Extracted from: https://www.fao.org/faostat/en/#data/FBS. Date of Access: 25-07-2023.
7. Google Cloud, 2023. Advanced Guide to Inception v3: https://cloud.google.com/tpu/docs/inception-v3-advanced
8. Macedo, H. E., Lehner, B., Nicell, J., Grill, G., Li, J., Limtong, A. and Shakya, R., 2022a. Distribution and characteristics of wastewater treatment plants within the global river network. *Earth System Science Data*, *14*(2), pp.559-577.
9. Macedo, H. E., Lehner, B., Nicell, J., Grill, G., Li, J., Limtong, A. and Shakya, R., 2022b. Supplement of distribution and characteristics of wastewater treatment plants within the global river network. *Earth System Science Data*, *14*(2), pp.559-577.
10. Moore, Daniel P., Li, Nathan P., Wendt, Lars P., Castañeda, Sierra R., Falinski, Mark M., Zhu, Jun-Jie, Song, Cuihong, Ren, Zhiyong Jason, Zondlo, Mark A., 2023. Underestimation of Sector-Wide Methane Emissions from United States Wastewater Treatment, E*nviron. Sci. Technol.* 2023, 57, 10, 4082–4090.
11. Australian Department of Sustainability, Environment, Water, Population and Communities (DCEWPC), 2011. National Pollutant Inventory: Emission estimation technique manual for sewage and wastewater treatment, 2011: https://www.dcceew.gov.au/sites/default/files/documents/fsewage.pdf
12. Parravicini, V., Nielsen, P.H., Thornberg, D. and Pistocchi, A., 2022. Evaluation of greenhouse gas emissions from the European urban wastewater sector, and options for their reduction. *Science of the Total Environment*, *838*, p.156322.
13. Republic of China (Taiwan). National Statistics. Total Population (End of Year, Persons). Extracted from: https://eng.stat.gov.tw/Point.aspx?sid=t.9&n=4208&sms=11713 . Date of Access: 10-08-2023.
14. Song, C., Zhu, J.J., Willis, J.L., Moore, D.P., Zondlo, M.A. and Ren, Z.J., 2023. Methane Emissions from Municipal Wastewater Collection and Treatment Systems. Environmental Science & Technology, 57(6), pp.2248-2261.
15. Tseng, Linda Y., Robinson, Alice K., Zhang, Xiaying, Xu, Xiaomei, Southon, John, Hamilton, Andrew J., Sobhani, Reza, Stenstrom, Michael K., and Rosso, Diego, 2016.

Preferential Paths of Fossil Carbon within Water Resource Recovery Facilities via Radiocarbon Analysis, Environ. Sci. Technol. 2016, 50, 22, 12166–12178

16. Turovskiy, Izrail S., and P. K. Mathai. 2006. *Wastewater sludge processing*. John Wiley & Sons.
17. US Environmental Protection Agency, 2019. Global Non-CO2 Greenhouse Gas Emission Projections & Mitigation - 2015-2020: https://www.epa.gov/sites/default/files/2019-09/documents/epa_non-co2_greenhouse_gases_rpt-epa430r19010.pdf.
18. United States Geological Survey (USGS), 2018. Wastewater Treatment Water Use**:** https://www.usgs.gov/special-topics/water-science-school/science/wastewater-treatment-water-use.
19. World Bank Group. Population Estimates and Projections. Extracted from: https://datacatalog.worldbank.org/search/dataset/0037655/Population-Estimates-and-Projections, Date of Access: 25-07-2023.
20. World Health Organization, 2018. Progress on wastewater treatment: Piloting the monitoring methodology and initial findings for SDG indicator 6.3.1 https://www.who.int/publications/i/item/9789241514897.