



A Modular Methane Mapping Tool (M3T): Introduction to the *M3T* R Package

Kristian D. Hajny^{1,§}, Joseph Pitt², Paul B. Shepson¹

¹School of Marine and Atmospheric Sciences, Stony Brook University, Stony Brook, NY, 11794, USA

²Atmospheric Chemistry Research Group, School of Chemistry, University of Bristol, Bristol, UK.

[§]Now at GTI Energy, Des Plaines, IL, 60018, USA

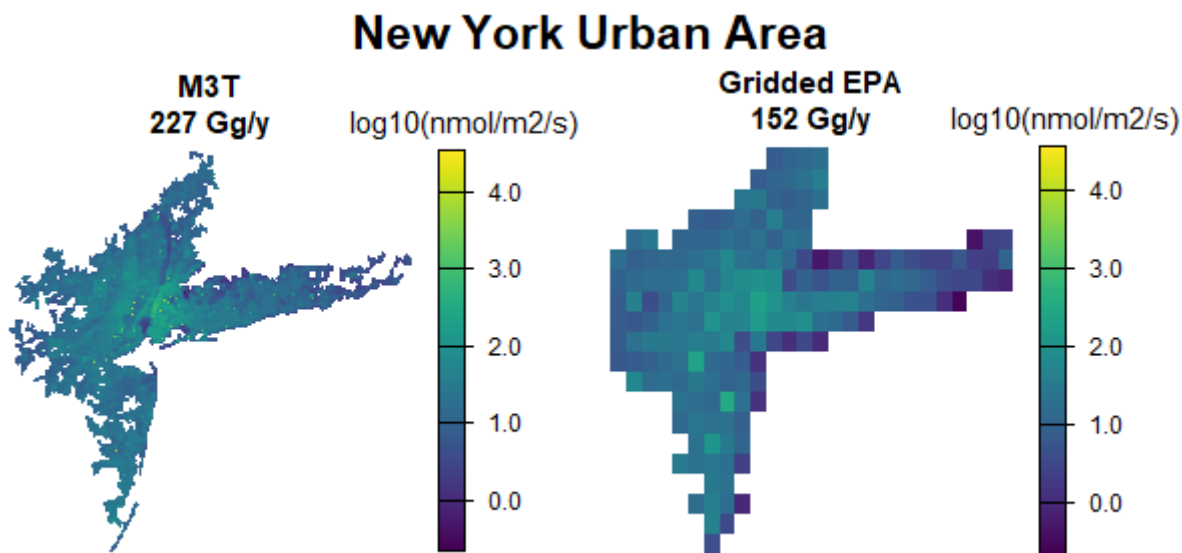
Correspondence to: Kristian D. Hajny (kris.hajny@gmail.com)

8



Abstract. Many cities have an interest in understanding and mitigating their greenhouse gas emissions. Impressive progress has been made in gridded carbon dioxide emission products, but there is still significant uncertainty in urban methane sources and their magnitudes. There have been several recent works that built regional gridded methane estimates using a variety of methods. Typically, these are built to update the existing products with more recent data/methods or for higher resolution data as it allows measurement-based analyses to better adjust emissions estimates, given the complex, heterogeneous mix of sources in urban areas. This paper introduces the Modular Methane Mapping Tool (M3T) to support these efforts. M3T is a tool that can generate an ensemble of gridded methane emissions inventories focused primarily on sectors relevant to urban emissions using research-based methods. The tool is focused on urban areas as existing inventories suggest they represent approximately 10% of all anthropogenic methane emissions across Continental United States (CONUS) and cities often have the autonomy to affect their emissions through legislation. M3T can generate inventories at any resolution that is 0.01 degrees (~1 km) or coarser for any area within the CONUS, and any year after 2011 using publicly available data. We compare 2019 output to the existing Environmental Protection Agency product for select urban areas, including the largest emitter of the New York urban area. Average emissions across M3T ensemble members are low relative to measurement studies, though the thermogenic fraction is in line with studies using ethane. While some ensemble members have methane emissions that are more consistent with measurement studies, these members have much lower thermogenic fractions. This highlights that there are still unaccounted for or underestimated biogenic and thermogenic sources. M3T is meant to support research efforts to better understand methane emissions as it allows multiple bottom-up methods and emission factors to be easily compared against measurements. Ideally, the tool will also expand as new research is conducted.

Graphical abstract





1 Introduction

Methane (CH₄) is an important greenhouse gas with a global warming potential (GWP) 83 times that of carbon dioxide (CO₂) over a 20-year time frame, or 30 times greater on a 100-year time frame, on a mass basis (Forster et al., 2021). Broadly, CH₄ sources can be divided into biogenic, thermogenic (i.e., natural gas), and pyrogenic (i.e., incomplete combustion of organic material, e.g., wildfires) processes, each with a mix of natural and anthropogenic sources (Saunio et al., 2020, 2025). CH₄ has been the target of many recent emissions mitigation efforts as its higher GWP and shorter lifetime mean that reductions will lead to a more immediate climate impact. Until recently, United States (U.S.) regulations required facilities generating at least 25,000 metric tons CO₂ equivalents (MT CO₂e) to report their CO₂, CH₄, and nitrous oxide (N₂O) emissions to the Environmental Protection Agency's (EPA) Greenhouse Gas Reporting Program (GHGRP) (Electronic Code of Federal Regulations, 2009a). The Greenhouse Gas Inventory (GHGI) then relied in part on these data to build national total estimates (EPA, 2024; GHGRP and the U.S. Inventory of Greenhouse Gas Emissions and Sinks, 2025). Continuous datasets like these allow researchers and policy makers to track changes over time and better understand the effectiveness of mitigation policies. However, gridded inventories at sub-national scales are of interest as they allow a more granular examination of these impacts and can be directly compared to measurements (Karion et al., 2023; Pitt et al., 2024; Sargent et al., 2021).

A number of different gridded emissions products have been developed with multiple options available for CH₄ at the global (Climate TRACE, 2025; Hoesly et al., 2018; Janssens-Maenhout et al., 2019; Soulie et al., 2024), national (Defra et al., 2025; Guo et al., 2025; Lyu et al., 2025; Maasakkers et al., 2016, 2023), and regional scale (Karion et al., 2023; Lamb et al., 2016; Loman et al., 2025; McKain et al., 2015; Mostafavi Pak et al., 2021; Pitt et al., 2024; Sargent et al., 2021). Some have focused solely on a particular sector (Bloom et al., 2017; Environmental Defense Fund, 2021; Scarpelli et al., 2022) while others incorporate a variety of emitted species, such as air pollutants, to create a self-consistent product given many CH₄ sources co-emit air pollutants (Janssens-Maenhout et al., 2019; Lyu et al., 2025). The most relevant for this work is the Gridded EPA (GEPA) product at a 0.1 x 0.1 deg resolution for the years 2012 to 2020 (including an express extension) for the contiguous U.S. (CONUS) (Maasakkers et al., 2023; McDuffie et al., 2023). GEPA is broken down by emitting sector and disaggregates GHGI national emissions using proxies, the same proxies as used to develop the GHGI where possible. The GHGI relies largely on bottom-up methods that directly calculate emissions using emission factors (EFs) that represent the emissions per unit activity (e.g., CH₄ emitted per gallon of wastewater flow) and activity factors representing the activity count (e.g., gallons of wastewater flow at each wastewater treatment facility) (EPA, 2024). Some of these proxy or activity datasets are proprietary and not publicly available. Importantly, recent literature has suggested the GHGI underestimates emissions from certain sectors, sometimes by a significant fraction (Alvarez et al., 2018; Cusworth et al., 2024; Dogniaux et al., 2025; Moore et al., 2025; Nesser et al., 2024; Weller et al., 2020). The 2019 GEPA shows that emissions within urban areas as defined by the Census urban area tigerlines for the same year (TIGER/Line Shapefiles from the Geography program) represent 10% of all anthropogenic emissions across CONUS. For comparison, the total emissions across all fossil fuel production related sectors (all coal, petroleum, and natural gas sectors excluding natural gas distribution and post-meter) represents ~37%.



Top-down methods instead rely on concentration measurements to quantify and understand emissions. Inverse modelling methods are often used to simulate the expected atmospheric concentrations according to gridded initial emissions estimates and adjust the gridded emissions to best match the observed concentrations after accounting for associated uncertainties (including modelling, measurement, and gridded emissions uncertainties).

There is increasing interest in characterizing and tracking urban CH₄ emissions because cities have policy levers they can use to influence those emissions. In fact, many have joined initiatives to reduce their emissions (C40 Cities - A global network of mayors taking urgent climate action, 2025; Climate Mayors, 2025). Several bottom-up and top-down studies have focused on urban methane sources to support these efforts. A recent meta-analysis by Vollrath et al. (2025) demonstrated that the overwhelming majority of urban methane studies in the U.S. and Canada have shown higher top-down estimated emissions than bottom-up estimates. The average ratio was 3.9, though it was also highly variable with a one sigma uncertainty of 6.7. Some studies have also seen new evidence of seasonal trends in urban CH₄ emissions that are correlated with natural gas consumption, though these are still not fully understood (Karion et al., 2023; Mueller et al., 2025; Pitt et al., 2024; Sargent et al., 2021; Zeng et al., 2023). The complex mix of point (e.g., power plants) and area (e.g., natural gas distribution) sources across an urban area means that the coarse resolution (0.1 deg) of global products and GEPA limit the information that can be gained using measurements.

In this work we introduce the Modular Methane Mapping Tool (M3T), which generates gridded CH₄ inventories within CONUS using a mix of disaggregation methods (similar to GEPA) and bottom-up methods for a user-defined year, domain, and resolution. M3T is largely based on the work of Pitt et al. (2024). It has some added methods, improved flexibility/modularity, has been automated, and has been made more user-friendly. As was discussed in Pitt et al. (2024), M3T is primarily focused on sources of urban CH₄ emissions and relies on GEPA for sources unlikely to be significant in most urban environments, such as oil and gas production. Here we describe the tool, and provide some initial insights from a 2019, 0.01 deg resolution CONUS inventory developed using M3T. Rather than providing an inventory, M3T provides users with clear configuration options to generate an ensemble of feasible inventories, as many sectors are still poorly understood and estimation methodologies are actively being developed. Such output can be useful to understand changes over time, compare against measurements, improve our understanding of emission sources, provide a proxy for uncertainty, or act as a point of comparison to investigate new data/estimation methods. Our goal is for this tool to further enhance the ability of inventories to support those working to understand, track, and mitigate CH₄ emissions, including those making policy decisions at various scales.

2 Methods

2.1 The M3T package

M3T is coded entirely in R, is freely available on GitHub, and will be submitted to the Comprehensive R Archive Network (CRAN). It has the dependencies of the terra (Hijmans, 2025), ncdf4 (Pierce, 2025), readxl (Wickham and Bryan, 2025),



94 jsonlite (Ooms, 2014), and dplyr (Wickham et al., 2023) packages that are used in spatial data storage and analysis, properly
95 loading input data, and general processing. M3T relies entirely on publicly available datasets as detailed in its help
96 documentation. During normal use M3T relies on datasets built into the package and downloaded from a connected Zenodo
97 repository (Hajny et al., 2026). This means M3T generally requires internet access to run. Users can instead choose to set the
98 code to download the most recent data from their sources or provide file-paths to local copies. The datasets are downloaded
99 using a combination of Application Programming Interface (API), file transfer protocol (FTP), and some limited web scraping
100 methods to automatically download the needed data when the code is set to download. Web scraping is limited to identifying
101 the most up-to-date download link for certain data files. Some datasets do not have code to automatically download data.
102 Datasets utilized by M3T are discussed in detail in the methods sections below and the help documentation for the configuration
103 (M3T_config).

104 One of the main values offered by M3T is its modularity. M3T includes a configuration environment with a wide
105 variety of options. Configuration options include the sectors to process, as some users may be focused exclusively on a specific
106 sector, how to access the datasets needed (i.e., download, local file-path, M3T built-in), the method to apply for the sectors
107 with multiple methods (see Sections 2.2 - 2.8), and emission factors (EF) to use in bottom-up approaches. The built-in options
108 include pre-processed data where possible making the run time much faster, but in some cases this data is coarsened compared
109 to the raw input to keep the files manageably small. The EFs default to reasonable/most-defensible values but can be manually
110 edited. Some of these defaults are based on data provided in the GHGI or other reporting programs while others are based on
111 the most recent literature values available to our knowledge. In the configuration help documentation there is detailed
112 information, including relevant DOIs or URLs, provided for every dataset and EF to allow users to easily trace the values
113 chosen. For certain sectors, users can also set EFs to the text “GHGI” instead of manually providing the activity and/or EF
114 data needed. The appropriate data will then be pulled from the GHGI Annex files. The following sections describe each sector,
115 assuming that the default EFs are used. Various options are discussed for many sectors and more than one can be selected in a
116 single run, which will produce multiple output inventories accordingly. This can be useful to compare methods and is faster
117 than separate runs given there are often some processing steps that are consistent across options.

118 The main processing function of M3T takes as inputs the year, domain (coordinates, resolution, and mapping), the
119 folder to save output, a verbose option to create sectoral visuals, and optional inputs regarding the companion Zenodo. As
120 GHGRP data is used for multiple sectors, the year is limited to those with data (2011 - 2022 as of writing). Other years can be
121 set, but the closest year of data will be used instead with a user update. The resolution cannot be finer than 0.01 x 0.01 deg (~1
122 km x 1 km) due to the resolution of some of the proxies used for certain sectors. Finer resolutions can be set but will be
123 automatically adjusted to this minimum if running these sectors with a user update.

124 Processing takes the data in lines, points, or gridded data that are all aggregated (or disaggregated from broader totals)
125 in the last step to a product with a consistent gridding. All data are kept at their finest resolution until gridding, an important
126 distinction as sources outside the user-defined domain are set to NA. For points, this excludes or includes the source in its



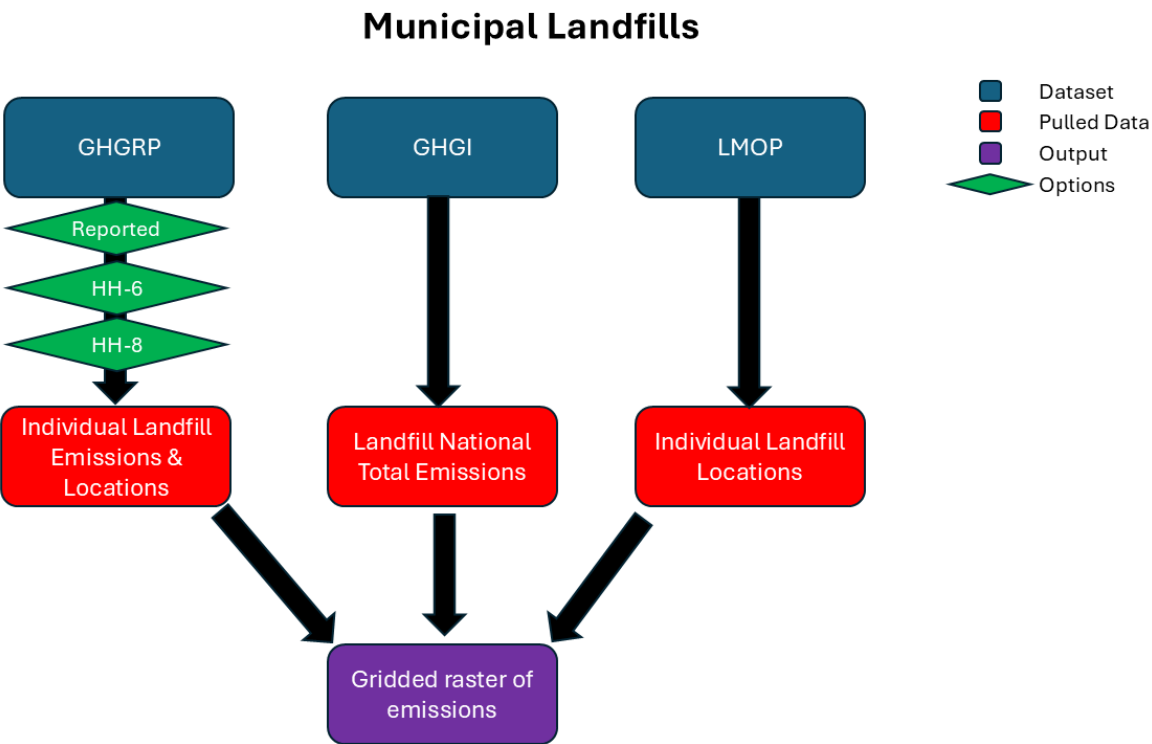
entirety whereas lines and gridded data are weighted based on the fraction of the gridcell within the user defined domain (i.e., if 20% of a gridcell is within the domain we multiply emissions in that gridcell by 20%).

For two sectors, the natural gas distribution sector (Section 2.3) and the stationary combustion sector (Section 2.5), there are multiple scales that the data can be aggregated to before disaggregation to the gridcell level. The relevant data for the natural gas distribution sector is available at the company level but cannot be easily combined at that scale so it is aggregated to the state level while the data for the stationary combustion sector is at the state level. Emissions data can be downscaled from the state level or first aggregated to the entire domain. The only difference between these options is the reliance on the input datasets for the distribution of emissions across state lines or on the downscaling proxy for this distribution. We recommend users avoid aggregating to the domain unless the domain is only a small number of states. It is important to consider that the domain method results will depend on the domain used and that spatial information available in the input data is being disregarded.

These same two sectors also rely on sectoral gridded fossil fuel CO₂ emissions as the proxy to downscale to the gridcell level. The Vulcan v4.0 (Gurney et al., 2025a, b) and ACES v2.0 inventories (Gately and Hutyra, 2022, 2017) are the only CO₂ inventories currently built into M3T for this purpose. M3T relies on the residential, commercial, industrial, and electric power sectors of these products. As these products have a resolution of 1 km x 1 km, this limits M3T to creating gridded maps at a 1 km x 1 km resolution (or equivalent in a different projection, such as ~0.01 deg x 0.01 deg) if natural gas distribution or stationary combustion are included. ACES is available from 2012 to 2017 while Vulcan is available for 2010 to 2022. The previous versions of Vulcan and ACES were compared in Gurney et al. (2020) which showed that they agree well in aggregate, but can differ significantly at the gridcell scale. Using CO₂ emissions inventories as a proxy like this is not ideal as the underlying mechanisms differ, namely CO₂ is a combustion product while CH₄ is emitted due to incomplete combustion or natural gas leakage. This is a subject for future development if more appropriate activity data is available.



148 **2.2 Municipal Solid Waste Landfills**



149
150 **Figure 1: Flowchart describing the methodology used for municipal landfill emissions. Blue rectangles are data sources for input,**
151 **green diamonds are options set in the configuration file, red rectangles are raw data, and purple rectangles are calculated output.**

152 Municipal solid waste landfill emissions are calculated from three separate input datasets as summarized in Figure 1. We begin
153 with the Greenhouse Gas Reporting Program (GHGRP) reported emissions for landfills with large enough emissions to report
154 ($\geq 25,000$ MT CO₂e). The GHGRP has two emissions calculation methods: HH-6 and HH-8. All reporting landfills must report
155 using equation HH-6 which relies on a first order decay model to estimate CH₄ generation and oxidation and then accounts for
156 gas captured from a landfill gas capture system if one is installed (Electronic Code of Federal Regulations, 2009b). Those that
157 have landfill gas capture systems also must report using equation HH-8, which instead back-calculates CH₄ generated using a
158 collection efficiency estimate for the landfill gas capture system (Electronic Code of Federal Regulations, 2009b). These are
159 referred to as generation-first (HH-6) and collection-first (HH-8) to be consistent with recent literature. Emission rates
160 calculated using either equation can be treated as the emissions from the landfill in the GHGRP (i.e., the “reported” emissions).
161 Importantly, which equation is used can also change from one reporting year to another for a given landfill.

162 A user of M3T can select in the configuration whether they would like to use the reported emission rates or
163 consistently rely on emission rates from only one of the equations. For example, if the configuration is set to prefer the
164 collection-first method then that emission rate is used for any landfill that has a landfill gas capture system and provides an
165 emission rate based on equation HH-8. In this case, any landfill without a landfill gas capture system (and thus unable to use



equation HH-8) will still rely on generation-first emission rates based on equation HH-6. Additionally, we account for the small fraction of facilities that are labelled “facility discontinued reporting without a valid reason” separately. For these facilities we rely on the GHGRP reported value for the nearest year available, which can potentially be a later year. It is also worth noting that facility total emissions include any reported emissions from incomplete combustion, though these are generally a small part of the total.

There is some recent research that has compared these methods or investigated their relationship with measurements. Stark et al. (2024) and Balasus et al. (2025) discussed that the generation-first method shows increasing emissions over the past decade while the collection-first method shows a decreasing trend and that facilities preferentially use the collection-first method. Moreso, they discussed that if all facilities used the generation-first method then national emissions would increase by a factor of ~ 1.5 , which would better match some top-down studies. This difference by method may partly explain why some research has suggested GHGRP reported emissions are a poor overall representation of landfill emissions based on top-down measurement campaigns (Cusworth et al., 2024; Dogniaux et al., 2025; Nesser et al., 2024; Scarpelli et al., 2024). Studies that looked at the underlying methods have noted the modelled CH_4 generation, bulk waste in place, or gas captured that are inputs to equations HH-6 and HH-8 correlate better with measured emission rates than the output of the equations (Howell et al., 2025; Krause et al., 2025; Srikanth et al., 2025) though others have shown poor correlation to waste in place (Scarpelli et al., 2024). Researchers have suggested the collection efficiency defaults in the GHGRP (Table HH-3 to Subpart HH of Part 98—Landfill Gas Collection Efficiencies, 2026), often $> 70\%$, are too high and that real collection efficiencies may also vary regionally (Howell et al., 2025; Krause et al., 2025; Nesser et al., 2024; Srikanth et al., 2025). Several of these studies also point to some relationships between precipitation or operational conditions and emissions, but not seasonality (Howell et al., 2025; Scarpelli et al., 2024; Srikanth et al., 2025) though others have seen distinct seasonality (Hallward-Driemeier et al., 2026). This information could be used to improve upon the GHGRP approach in the future.

While the GHGRP covers many landfills, smaller landfills below the reporting requirements are excluded. To account for these facilities, we first calculate the difference between the Greenhouse Gas Inventory (GHGI) national total emissions and the GHGRP reported national total. As small landfills are not required to report their emissions, the GHGI needs to scale up GHGRP net CH_4 emissions to represent the national total. In brief, they estimate the ratio of waste in place for small landfills using the Landfill Methane Outreach Program (LMOP) and a commercial product from the Waste Business Journal (Waste Business Journal - Directory of Waste Processing & Disposal Sites, 2025) to that of GHGRP reporting facilities, as is described in detail in the GHGI (EPA, 2024). Using this waste in place ratio they estimate a 9% upscaling for 2005 - 2016 and 11% for 2017 - 2022. To best mirror this, we use the reported total in our calculation of GHGI - GHGRP emissions regardless of the configuration settings. We then distribute this residual evenly across all landfill locations in the LMOP after removing any facilities that also report to the GHGRP. We choose to evenly distribute emissions rather than using a proxy such as waste in place in part because not all facilities reporting to LMOP include their waste in place and because research on how waste in place relates to measured emission rates is mixed (Howell et al., 2025; Scarpelli et al., 2024; Srikanth et al., 2025). We do not consider landfills that are only present in the Waste Business Journal dataset as we do not have access to this commercial



dataset. There has been some research showing that historical landfills (i.e., closed before reporting requirements), including those that may not be included in a dataset like LMOP, may still be significant sources of CH₄ and such facilities are not accounted for here (Williams et al., 2022). This is due to both a lack of appropriate methods to estimate their emissions and the lack of a dataset providing locations and relevant characteristics (e.g., age, waste in place) for such facilities.

When investigating these methods, we also identified a number of landfill year combinations with reported emissions that do not match either of the two reporting methods. While the EPA has been made aware and confirmed that this appears to be an error, it is something users should be aware of. Most of these errors are for reported emission rates between 2011 and 2012 and can either represent a landfill reporting 0 emissions while both equations provide non-zero emission rates (e.g., <https://ghgdata.epa.gov/flight/details/1005518/2011/E>) or cases where the reported value is non-zero, but does not match that of either equation (e.g., <https://ghgdata.epa.gov/flight/details/1002493/2010/E>). A csv detailing the landfills whose reported emissions differed from either reporting method at the time of writing is provided as Supporting Information (SI) material.

2.3 Natural Gas Distribution - including post-meter

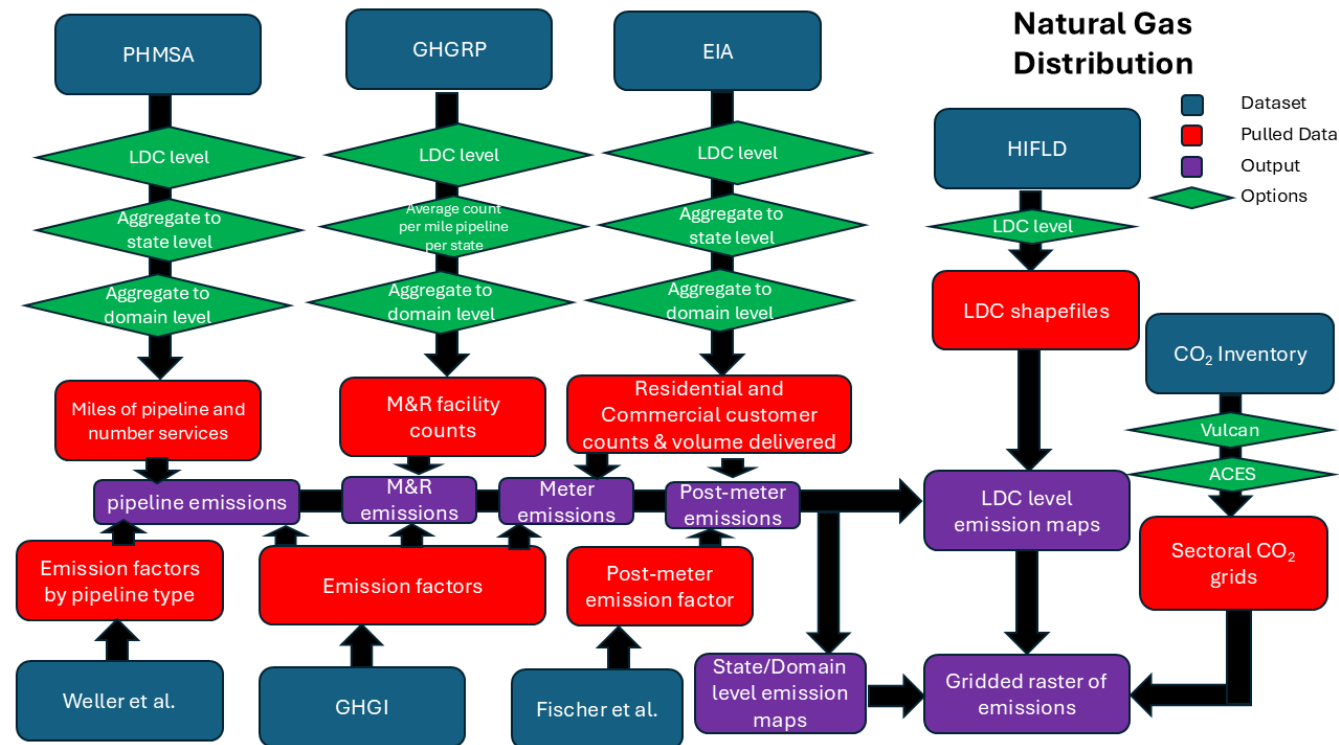


Figure 2: Flowchart describing the methodology used for natural gas distribution emissions. Blue rectangles are data sources for input, green diamonds are options set in the configuration file, red rectangles are raw data, and purple rectangles are calculated output. Arrows crossing through multiple purple rectangles indicate summation across subsectors.



Emissions from the natural gas distribution system are calculated by merging a wide variety of different datasets. Unfortunately, many of these datasets lack consistent identifiers or represent different years, making it difficult to merge the datasets at the Local Distribution Company (LDC) level in an automated manner. There is code in the M3T Zenodo to work with these datasets to prepare the input data for M3T, but it requires manual input and edits. As calculating emissions after aggregating data to the state level has been completely automated, it is recommended. Aggregating data to the entire domain of interest is also an option, though we discourage this choice should the domain be larger than a few states as discussed in Section 2.1. The datasets available at the LDC level include Pipelines and Hazardous Materials Safety Administration (PHMSA) data on the mileage of pipeline by pipeline vintage and material and the number of services, GHGRP Metering and Regulating (M&R) station counts and emissions data for LDCs that are required to report to the GHGRP, Energy Information Administration (EIA) data on the volume of natural gas delivered and customer count separated by customer type (e.g., residential, commercial, industrial), and the Homeland Infrastructure Foundation-Level Data (HIFLD) LDC service territory maps. As HIFLD's open data portal has been discontinued, archived versions of the data can be found through DataLumos (Data Rescue Project, 2025). Though the GHGRP Facility Level Information on GreenHouse gases Tool (FLIGHT) displays LDC service territory maps, these maps are not publicly available for download. However, we do recommend they be used as reference to update the older HIFLD maps given how frequently LDCs merge, split, expand, etc. if calculating at the LDC level. In the LDC level calculation, any LDC that cannot be matched across datasets is assigned to all territories in a state not covered by another LDC.

Multiple subsectors are calculated separately and then combined to estimate total natural gas distribution emissions. The PHMSA miles of pipeline by pipeline material is combined with the Weller et al. (2020) reported EFs by pipeline material to get pipeline emissions, though the uncertainties associated with these EFs are large. For service pipelines, pressure relief valves, pipeline blowdowns, and mishaps, we use GHGI EFs in combination with PHMSA activity data. Since the GHGRP data on the number of M&R stations is limited to only LDCs that report to the GHGRP, we estimate the average number of M&R facilities per mile of pipeline for each state and apply this to the PHMSA miles of pipeline to estimate M&R facility counts, separately for above and below grade facilities. For the few states with no LDC's that report to the GHGRP, the average M&R facility count per mile from neighbouring states is used. If processing at the LDC level, reported counts are used for those facilities that report to the GHGRP while the state average counts per mile of pipeline method is used for all other LDCs. We combine these M&R facility counts with GHGI EFs separated by function and pressure. This assumes the national breakdown of function and pressure is consistent spatially. Emissions from customer meters are calculated using GHGI EFs and EIA data on the number of customers separated by type (residential, industrial, commercial). Lastly, post-meter emissions are calculated by combining the volume of natural gas delivered to residential customers from the EIA with the Fischer et al. (2018) EF of 0.5%. Note that this EF is based on a small subset of homes in one region and may not represent a national average well, especially across different types of homes (e.g., single v. multi-family dwellings). Additionally, as there are no data on the subject to the authors' knowledge, post-meter commercial and industrial emissions are assigned an EF of zero, though this is likely a poor assumption based on initial research (Michanowicz et al., 2024). The GHGI includes a commercial



post-meter estimate based on appliance EFs and estimated appliance counts, industrial emissions, and compressed natural gas vehicles in addition to residential post-meter. Residential post-meter is also calculated in the GHGI using a per-home emission factor calculated in the same Fischer et al. (2018) paper rather than the volume of gas delivered as used here.

Once emissions for each subsector have been calculated, they need to be spatially allocated. For this process we first split emissions into residential and commercial fractions using the EIA customer count by type of customer. If processing at the LDC level, we combine the LDC level emissions data with HIFLD LDC service area maps. We then use 1 km x 1 km gridded residential and commercial inventories of CO₂ to downscale emissions to gridcells. For meter emissions, we include the industrial meters proportionally in the residential and commercial fractions. We chose to do this as the industrial sector may have point and non-point sources, but emissions are dominated by a few large CO₂ point sources, many of which do not rely on natural gas in the first place.

2.4 Natural Gas Transmission

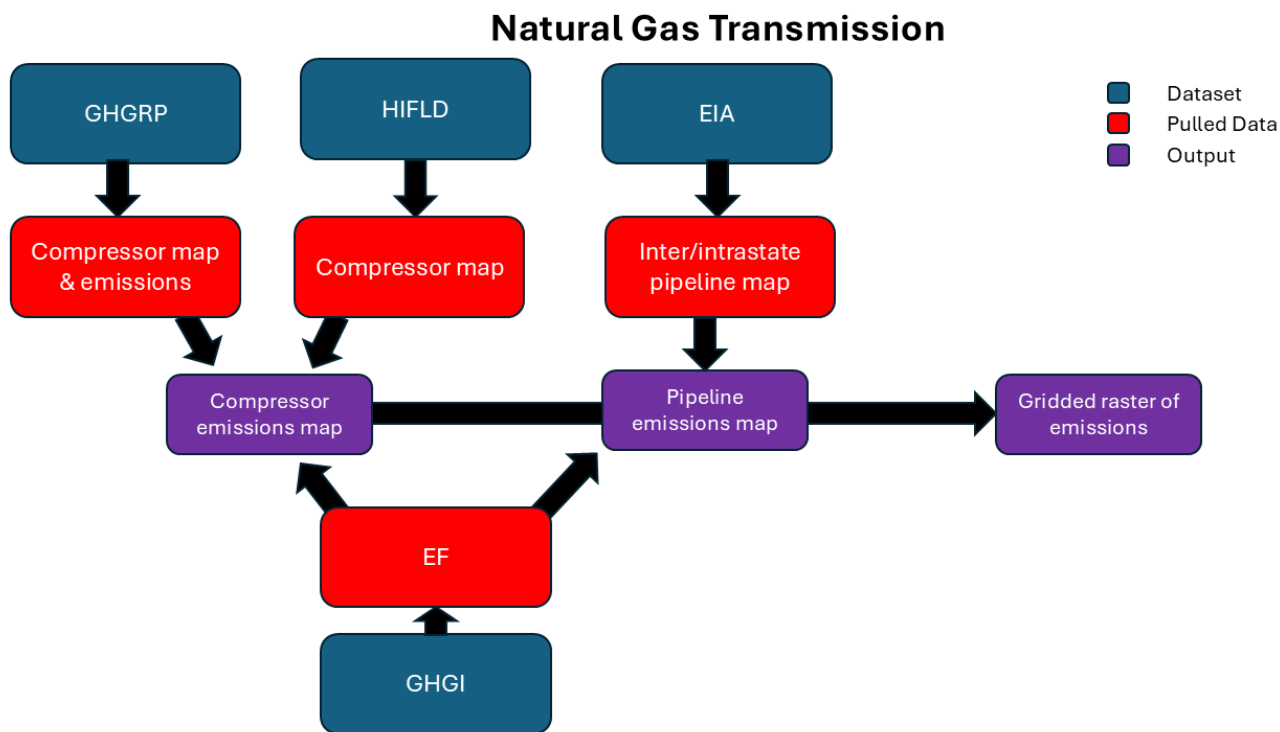


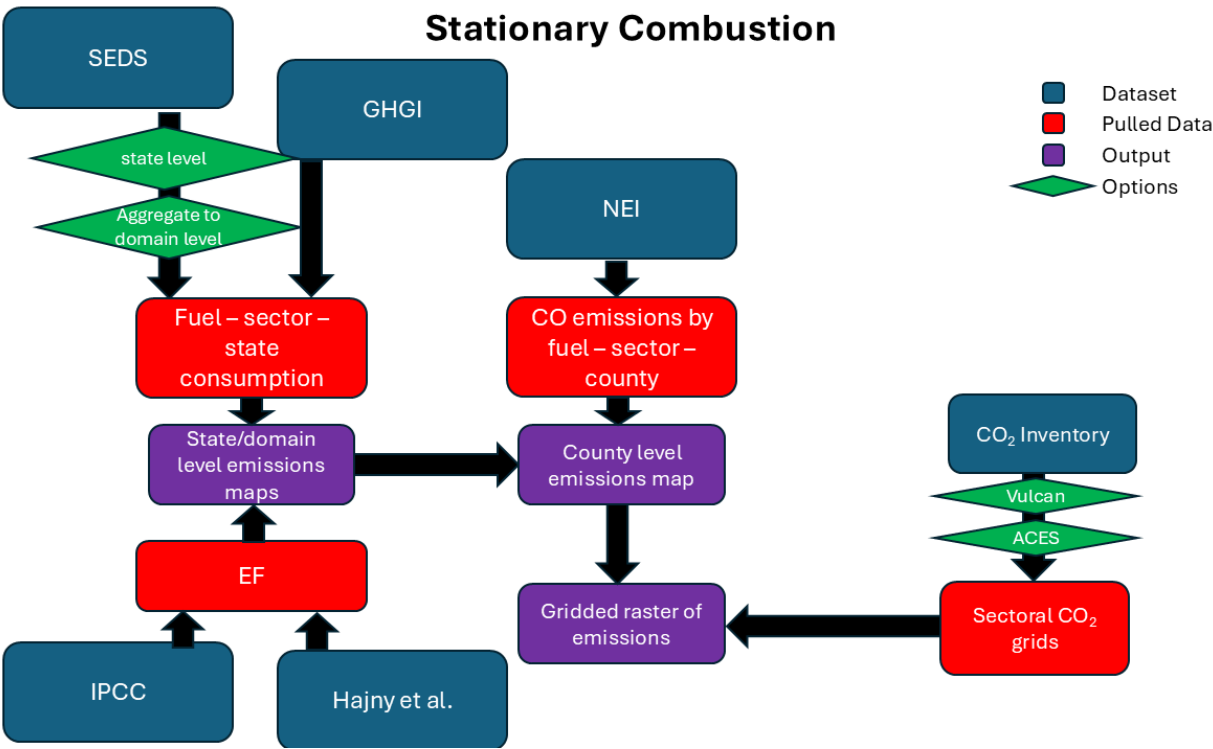
Figure 3: Flowchart describing the methodology used for natural gas transmission emissions. Blue rectangles are data sources for input, red rectangles are raw data, and purple rectangles are calculated output. Arrows crossing through multiple purple rectangles indicate summation across subsectors.

The natural gas transmission sector is one of the few without any variants. GHGI emissions from transmission metering and regulating stations, pipeline leaks, and pipeline vents are combined and divided by the miles of transmission pipe to get a



269 transmission pipeline EF. This EF is combined with EIA pipeline maps (U.S. EIA, 2025), assigning emissions uniformly across
270 the pipelines. The EIA map is not available as a function of time, so changes to the transmission pipeline network are not
271 considered. Although the GHGRP has maps and emissions for transmission compressors, it is limited to those large enough
272 that they are required to report their emissions to the GHGRP. We supplement the GHGRP with locations from a HIFLD
273 compressor dataset, though this dataset has since been discontinued and is no longer available. SI Section S2 describes the
274 process of aligning these datasets to reduce the risk of double counting. Both raw and processed files are included in the M3T
275 Zenodo (Hajny et al., 2026). As the HIFLD dataset includes only location information, a national EF is calculated using GHGI
276 emission and count data similar to how the pipeline EF is calculated. The sum of station total emissions (fugitives and
277 compressors), normal operations (dehydrator vents and flaring), pneumatic device bleed emissions, compressor exhaust
278 (engines, turbines, and generators), and station venting emissions for transmission is divided by the number of transmission
279 compressor stations to get a national compressor station EF. As generator emissions are separated into engine or turbine
280 related emissions rather than transmission and storage, the fraction of engine and turbine related emissions from transmission
281 are applied to the corresponding generator emissions. For transmission compressors in both HIFLD and the GHGRP, the
282 reported GHGRP values and HIFLD locations are used.

283 **2.5 Stationary Combustion**



284



Figure 4: Flowchart describing the methodology used for stationary combustion emissions. Blue rectangles are data sources for input, green diamonds are options set in the configuration config file, red rectangles are raw data, and purple rectangles are calculated output.

Stationary combustion emissions are calculated using fuel - sector - state specific consumption data from the State Energy Data System (SEDS), excluding residential coal (as the U.S. has none reported) and residential natural gas (as it is accounted for in the post-meter natural gas distribution sector). Emissions can be aggregated to the domain level before processing, though this should be reserved for small domains as described in Section 2.1, otherwise, it is recommended to stay at the state level. First, we calculate scaling factors by dividing the GHGI fuel - sector specific consumption data by the national SEDS equivalent. These are multiplied with the SEDS fuel - sector - state specific consumption data to avoid double counting emissions. This assumes the national scaling applies equally to all states and is typically a small downward adjustment other than for industrial consumption which is more significantly adjusted down to exclude agriculture and construction, which are handled separately, as discussed in the GHGI. We then utilize IPCC EFs (Gómez et al., 2006) to convert consumption to emissions, with the exception of the natural gas electric power production sector which instead relies on the similar EF reported in Hajny et al. (2019). The National Emissions Inventory (NEI) carbon monoxide (CO) emissions data at the county level is then used to disaggregate these state total emissions. We apportion the CH₄ emissions using the ratio of county CO emissions relative to the state total separately for each fuel - sector - county combination. Lastly, the county-level emissions are distributed to gridcells using sectoral fossil fuel CO₂ inventories. This assumes wood combustion follows similar spatial patterns as fossil fuel given these inventories do not include wood combustion. Fuel - state - sector combinations with no reported CO emissions are distributed entirely based on the sectoral CO₂ data. If the county has non-zero CO emissions but the sectoral CO₂ emissions have zero emissions in the county (primarily for point sources like the electric sector) the CH₄ emissions are equally distributed spatially across the county. These situations with zero CO or CO₂ emissions can lead to unexpected differences between the domain-level and state-level disaggregation. For example, if all counties in a state have no CO emissions for some fuel - state - sector combination then the state-level method will distribute state total emissions using the sectoral CO₂ emissions while the domain-level method will assign the state no emissions and distribute them to other states in the domain. Wood combustion is saved separately in the output as it would qualify as non-thermogenic which may be relevant for some studies.



2.6 Wastewater

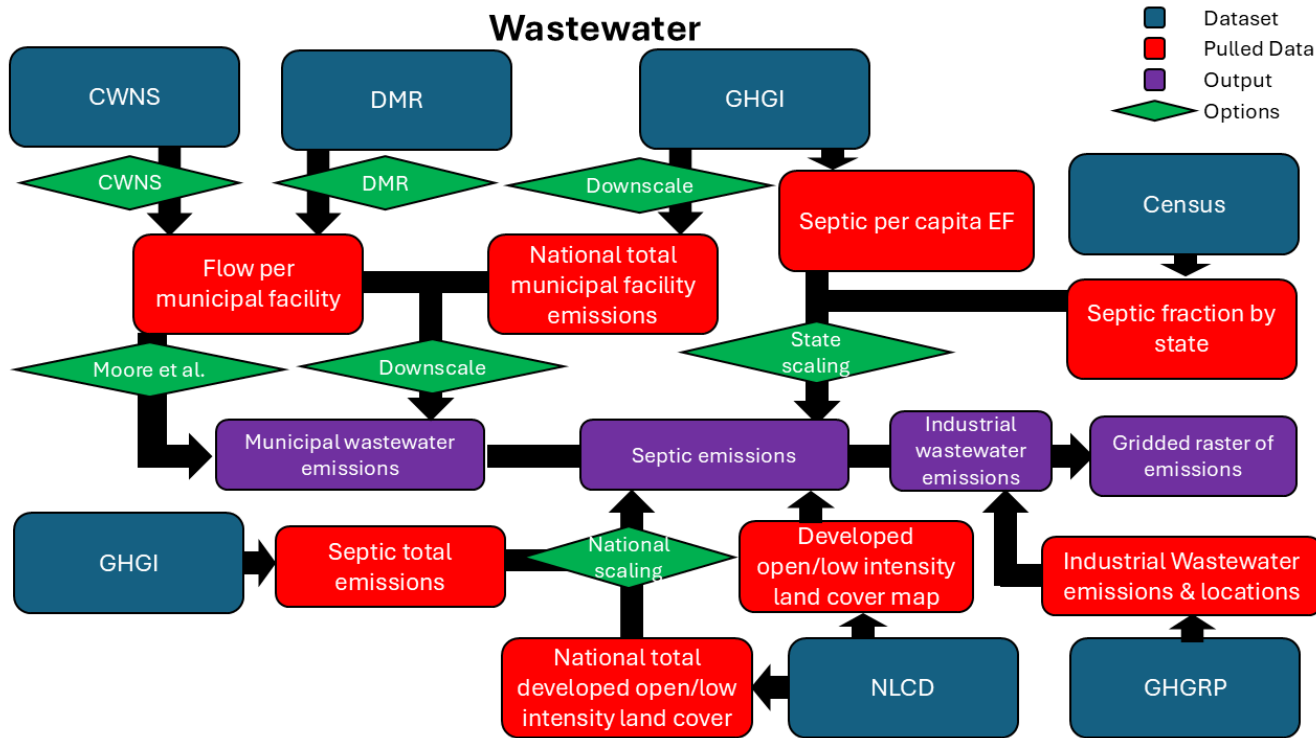


Figure 5: Flowchart describing the methodology used for wastewater emissions. Blue rectangles are data sources for input, green diamonds are options set in the configuration file, red rectangles are raw data, and purple rectangles are calculated output. Arrows crossing through multiple purple rectangles indicate summation across subsectors.

Wastewater emissions include septic systems, municipal wastewater treatment plants, and industrial wastewater treatment plants. To begin with, we account for industrial wastewater facilities by directly utilizing reported GHGRP emissions. We utilize wastewater flow per facility to estimate municipal wastewater treatment plant emissions. We have two methods for utilizing the flow data to calculate CH₄ emissions for each municipal wastewater treatment plant. The first is to utilize the log-log-linear relationship between emissions and flow discussed in Moore et al. (2023) using the updated dataset in Moore et al. (2025). This slightly updated relationship is $\log_{10}(\text{emissions in g/s}) = 1.28 * \log_{10}(\text{flow in m}^3/\text{s}) + 0.93$. The second approach is to downscale the GHGI national total CH₄ emissions for municipal wastewater treatment plants. The total is disaggregated to the individual facilities using the facility-level flow as a proxy.

There are also two relevant datasets with national data on wastewater flow: the Clean Watershed Needs Survey (CWNS) and the Discharge Monitoring Reports (DMR). The CWNS includes current total flow and projected flow estimates for individual facilities and is performed periodically, typically every four years (U.S. Code, 1972; Clean Watersheds Needs Survey (CWNS) – 2022 Report and Data, 2025). The most recent surveys are those from 2012 and 2022 (U.S. Code, 1972).



DMRs include a variety of effluent discharges from individual wastewater treatment plants as well as the total flow reported at least annually (Electronic Code of Federal Regulations, 2015). Though facilities must report DMRs to maintain their permitting, the CWNS is a voluntary survey. Additionally, many facilities have different locations and flow data even for the same years between these datasets though national totals are similar, meaning the user's choice of dataset will likely have an impact on the result at regional or finer spatial scales. There may be additional nuances to these datasets that impact their appropriateness for particular regions. For example, the 2012 CWNS has no data for the states of AK and SC, which affects emissions not only for those states, but will affect all states if using the downscaling method as national emissions are distributed only to the remaining CONUS states. Given this, we generally recommend using DMRs, and in particular, recommend against using the downscaling approach if relying on the 2012 CWNS input dataset (the code includes a user warning with these settings). We encourage more transparency in these datasets to better understand these discrepancies and include a brief email discussion of the differences between them as part of SI Section S1.

Lastly, we have a national and state-based method to estimate emissions from septic systems. For both approaches we apportion emissions evenly to all 30 m x 30 m National Land Cover Database (NLCD) gridcells that are classified as “Developed, Open Space”, or “Developed, Low Intensity” (United States Geological Survey, 2025). These land cover types are assumed to best represent areas with significant population, but a low enough population density such that septic systems are more likely than sewer systems. The state approach utilizes Census American Housing Survey data on the fraction of people using septic systems at the state level where available. However, only a handful of states report to the American Housing Survey and the survey is only performed every other year. For the majority of states that do not report to the American Housing Survey, the fraction of people using septic systems is estimated by taking the 1990 census data on septic fraction, the last year such data was collected from all states, and scaling the value based on the change in the national septic fraction value in the same timeframe. This national septic fraction is always reported in the American Housing Survey (i.e., every other year since 2011). This fraction is converted to emissions by combining it with up-to-date Census state population data and the GHGI EF in terms of g CH₄ per capita per day (Leverenz et al., 2010). For the national approach we use the GHGI national total septic emissions in mol/s and the total land area classified as “Developed, Open Space” or “Developed, Low Intensity” nationally in km² to calculate an EF in units of mol/s/km² that can then be applied to the NLCD data. The total land area with these classifications is calculated for each year using the NLCD for CONUS. AK NLCD data is more limited, but the total land area with these classifications for 2011 and 2016 were 1791 km² and 1799 km² (Jon Dewitz, 2020, 2024). Given the minimal change, a linear regression is calculated to estimate the AK total for each year to add to the CONUS total. This is still slightly mismatched to the GHGI national total estimate as other areas like Hawaii and Puerto Rico are not considered, and this would result in a slight high bias since this land area is the denominator of the EF.



2.7 Wetlands and Inland Freshwaters

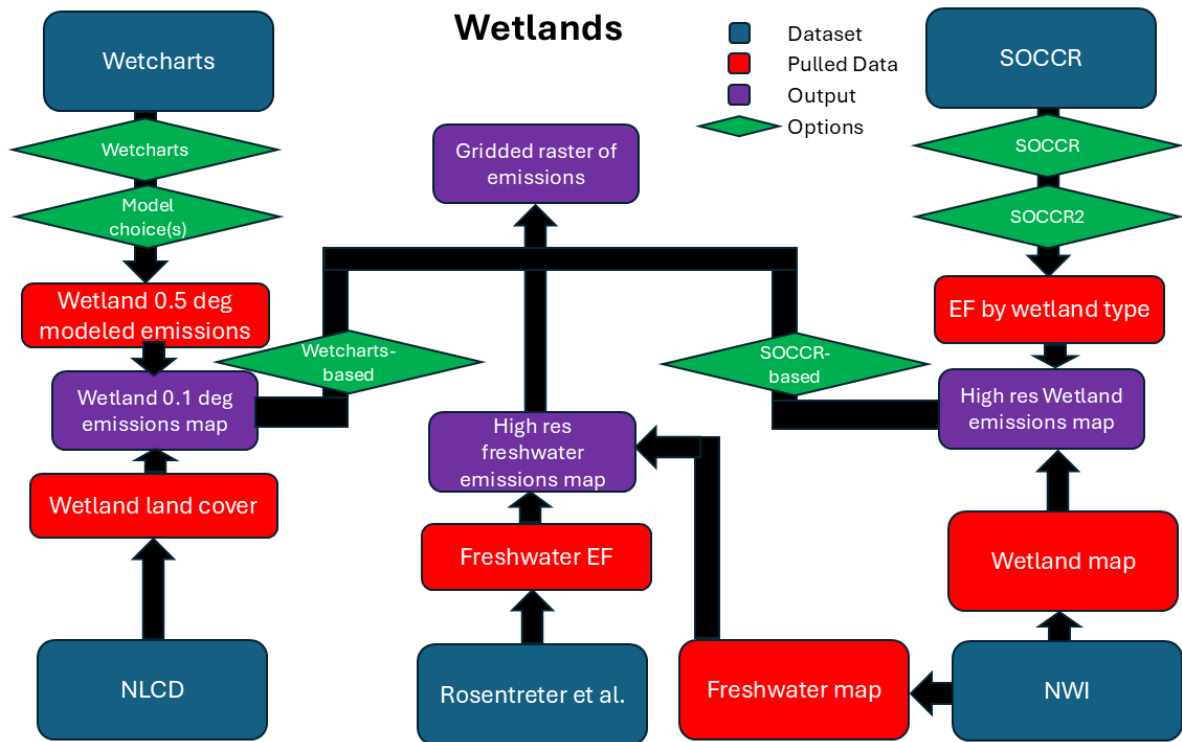


Figure 6: Flowchart describing the methodology used for wetland and inland freshwater emissions. Blue rectangles are data sources for input, green diamonds are options set in the configuration file, red rectangles are raw data, and purple rectangles are calculated output.

The wetlands and inland freshwaters sector includes wetlands, lakes, and rivers. Wetlands emissions can be built using two primary methods, the State of the Carbon Cycle Report (SOCCR) EFs (U.S. Global Change Research Program (USGCRP), 2007, 2018) or the WetCHARTs model ensemble (Bloom et al., 2017). Beginning with the WetCHARTs model, a user can first select which of the models in the ensemble to use. Either several ensemble members can be averaged together, or a single member can be used. Additionally, users can simultaneously run multiple subsets, should they choose. This was provided as an option given recent literature utilizing different subsets of ensemble members based on comparisons with GOSAT inversions (Lu et al., 2022; Ma et al., 2021; Nesser et al., 2024). We then downscale the WetCHARTs data from its native 0.5 deg x 0.5 deg resolution to 0.1 deg x 0.1 deg using 30 m x 30 m NLCD land cover data. The 30 m x 30 m NLCD is first aggregated to 0.1 deg x 0.1 deg, and then a copy is further aggregated to 0.5 deg x 0.5 deg. We use the ratio of 0.1 deg wetland land cover relative to the corresponding 0.5 deg data to downscale WetCHARTs emissions. These 0.1 deg x 0.1 deg WetCHARTs fluxes can then be used as the wetland subsector's emissions. Note we do not disaggregate to the inventory resolution, but instead consistently to 0.1 deg x 0.1 deg given the assumptions inherent to this downscaling.



Using the SOCCR EFs as an alternative to WetCHARTs requires National Wetland Inventory (NWI) data as well. First the high resolution NWI polygons for each state in the domain are split into the various wetland types to align with those reported in SOCCR. These polygons are then converted to rasters that represent the fractional coverage in each gridcell. To combine across states, the maximum value in each gridcell is used as the datasets are designed to include some overlap across state files. These gridcells are then combined with the SOCCR EFs, separately for each wetland type, to produce fluxes. The user can select between SOCCR version 1 (U.S. Global Change Research Program (USGCRP), 2007) or version 2 (U.S. Global Change Research Program (USGCRP), 2018), with version 2 including some separate EFs by watershed. EFs are calculated as the arithmetic average across the research presented in the report, separated by wetland type and region. The average across all data is used for regions without data. These fluxes can then be used as the wetland subsector. The NWI data is not available as a function of time, so changes over time are not considered.

Lastly, freshwater emissions from lakes and rivers are incorporated. The NWI includes freshwater classes as well and the same method used for SOCCR is used to prepare these data. We use the median flux from rivers and fluxes from the largest lake class as reported in Rosentreter et al. (2021). We choose this lake flux as McDonald et al. (2012) showed that large lakes ($> 1 \text{ km}^2$) constitute the majority of total lake area in CONUS (71% or 90% if including the great lakes).

2.8 Remaining Sources

M3T is focused on sectors considered critical for urban CH_4 emissions. As such, sectors that are generally exogenous to urban activity or are considered small sources are not estimated in the tool and are instead automatically pulled from GEPA (Maasakkers et al., 2016, 2023; McDuffie et al., 2023). This includes agricultural emissions (composting, enteric fermentation, manure, rice cultivation, field burning), oil and gas emissions before the transmission stage (exploration, production, processing, refining, petroleum transport, abandoned wells), coal mining emissions (active and abandoned coal mining), industrial landfills, and finally, industrial emissions from the ferroalloy and petrochemical industries. There may be updates to these sectors since GEPA's development such as research showing seasonal (Hu et al., 2025; Varon et al., 2026) and diurnal (Barkley et al., 2025) trends in upstream oil and gas emissions that could be considered for future updates, but these are considered a lower priority given the focus on urban emissions. The exact sectors used are described in SI Table S1.

2.9 M3T Use

In this section we provide a brief summary describing how to run M3T to develop gridded data for all sectors for a particular region and year of interest. We recommend users interested in further details refer to the GitHub page and help files included in the package. Typical users should not need to view most of the functions in M3T. Instead, they should only be concerned with functions to interact with the configuration (M3T_get_config and M3T_set_config) and the "main" function (CH4_inventory_build) that subsequently runs all sectors. The configuration is described in Section 2.1, but in brief it is where a user can specify EFs, their choice of method for sectors with multiple options, data sources, and the sectors they want to process. Default configuration method settings are based on literature where available. For all sectors only a single method is



set by default, as summarized in the help files and SI Section S1. To run the CH4_inventory_build function a user would need to follow the steps described below.

1. Download and load in the package
 - a. From GitHub
 - i. `devtools::install_github("https://github.com/Kristian-hajny/M3T"); library(M3T)`
 - b. From CRAN once submitted
 - i. `install.packages("M3T"); library(M3T)`
2. View and modify the configuration file as desired, ideally creating a simple run script for ease of reuse
 - a. View detailed descriptions of configuration options
 - i. `help(M3T_config)`
 - b. Optionally run `M3T_get_config()`
 - i. This will print all options. Individual options can be checked as input, e.g.,
`M3T_get_config("Process_landfills")`
 - c. Optionally run `M3T_set_config(A = X)`
 - i. Adjust any configuration options, e.g., `M3T_set_config(Process_landfills = FALSE)`
3. Run the main function with desired inputs (below is an example)
 - a. `CH4_inventory_build(inventory_year = 2018,`
`domain      = c("AL","GA"),`
`domain_res   = 0.01,`
`domain_crs   = "epsg:4326",`
`verbose      = TRUE)`

The CH4_inventory_build function only requires the definition of the year to calculate the inventory, a valid domain definition, and the verbose option. Two variables related to the companion Zenodo can also be provided specifying a local copy of the Zenodo files or a specific version of the Zenodo to rely on. As input datasets have limited years available, we recommend limiting runs to those between 2011 and 2023 based on the range of years available in the necessary datasets at the time of writing, though future years could be run easily assuming input datasets are updated over time and their locations/formats do not significantly change. The domain is the intended area for the inventory calculation, and can be state name(s) or Federal Information Processing Standards (FIPS) code(s) or abbreviation(s), urban area census code(s) or exact name(s) as used in the appropriate year's Census Urban Area files, four coordinates for a user defined rectangle, "CONUS", "custom" to interactively draw a domain polygon, or a file-path to load a polygon or raster file. Additionally, a user sets the resolution (res) and coordinate reference system (CRS) or mapping system. The resolution should be provided in the same units as the desired mapping system (e.g., a m gridded CRS should have a resolution in m while a latitude/longitude CRS should have a resolution in degrees). Lastly, verbose is a true/false parameter indicating whether the user would like the code to also output visuals while running.



Upon running the function, the code will load the configuration settings and begin processing sectors with user updates to the console periodically. Each sector will be processed in sequence, providing updates to the user at the start and end of each sector as well as certain steps during processing for those that can take longer to process. Each run will also save a text file called Run_settings.txt to the input folder with the inputs to the main function and configuration settings used for that particular run. The output includes clearly named sectoral totals for each variation and a sub-folder for each sector with clearly named files for each variation and subsector. Given the flexibility of M3T, we suggest any works based on M3T results include the content of this text file for transparency.

3 Results

To demonstrate the potential output of M3T, we present a few initial analyses across nearly all possible variations for CONUS at a 0.01 degree x 0.01 degree resolution for the year 2019. Here we disaggregate natural gas distribution including post-meter and stationary combustion emissions from the state-level only, not the LDC or domain-level, given the large size of the domain and non-automated nature of the LDC-level disaggregation. We discuss the ten urban areas with the largest emissions and then we discuss the variability in each sector across all variations using the urban area with the largest emissions: the New York urban area. Lastly, we briefly compare the inventories developed by M3T to equivalent GEPA inventories for two of the ten urban areas with the largest emissions (New York and Los Angeles). All M3T output here is the average across all variations considered with errors presented representing the range unless otherwise stated.

3.1 Comparison Between Cities

Figure 7 shows the sectoral CH₄ emissions estimated by M3T and GEPA for the ten urban areas with the largest CH₄ emissions according to M3T. Importantly, these emissions are scope 1 emissions (i.e., emissions are assigned to the point of emission), and only sources within the census-defined urban areas are considered. As cities often locate certain emission sources related to city-based activity (e.g., landfills) outside of the urban core, this likely biases some sources low compared to scope three emissions (i.e., emissions are assigned to the responsible party). Landfills are the largest source for seven of these ten urban areas, natural gas distribution for two of the ten, and wetlands and inland waters for 1 of 10, although post-meter, wastewater, and “other thermogenic” sources (i.e., those from GEPA) are significant contributors as well. In all cases, stationary combustion and natural gas transmission represent only minor contributions to the total. In general, we see good agreement between this work and GEPA for sectoral and total emissions, as is to be expected given the similarity in methods for several sectors. Differences in point source emissions like landfills are due partly to differences in methodology and partly to differences in resolution as gridcells that are partially within the urban area outline are weighted by the fraction of the gridcell within the urban area, and this more significantly affects the 0.1 deg x 0.1 deg resolution GEPA gridcells. Note that all landfill emissions will be entirely included or excluded and treated as a point if running M3T specifically for an urban area rather than pulling the urban area from a national output as is done here.

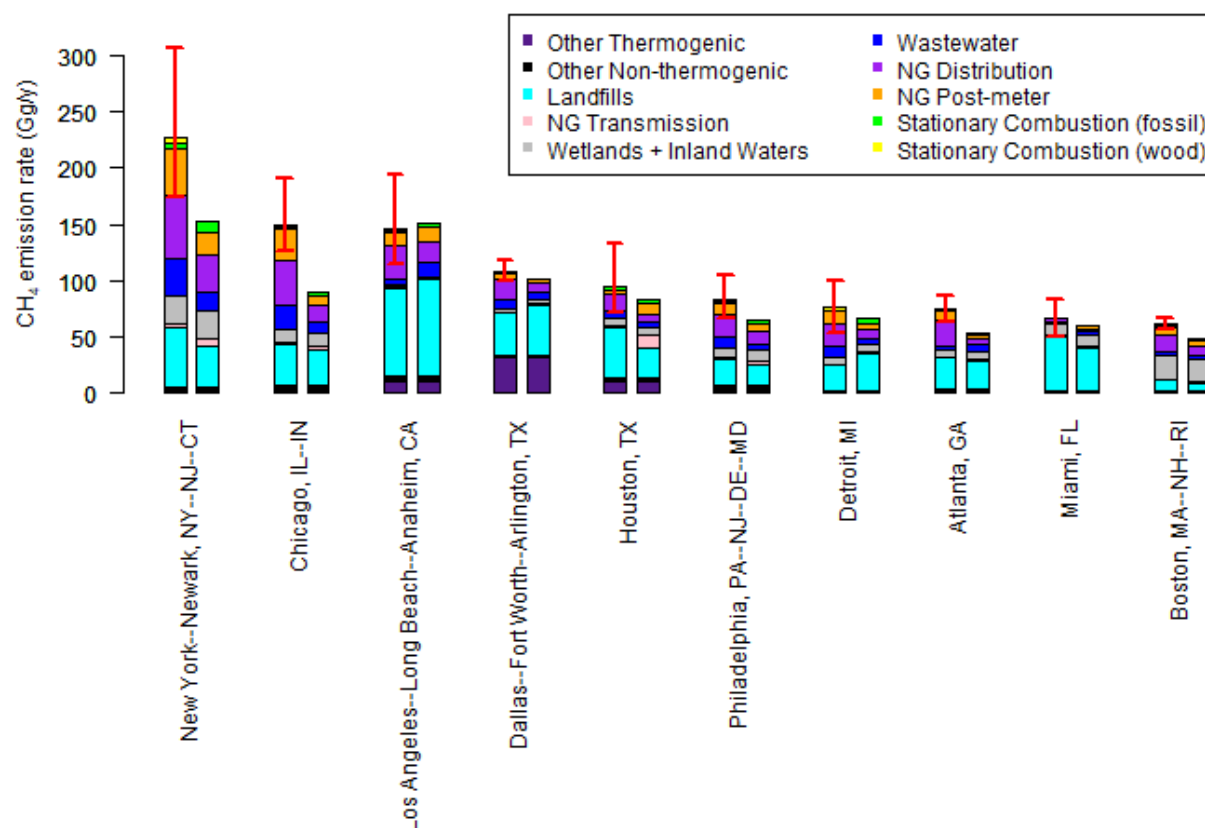


Figure 7: Stacked bar chart displaying the CH₄ emissions for the ten urban areas with the largest emissions according to this work and their sectoral breakdown. Values represent the average across all variations for each sector and red error bars on the total represent the range across all variations. Bars on the left for each urban area represent the results from M3T while those on the right represent values from GEPA. Natural gas is abbreviated as NG here. Wetland values from this work are included in GEPA values, as there is no wetland source and all GEPA stationary combustion emissions are labelled fossil, as fossil and wood are not differentiated.

An interesting observation that can be made from this sectoral information is that the sum of the natural gas distribution and post-meter sectors is a significant source for most urban areas, generally higher than in GEPA, with the exception of the Miami, Florida urban area. While warmer parts of the country require less natural gas for residential heating, we do not see this same behaviour in Los Angeles or Atlanta, which also have warmer climates. As M3T uses a bottom-up approach for this sector, we can investigate the relevant activity data for these sectors. This is simplest for the post-meter sector, which is based on the EIA data on residential natural gas delivered. This delivery data shows that Florida delivers considerably less natural gas than other similarly warm states, especially when considering its large size. If we rank states by the per capita natural gas delivered to residential customers then Florida is the lowest at rank 49 (excluding Alaska and Hawaii but including the District of Columbia). While some neighbouring states with similarly warm, humid climates like Louisiana



and Alabama are similarly low at 41 and 44, other neighbouring states like Mississippi and Georgia are much higher at 2 and 33. While this analysis assumes the EIA data is accurate and cannot determine the reason for lower residential natural gas use in Florida, it does demonstrate an interesting regional feature of CH₄ emission sources that can be identified.

We demonstrate the variability in individual sectors for the New York urban area in Figure 8. While this will look different for every urban area, the New York urban area has significant emissions from most sectors making it useful for discussion. This figure shows that the methodological variations affect the wetland, landfill, and wastewater emissions much more than other sectors. To briefly recap from Sections 2.2, 2.6, and 2.7, municipal landfill emissions are calculated using a first order decay equation or, assuming there is a gas capture system, a gas capture efficiency calculation. The municipal treatment plants in the wastewater sector can either rely on the GHGI or the empirical relationship determined in Moore et al. (2025), who reported nearly 2x the emissions as for the GHGI. They can also rely on either the CWNS or DMR for the activity data. There is also a state and national method to estimate septic emissions which show similar total estimates but can differ significantly spatially. Lastly, the wetlands sector can rely on three distinct products to estimate emissions: SOCCR, SOCCR version 2, and WetCHARTs. By comparison, variability in stationary combustion, natural gas distribution, and post-meter emissions stems only from the different CO₂ inventories used to disaggregate the emissions from the state total to the gridcell: ACES or Vulcan. Gurney et al. (2020) discussed that there are large differences between these products at the gridcell scale, but the products agree well at broader spatial scales. However, this does not consider the impact of adjusting EFs. For example, if we increase the leak rate for post-meter from 0.5 to 2.5 as per Karion et al. (2023), given the limited data used to inform this EF, then the post-meter emissions would increase proportionally (i.e., 5 times).

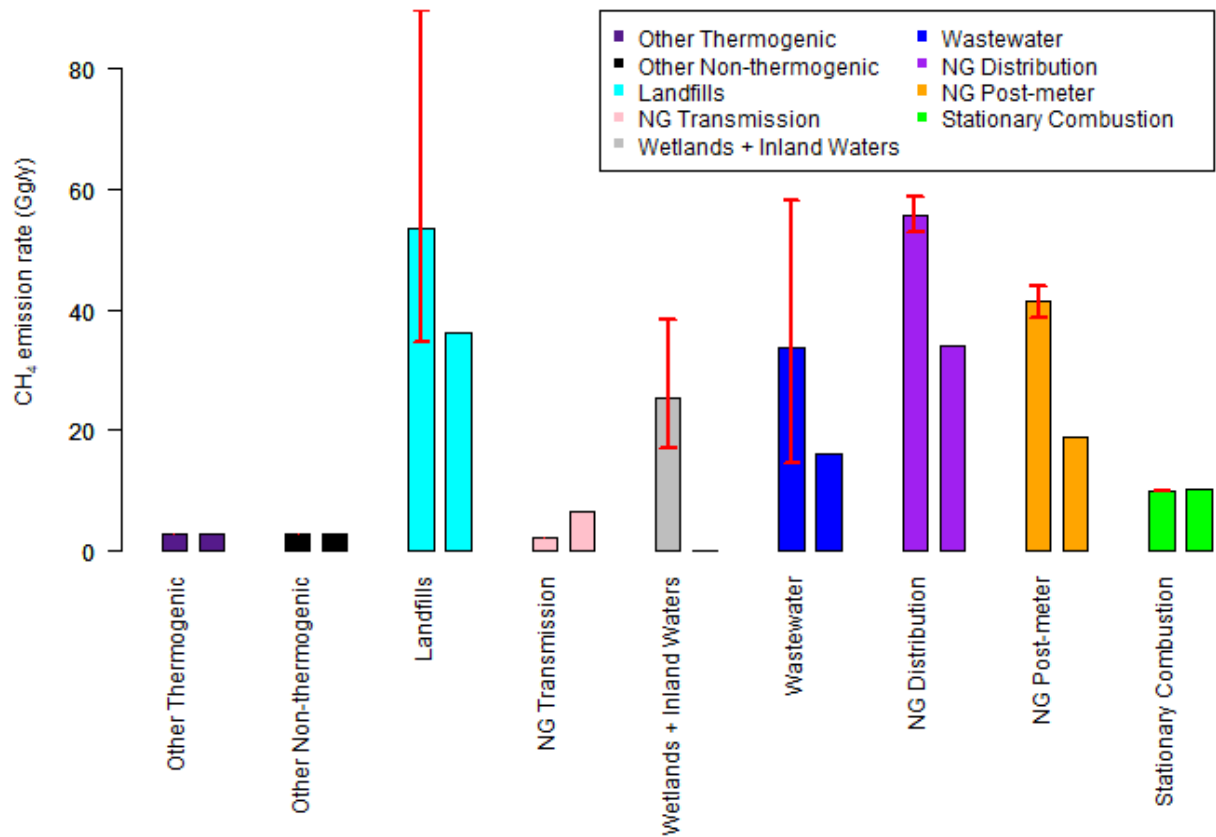


Figure 8: Bar chart displaying the sectoral CH₄ emissions for the New York urban area. Values represent the average across all variations and error bars represent the range across all variations. Bars on the left for each sector represent M3T results while those on the right represent values from GEPA. Natural gas is abbreviated as NG here. GEPA values match exactly for “Other” sources as GEPA values are used for “Other” sources. GEPA does not include wetlands. Stationary combustion is not differentiated here as GEPA does not differentiate between the two and any variability would affect both fossil fuel and wood combustion estimates.

We also compare the M3T output to GEPA spatially. Figure 9 shows the 0.01 deg resolution M3T output and 0.1 deg resolution GEPA output for the Los Angeles and New York urban areas, as well as the differences between them when aggregated to the same resolution. In Los Angeles, several 0.1 deg gridcells that are dominated by industrial landfill emissions taken directly from the GEPA are clear. While there is good agreement in Los Angeles total emissions, the spatial distribution of emissions still shows some differences.

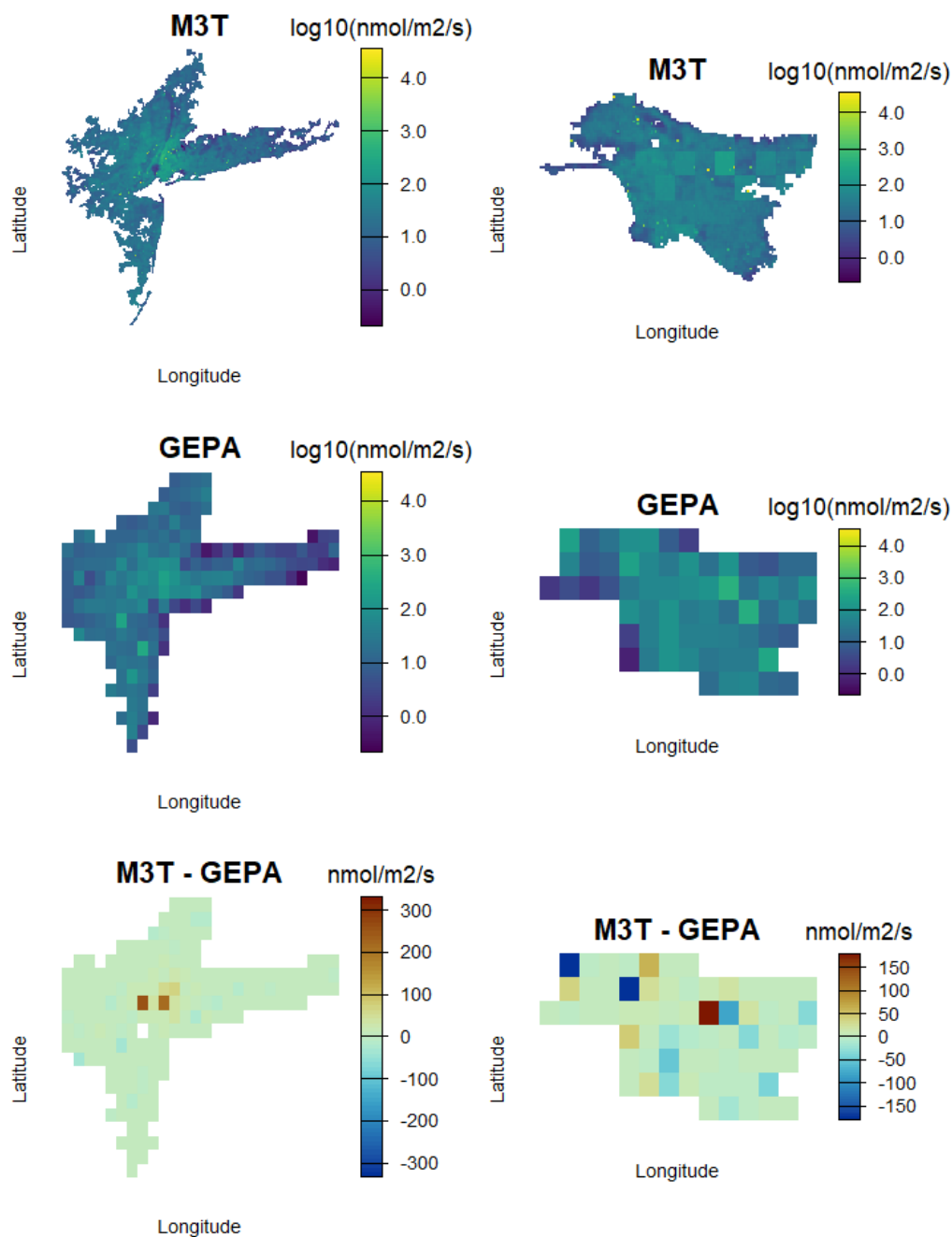


Figure 9: Maps showing the M3T output (top), GEPA (middle), and difference between them after aggregating M3T to the same resolution (bottom) for the New York (left) and Los Angeles (right) urban areas. The average is used in M3T for sectors with multiple variations. The urban area total emissions for New York are 226.7 Gg/year according to M3T and 152.3 Gg/year according to GEPA. The urban area total emissions for Los Angeles are 146.8 Gg/year according to M3T and 151.0 Gg/year according to GEPA.



3.2. Comparison to Literature

The New York urban area has been studied by several recent top-down measurement campaigns using airborne measurements. In addition to the total emissions, several of these studies have also investigated the fraction of the emissions that came from thermogenic sources. Plant et al. (2019) used airborne measurements of ethane and CH₄ from 2018 in combination with reported natural gas composition data to estimate the fraction of emissions in several urban areas, including New York, that came from thermogenic sources (i.e., natural gas). They also combined their measured CH₄ to CO₂ or CO ratio with inventory estimates of CO₂ or CO to estimate emissions from multiple urban areas. Floerchinger et al. (2021) used similar methods to estimate the thermogenic fraction using airborne measurements from 2017 and 2018 across seasons. Note that their March 2018 estimate is greater than 100%, likely as a result of systematic errors such as the impact of entrainment of free tropospheric air. Using airborne measurements from 2018 - 2020 and an inventory developed similarly to M3T, Pitt et al. (2024) calculated total emissions and the thermogenic fraction for the New York urban area using a sectoral inversion which took advantage of the high resolution of the inventory. Note that while all works defined the New York urban area using the census definition, they handled gridcells partially within the New York urban area differently which introduces some additional variability across them. For example, the estimate reported in Pitt et al. (2024) is 1.4 times the estimate of Plant et al. (2019), but if a consistent approach to aggregating emissions is employed to the results of both studies this ratio is only 1.1. These results are summarized in Table 1 and show that top-down values are consistently greater than inventories, including M3T, while the thermogenic fraction is in good agreement with top-down estimates. Here we also present estimates using the maximum across all M3T variations for comparison. While this increase is in better agreement with top-down measurements, the increase comes primarily from biogenic sources, so the thermogenic fraction reduces considerably. Schiferl et al. (2025) recently offered one potential source for this underestimate. They used long term CO and CH₄ measurements in the New York area to suggest that there are additional incomplete combustion emissions, particularly from winter to spring, that are being underestimated by inventories.



Table 1: Emission rates and thermogenic fraction estimated for the New York urban area across several studies.

Source	Data Year	NY Emissions (Gg/y)	Thermogenic Fraction (%)
Plant et al. (2019) CO ₂ ratio method	April/May 2018	430 [330, 560] (95% confidence interval)	87 [75, 97] (95% confidence interval)
Plant et al. (2019) CO ratio method	April/May 2018	450 [210, 750] (95% confidence interval)	87 [75, 97] (95% confidence interval)
Pitt et al. (spatial) (2024)	9 flights in November, February, and March, 2018 - 2020	296 ± 87 (1 sigma)	NA
Pitt et al. (sectoral) (2024)	9 flights in November, February, and March, 2018 - 2020	330 ± 140 (1 sigma)	71 ± 19 (1 sigma)
Floerchinger et al. (2021)	September 2017	NA	81.5 [80.9, 82.0] (95% confidence interval)
Floerchinger et al. (2021)	March 2018	NA	119 [116, 121] (95% confidence interval)
M3T mean across variations	2019	227	90.9
M3T max across variations	2019	306	59.0
GEPA including mean wetland from M3T	2019	152	90.0

6 Conclusions

Given the wide variety of datasets utilized by M3T, not all potential nuances may be taken into account, and we suggest users carefully investigate output for potential anomalies. We urge users to create GitHub issues to better inform other users accordingly, allowing M3T to be edited to account for identified issues. Issues can also be submitted to ask questions, point out errors, or suggest other improvements. Plotting of sectoral and sub-sectoral visuals is included with the verbose option to simplify identifying potential concerns. Additionally, there may be flaws in the underlying input data, such as the CWNS and landfill GHGRP discrepancies discussed in their respective methods sub-sections.

While M3T offers a modular, user-friendly tool to develop gridded inventories, it still has significant room for growth. Table 1 shows that, at least for some urban areas, M3T gridded emissions are still biased low compared to measurements, as has been shown across studies and bottom up CH₄ inventories (Vollrath et al., 2025). Gridded uncertainties are critical for



inverse emissions modelling and are not yet incorporated. Maasakkers et al. (2023) highlighted the increase in per-gridcell uncertainty as emissions are gridded at finer resolutions though the more granular data available with this tool is still valuable as it allows inversion analyses to better delineate emissions given the underlying heterogeneity of methane sources in urban areas (Karion et al., 2023; Pitt et al., 2024). It is well known that uncertainties in emission inventory products are difficult to calculate, as uncertainties are often lacking for both activity and EF data. Seasonality has also been discussed for some CH₄ emission sources and recent work has shown seasonality in total emissions for urban areas (Karion et al., 2023; Mueller et al., 2025; Sargent et al., 2021; Zeng et al., 2023) and fossil fuel production regions (Hu et al., 2025; Varon et al., 2026). This is in addition to finer temporal resolution variability (e.g., weekday - weekend, diurnal) that may exist (Barkley et al., 2025), as has been shown for CO₂ (Gately and Hutyra, 2022; Gurney et al., 2025b). M3T is currently built solely for annual emissions. There also exist additional sources worth consideration but lacking in data, such as wildfires, manholes and sewer systems, incomplete vehicle combustion, leakage of compressed natural gas fuel, and historical landfills. Lastly, using CO and CO₂ emissions inventories as a proxy for stationary combustion and natural gas distribution can misapportion emissions as the underlying mechanisms differ, namely CO₂ is a combustion product while CH₄ is emitted due to incomplete combustion or natural gas leakage. Recent literature on CO₂ inventories has discussed the importance of appropriate proxies or models to represent the underlying emissions (Shi et al., 2025; Sun et al., 2026). To address several of these shortcomings additional studies focused on the underlying processes or new publicly available activity datasets are needed. The modular, open-source nature of M3T can facilitate the incorporation of updated emission factors and emission models from such future studies.

M3T was developed to support further research into urban CH₄ emissions by providing flexible, high-resolution gridded emission estimates. Unlike other gridded emissions products, M3T is not an emissions map, but instead a publicly available tool that can be used to create emissions maps with user defined resolution, extent, year, and grid. Most importantly, this allows users to adjust EFs, consider multiple possible methodologies, and ideally compare these variations against measurements to further the field and quantify performance across calculation methods. We have presented the methods used by M3T, discussed some of its current limitations, and presented initial analyses with high resolution 2019 CONUS output. By making the code publicly available and presenting it clearly here, we hope researchers not only make use of the tool for their analyses but also incorporate their work into M3T to further develop it into a more capable, reliable, and valuable tool.

Code and Data Availability

The M3T is being submitted to CRAN and is currently publicly available on GitHub via (<https://github.com/Kristian-hajny/M3T>) (Hajny and Pitt, 2026b) and Zenodo (<https://doi.org/10.5281/zenodo.21500785>) (Hajny and Pitt, 2026a). All required input data is included in the package or the publicly available Zenodo with supporting data (<https://doi.org/10.5281/zenodo.17328718>) (Hajny et al., 2026).



592 **Author Contributions**

593 PBS and KDH developed the concept of M3T expanding from past work. KDH and JP developed the methodology and
594 software. KDH prepared the manuscript. All coauthors reviewed the manuscript.

595 **Competing Interests**

596 None of the authors have any competing interests.

597 **Acknowledgements**

598 We would like to thank Kim Mueller and Anna Karion for their thoughtful feedback in the development of M3T and their
599 review of this manuscript. In addition, we would like to thank Zachary Weller for his input on the natural gas distribution
600 sector, Pawlok Dass for his input on our use of CO₂ inventories, and Dan Moore for his input on the wastewater sector.

601 **Financial Support**

602 Funding for this work was provided by the National Institute for Standards and Technology (NIST) grant 70NANB19H167.

603 **Supporting Information**

604 GEPA sectors used in M3T (Table S1), Detailed information regarding default configuration settings for all sectors (Section
605 S1), The approach used to align GHGRP and HIFLD transmission compressor data (Section S2), Analyses of per capita and
606 per area emissions (Section S2).

607 A csv file listing all GHGRP landfills with reported emissions that differ from both reporting methods
608 (GHGRP_landfill_errors.csv) and the R script used to generate the file (GHGRP_landfill_errors.R). Excel files providing the
609 sectoral emissions for all urban areas for GEPA (GEPA_urban_emissions_nmol_s.csv) and M3T
610 (Urban_emissions_nmol_s.csv). A NetCDF file containing the 2019 CONUS M3T emissions for the minimum, mean, and
611 maximum across ensemble members in nmol/m²/s (M3T_2019_CONUS.nc).

612



613 References

- 614 Alvarez, R. A., Zavala-Araiza, D., Lyon, D. R., Allen, D. T., Barkley, Z. R., Brandt, A. R., Davis, K. J., Herndon, S. C., Jacob,
615 D. J., Karion, A., Kort, E. A., Lamb, B. K., Lauvaux, T., Maasakkers, J. D., Marchese, A. J., Omara, M., Pacala, S. W., Peischl,
616 J., Robinson, A. L., Shepson, P. B., Sweeney, C., Townsend-Small, A., Wofsy, S. C., and Hamburg, S. P.: Assessment of
617 methane emissions from the U.S. oil and gas supply chain, *Science*, 361, 186–188, <https://doi.org/10.1126/science.aar7204>,
618 2018.
- 619 C40 Cities - A global network of mayors taking urgent climate action: <https://www.c40.org/>, last access: 10 June 2025.
- 620 Climate Mayors: <https://www.climatemayors.org>, last access: 10 June 2025.
- 621 Waste Business Journal - Directory of Waste Processing & Disposal Sites: <http://www.wastebusinessjournal.com/diratlas.htm>,
622 last access: 13 October 2025.
- 623 Balasus, N., Jacob, D. J., Maxemin, G., Jenks, C., Nesser, H., Maasakkers, J. D., Cusworth, D. H., Scarpelli, T. R., Varon, D.
624 J., and Wang, X.: Satellite monitoring of annual US landfill methane emissions and trends, *Environ. Res. Lett.*, 20, 024007,
625 <https://doi.org/10.1088/1748-9326/ada2b1>, 2025.
- 626 Barkley, Z. R., Davis, K. J., Miles, N. L., and Richardson, S. J.: Examining Daily Temporal Characteristics of Oil and Gas
627 Methane Emissions in the Delaware Basin Using Continuous Tower Observations, *Journal of Geophysical Research:*
628 *Atmospheres*, 130, e2024JD042050, <https://doi.org/10.1029/2024JD042050>, 2025.
- 629 Bloom, A. A., Bowman, K. W., Lee, M., Turner, A. J., Schroeder, R., Worden, J. R., Weidner, R., McDonald, K. C., and
630 Jacob, D. J.: A global wetland methane emissions and uncertainty dataset for atmospheric chemical transport models
631 (WetCHARTs version 1.0), *Geoscientific Model Development*, 10, 2141–2156, <https://doi.org/10.5194/gmd-10-2141-2017>,
632 2017.
- 633 Climate TRACE: <https://climatetrace.org/faqs>, last access: 10 June 2025.
- 634 Cusworth, D. H., Duren, R. M., Ayasse, A. K., Jiorle, R., Howell, K., Aubrey, A., Green, R. O., Eastwood, M. L., Chapman,
635 J. W., Thorpe, A. K., Heckler, J., Asner, G. P., Smith, M. L., Thoma, E., Krause, M. J., Heins, D., and Thornehoe, S.:
636 Quantifying methane emissions from United States landfills, *Science*, 383, 1499–1504,
637 <https://doi.org/10.1126/science.adi7735>, 2024.
- 638 Data Rescue Project: Federal GIS Data Saved and Archived, Data Rescue Project, 2025.
- 639 Defra, DESNZ, and The Devolved Administrations: The UK National Atmospheric Emissions Inventory (NAEI), © Crown
640 2025 copyright Defra & DESNZ via naei.energysecurity.gov.uk licenced under the Open Government Licence (OGL).
641 [dataset], <https://doi.org/http://naei.energysecurity.gov.uk/>, 2025.
- 642 Dogniaux, M., Maasakkers, J. D., Girard, M., Jervis, D., McKeever, J., Schuit, B. J., Sharma, S., Lopez-Noreña, A., Varon, D.
643 J., and Aben, I.: Global satellite survey reveals uncertainty in landfill methane emissions, *Nature*, 647, 397–402,
644 <https://doi.org/10.1038/s41586-025-09683-8>, 2025.
- 645 Electronic Code of Federal Regulations: 40 Code of Federal Regulations §98.2, 2009a.
- 646 Electronic Code of Federal Regulations: 40 Code of Federal Regulations §98.343, 2009b.
- 647 Electronic Code of Federal Regulations: 40 Code of Federal Regulations §127, 2015.



- 648 Environmental Defense Fund: Permian Map, 2021.
- 649 EPA: Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990 - 2022, U.S. Environmental Protection Agency, 2024.
- 650 Fischer, M. L., Chan, W. R., Delp, W., Jeong, S., Rapp, V., and Zhu, Z.: An Estimate of Natural Gas Methane Emissions from
651 California Homes, *Environ. Sci. Technol.*, 52, 10205–10213, <https://doi.org/10.1021/acs.est.8b03217>, 2018.
- 652 Floerchinger, C., Shepson, P. B., Hajny, K., Daube, B. C., Stirm, B. H., Sweeney, C., and Wofsy, S. C.: Relative flux
653 measurements of biogenic and natural gas-derived methane for seven U.S. cities, *Elementa: Science of the Anthropocene*, 9,
654 000119, <https://doi.org/10.1525/elementa.2021.000119>, 2021.
- 655 Forster, P., Storelvmo, T., Armour, K., Collins, W., Dufresne, J.-L., Frame, D., Lunt, D. J., Mauritsen, T., Palmer, M. D.,
656 Watanabe, M., Wild, M., and Zhang, H.: The Earth's Energy Budget, Climate Feedbacks, and Climate Sensitivity, in: *Climate*
657 *Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the*
658 *Intergovernmental Panel on Climate Change*, edited by: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C.,
659 Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock,
660 T. K., Waterfield, T., Yelekçi, O., Yu, R., and Zhou, B., Cambridge University Press, Cambridge, United Kingdom and New
661 York, NY, USA, 923–1054, 2021.
- 662 Gately, C. and Hutyra, L. R.: Anthropogenic Carbon Emission System, 2012-2017, Version 2, ORNL DAAC,
663 <https://doi.org/10.3334/ORNLDAAAC/1943>, 2022.
- 664 Gately, C. K. and Hutyra, L. R.: Large Uncertainties in Urban-Scale Carbon Emissions, *Journal of Geophysical Research:*
665 *Atmospheres*, 122, 11,242-11,260, <https://doi.org/10.1002/2017JD027359>, 2017.
- 666 Gómez, D. R., Watterson, J. D., Americano, B. B., Ha, C., Marland, G., Matsika, E., Nenge Namayanga, L., Osman-Elasha,
667 B., Kalenga Saka, J. D., and Treanton, K.: 2006 IPCC Guidelines for National Greenhouse Gas Inventories - Stationary
668 Combustion, 2006.
- 669 Guo, F., Dai, F., Gong, P., and Zhou, Y.: CHN-CH₄: A Gridded (0.1°×0.1°) Anthropogenic Methane
670 Emission Inventory of China from 1990 to 2020, *Earth System Science Data Discussions*, 1–25, [https://doi.org/10.5194/essd-](https://doi.org/10.5194/essd-2025-178)
671 [2025-178](https://doi.org/10.5194/essd-2025-178), 2025.
- 672 Gurney, K., Dass, P., Kato, A., Gawuc, L., Aslam, B., and Sun, H.: Vulcan version 4.0 high-resolution annual fossil fuel and
673 cement production carbon dioxide emissions in the United States for the 2010-2022 time period (4.0),
674 <https://doi.org/10.5281/zenodo.15446748>, 2025a.
- 675 Gurney, K. R., Song, Y., Liang, J., and Roest, G.: Toward Accurate, Policy-Relevant Fossil Fuel CO₂ Emission Landscapes,
676 *Environ. Sci. Technol.*, 54, 9896–9907, <https://doi.org/10.1021/acs.est.0c01175>, 2020.
- 677 Gurney, K. R., Dass, P., Kato, A., Gawuc, L., Aslam, B., and Sun, H.: Vulcan version 4.0 high-resolution annual carbon
678 dioxide emissions in the U.S. for the 2010–2022 time period, *Sci Data*, 12, 1946, [https://doi.org/10.1038/s41597-025-06391-](https://doi.org/10.1038/s41597-025-06391-w)
679 [w](https://doi.org/10.1038/s41597-025-06391-w), 2025b.
- 680 Hajny, K. and Pitt, J.: Kristian-hajny/M3T: v1.0.0, , <https://doi.org/10.5281/zenodo.21500785>, 2026a.
- 681 Hajny, K. and Pitt, J.: M3T, 2026b.
- 682 Hajny, K., Shepson, P., and Pitt, J.: Modular Methane Mapping Tool (M3T) Supporting Data,
683 <https://doi.org/10.5281/zenodo.17328718>, 2026.



- 684 Hajny, K. D., Salmon, O. E., Rudek, J., Lyon, D. R., Stuff, A. A., Stirm, B. H., Kaeser, R., Floerchinger, C. R., Conley, S.,
685 Smith, M. L., and Shepson, P. B.: Observations of Methane Emissions from Natural Gas-Fired Power Plants, *Environ. Sci.*
686 *Technol.*, 53, 8976–8984, <https://doi.org/10.1021/acs.est.9b01875>, 2019.
- 687 Hallward-Driemeier, A., Zhao, Y., Drews, M., Sargent, M., Wofsy, S., Barton-Grimley, R., Yerasi, A., Collins, J., Nehrir, A.,
688 and Commame, R.: Seasonal Landfill Methane Emissions Driven by Temperature and Pressure, *Environ. Sci. Technol.*, 60,
689 13356–13367, <https://doi.org/10.1021/acs.est.5c16757>, 2026.
- 690 Hijmans, R. J.: *terra: Spatial Data Analysis*, 2025.
- 691 Hoesly, R. M., Smith, S. J., Feng, L., Klimont, Z., Janssens-Maenhout, G., Pitkanen, T., Seibert, J. J., Vu, L., Andres, R. J.,
692 Bolt, R. M., Bond, T. C., Dawidowski, L., Kholod, N., Kurokawa, J., Li, M., Liu, L., Lu, Z., Moura, M. C. P., O'Rourke, P.
693 R., and Zhang, Q.: Historical (1750–2014) anthropogenic emissions of reactive gases and aerosols from the Community
694 Emissions Data System (CEDS), *Geoscientific Model Development*, 11, 369–408, <https://doi.org/10.5194/gmd-11-369-2018>,
695 2018.
- 696 Howell, K., Scarpelli, T., Duren, R., Thorpe, A., Asner, G., Heckler, J., Green, R., Brantley, H., and Cusworth, D.: Informing
697 landfill emission reporting programs through remote sensing, <https://eartharxiv.org/repository/view/10478/>, 11 October 2025.
- 698 Hu, L., Andrews, A. E., Montzka, S. A., Miller, S. M., Bruhwiler, L., Oh, Y., Sweeney, C., Miller, J. B., McKain, K., Ibarra
699 Espinosa, S., Davis, K., Miles, N., Mountain, M., Lan, X., Crotwell, A., Madronich, M., Mefford, T., Michel, S., and
700 Houwelling, S.: An Unexpected Seasonal Cycle in U.S. Oil and Gas Methane Emissions, *Environ. Sci. Technol.*, 59, 9968–
701 9979, <https://doi.org/10.1021/acs.est.4c14090>, 2025.
- 702 Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., Bergamaschi, P., Pagliari, V.,
703 Olivier, J. G. J., Peters, J. A. H. W., van Aardenne, J. A., Monni, S., Doering, U., Petrescu, A. M. R., Solazzo, E., and Oreggioni,
704 G. D.: EDGAR v4.3.2 Global Atlas of the three major greenhouse gas emissions for the period 1970–2012, *Earth System*
705 *Science Data*, 11, 959–1002, <https://doi.org/10.5194/essd-11-959-2019>, 2019.
- 706 Jon Dewitz: National Land Cover Database (NLCD) 2016 Products (ver. 3.0, November 2023),
707 <https://doi.org/10.5066/P96HHBIE>, 2020.
- 708 Jon Dewitz: National Land Cover Database (NLCD) 2011 Land Cover Conterminous United States (ver. 2.0, May 2024),
709 <https://doi.org/10.5066/P97S2IID>, 2024.
- 710 Karion, A., Ghosh, S., Lopez-Coto, I., Mueller, K., Gourdji, S., Pitt, J., and Whetstone, J.: Methane Emissions Show Recent
711 Decline but Strong Seasonality in Two US Northeastern Cities, *Environ. Sci. Technol.*, 57, 19565–19574,
712 <https://doi.org/10.1021/acs.est.3c05050>, 2023.
- 713 Krause, M. J., Thoma, E. D., Bryant, A., Brantley, H., MacDonald, M., Green, R., and Thornehoe, S.: A High-Resolution
714 Satellite Survey of Methane Emissions from 60 North American Municipal Solid Waste Landfills, *Environ. Sci. Technol.*, 59,
715 15080–15091, <https://doi.org/10.1021/acs.est.5c01409>, 2025.
- 716 Lamb, B. K., Cambaliza, M. O. L., Davis, K. J., Edburg, S. L., Ferrara, T. W., Floerchinger, C., Heimbürger, A. M. F., Herndon,
717 S., Lauvaux, T., Lavoie, T., Lyon, D. R., Miles, N., Prasad, K. R., Richardson, S., Roscioli, J. R., Salmon, O. E., Shepson, P.
718 B., Stirm, B. H., and Whetstone, J.: Direct and Indirect Measurements and Modeling of Methane Emissions in Indianapolis,
719 Indiana, *Environ. Sci. Technol.*, 50, 8910–8917, <https://doi.org/10.1021/acs.est.6b01198>, 2016.
- 720 Leverenz, H. L., Tchobanoglous, G., and Darby, J. L.: *Evaluation of Greenhouse Gas Emissions from Septic Systems*, Water
721 Environment Research Foundation, Alexandria, VA, 2010.



- 722 Loman, M. L., Murray, L. T., Leibensperger, E. M., and Maasakkers, J. D.: A High-Resolution Inventory of Anthropogenic
723 Methane Emissions in New York State, *Environ. Sci. Technol.*, 59, 16933–16946, <https://doi.org/10.1021/acs.est.5c07245>,
724 2025.
- 725 Lu, X., Jacob, D. J., Wang, H., Maasakkers, J. D., Zhang, Y., Scarpelli, T. R., Shen, L., Qu, Z., Sulprizio, M. P., Nesser, H.,
726 Bloom, A. A., Ma, S., Worden, J. R., Fan, S., Parker, R. J., Boesch, H., Gautam, R., Gordon, D., Moran, M. D., Reuland, F.,
727 Villasana, C. A. O., and Andrews, A.: Methane emissions in the United States, Canada, and Mexico: evaluation of national
728 methane emission inventories and 2010–2017 sectoral trends by inverse analysis of in situ (GLOBALVIEWplus CH₄ ObsPack)
729 and satellite (GOSAT) atmospheric observations, *Atmospheric Chemistry and Physics*, 22, 395–418,
730 <https://doi.org/10.5194/acp-22-395-2022>, 2022.
- 731 Lyu, C., Harkins, C., Li, M., Mueller, K., Prothero, J., Verreyken, B., Miller, J. B., Lehman, S. J., Peischl, J., Gilman, J. B.,
732 Warneke, C., Coggon, M. M., Stockwell, C. E., Brown, S. S., Zuraski, K., Lamplugh, A., Gurney, K. R., Gawuc, L., Dass, P.,
733 Hoesly, R. M., Smith, S. J., Oda, T., Hutyra, L. R., Gately, C. K., Granier, C., Whetstone, J. R., and McDonald, B. C.:
734 Development of the United States GRreenhouse Gas and Air Pollutants Emissions System (GRA2PES), *Journal of Geophysical*
735 *Research: Atmospheres*, 130, e2025JD043597, <https://doi.org/10.1029/2025JD043597>, 2025.
- 736 Ma, S., Worden, J. R., Bloom, A. A., Zhang, Y., Poulter, B., Cusworth, D. H., Yin, Y., Pandey, S., Maasakkers, J. D., Lu, X.,
737 Shen, L., Sheng, J., Frankenberg, C., Miller, C. E., and Jacob, D. J.: Satellite Constraints on the Latitudinal Distribution and
738 Temperature Sensitivity of Wetland Methane Emissions, *AGU Advances*, 2, e2021AV000408,
739 <https://doi.org/10.1029/2021AV000408>, 2021.
- 740 Maasakkers, J. D., Jacob, D. J., Sulprizio, M. P., Turner, A. J., Weitz, M., Wirth, T., Hight, C., DeFigueiredo, M., Desai, M.,
741 Schmeltz, R., Hockstad, L., Bloom, A. A., Bowman, K. W., Jeong, S., and Fischer, M. L.: Gridded National Inventory of U.S.
742 Methane Emissions, *Environ. Sci. Technol.*, 50, 13123–13133, <https://doi.org/10.1021/acs.est.6b02878>, 2016.
- 743 Maasakkers, J. D., McDuffie, E. E., Sulprizio, M. P., Chen, C., Schultz, M., Brunelle, L., Thrush, R., Steller, J., Sherry, C.,
744 Jacob, D. J., Jeong, S., Irving, B., and Weitz, M.: A Gridded Inventory of Annual 2012–2018 U.S. Anthropogenic Methane
745 Emissions, *Environ. Sci. Technol.*, 57, 16276–16288, <https://doi.org/10.1021/acs.est.3c05138>, 2023.
- 746 McDonald, C. P., Rover, J. A., Stets, E. G., and Striegl, R. G.: The regional abundance and size distribution of lakes and
747 reservoirs in the United States and implications for estimates of global lake extent, *Limnology and Oceanography*, 57, 597–
748 606, <https://doi.org/10.4319/lo.2012.57.2.0597>, 2012.
- 749 McDuffie, E., E., Maasakkers, J., D., Sulprizio, M., P., Chen, C., Schultz, M., Brunelle, L., Thrush, R., Steller, J., Sherry, C.,
750 Jacob, D., J., Jeong, S., Irving, B., and Weitz, M.: Gridded EPA U.S. Anthropogenic Methane Greenhouse Gas Inventory
751 (gridded GHGI), 2023.
- 752 McKain, K., Down, A., Raciti, S. M., Budney, J., Hutyra, L. R., Floerchinger, C., Herndon, S. C., Nehrkorn, T., Zahniser, M.
753 S., Jackson, R. B., Phillips, N., and Wofsy, S. C.: Methane emissions from natural gas infrastructure and use in the urban
754 region of Boston, Massachusetts, *Proceedings of the National Academy of Sciences*, 112, 1941–1946,
755 <https://doi.org/10.1073/pnas.1416261112>, 2015.
- 756 Michanowicz, D., Lebel, E., Lucha, N., Huang, G., Finnegan, C., Shankute, A., Galarza, C., Sparks, T., Rowland, S. T., Hill,
757 L. A. L., Kashtan, Y., Jackson, R. B., and Shonkoff, S. B. C.: Climate and Health-Damaging Pollutant Emissions from Natural
758 Gas and Electric Cooking Appliances in Commercial Kitchens, *AGU Fall Meeting Abstracts*, ADS Bibcode:
759 2024AGUFMGMH41C2714M, GH41C-2714, 2024.



- 760 Moore, D. P., Li, N. P., Wendt, L. P., Castañeda, S. R., Falinski, M. M., Zhu, J.-J., Song, C., Ren, Z. J., and Zondlo, M. A.:
761 Underestimation of Sector-Wide Methane Emissions from United States Wastewater Treatment, *Environ. Sci. Technol.*, 57,
762 4082–4090, <https://doi.org/10.1021/acs.est.2c05373>, 2023.
- 763 Moore, D. P., Li, N. P., Song, C., Zhu, J.-J., Yi, H., Tao, L., McSpirt, J., Sevostianov, V. I., Wendt, L. P., Rojas-Robles, N.
764 E., Hopkins, F. M., Ren, Z. J., and Zondlo, M. A.: Comprehensive assessment of the contribution of wastewater treatment to
765 urban greenhouse gas and ammonia emissions, *Nat Water*, 3, 1114–1124, <https://doi.org/10.1038/s44221-025-00490-z>, 2025.
- 766 Mostafavi Pak, N., Heerah, S., Zhang, J., Chan, E., Worthy, D., Vogel, F., and Wunch, D.: The Facility Level and Area
767 Methane Emissions inventory for the Greater Toronto Area (FLAME-GTA), *Atmospheric Environment*, 252, 118319,
768 <https://doi.org/10.1016/j.atmosenv.2021.118319>, 2021.
- 769 Mueller, K. L., Karion, A., Lopez-Coto, I., Marrs, J., Yadav, V., Plant, G., Pitt, J., Barkley, Z. R., and Whetstone, J.: Scaling
770 Urban Methane Emissions: Utility of Single-Site Measurements in Five Urban Domains, *Environ. Sci. Technol.*, 59, 14399–
771 14409, <https://doi.org/10.1021/acs.est.5c03844>, 2025.
- 772 Nesser, H., Jacob, D. J., Maasakkers, J. D., Lorente, A., Chen, Z., Lu, X., Shen, L., Qu, Z., Sulprizio, M. P., Winter, M., Ma,
773 S., Bloom, A. A., Worden, J. R., Stavins, R. N., and Randles, C. A.: High-resolution US methane emissions inferred from an
774 inversion of 2019 TROPOMI satellite data: contributions from individual states, urban areas, and landfills, *Atmospheric*
775 *Chemistry and Physics*, 24, 5069–5091, <https://doi.org/10.5194/acp-24-5069-2024>, 2024.
- 776 Ooms, J.: The jsonlite Package: A Practical and Consistent Mapping Between JSON Data and R Objects,
777 <https://doi.org/10.48550/arXiv.1403.2805>, 12 March 2014.
- 778 Pierce, D.: ncdf4: Interface to Unidata netCDF (Version 4 or Earlier) Format Data Files, 2025.
- 779 Pitt, J. R., Lopez-Coto, I., Karion, A., Hajny, K. D., Tomlin, J., Kaeser, R., Jayarathne, T., Stirm, B. H., Floerchinger, C. R.,
780 Loughner, C. P., Commane, R., Gately, C. K., Hutrya, L. R., Gurney, K. R., Roest, G. S., Liang, J., Gourdji, S., Mueller, K.
781 L., Whetstone, J. R., and Shepson, P. B.: Underestimation of Thermogenic Methane Emissions in New York City, *Environ.*
782 *Sci. Technol.*, 58, 9147–9157, <https://doi.org/10.1021/acs.est.3c10307>, 2024.
- 783 Plant, G., Kort, E. A., Floerchinger, C., Gvakharia, A., Vimont, I., and Sweeney, C.: Large Fugitive Methane Emissions From
784 Urban Centers Along the U.S. East Coast, *Geophysical Research Letters*, 46, 8500–8507,
785 <https://doi.org/10.1029/2019GL082635>, 2019.
- 786 Rosentreter, J. A., Borges, A. V., Deemer, B. R., Holgersson, M. A., Liu, S., Song, C., Melack, J., Raymond, P. A., Duarte, C.
787 M., Allen, G. H., Olefeldt, D., Poulter, B., Battin, T. I., and Eyre, B. D.: Half of global methane emissions come from highly
788 variable aquatic ecosystem sources, *Nat. Geosci.*, 14, 225–230, <https://doi.org/10.1038/s41561-021-00715-2>, 2021.
- 789 Sargent, M. R., Floerchinger, C., McKain, K., Budney, J., Gottlieb, E. W., Hutrya, L. R., Rudek, J., and Wofsy, S. C.: Majority
790 of US urban natural gas emissions unaccounted for in inventories, *Proceedings of the National Academy of Sciences*, 118,
791 e2105804118, <https://doi.org/10.1073/pnas.2105804118>, 2021.
- 792 Saunio, M., Stavert, A. R., Poulter, B., Bousquet, P., Canadell, J. G., Jackson, R. B., Raymond, P. A., Dlugokencky, E. J.,
793 Houweling, S., Patra, P. K., Ciais, P., Arora, V. K., Bastviken, D., Bergamaschi, P., Blake, D. R., Brailsford, G., Bruhwiler,
794 L., Carlson, K. M., Carrol, M., Castaldi, S., Chandra, N., Crevoisier, C., Crill, P. M., Covey, K., Curry, C. L., Etiope, G.,
795 Frankenberg, C., Gedney, N., Hegglin, M. I., Höglund-Isaksson, L., Hugelius, G., Ishizawa, M., Ito, A., Janssens-Maenhout,
796 G., Jensen, K. M., Joos, F., Kleinen, T., Krummel, P. B., Langenfelds, R. L., Laruelle, G. G., Liu, L., Machida, T., Maksyutov,
797 S., McDonald, K. C., McNorton, J., Miller, P. A., Melton, J. R., Morino, I., Müller, J., Murguía-Flores, F., Naik, V., Niwa, Y.,
798 Noce, S., O'Doherty, S., Parker, R. J., Peng, C., Peng, S., Peters, G. P., Prigent, C., Prinn, R., Ramonet, M., Regnier, P., Riley,



- 799 W. J., Rosentreter, J. A., Segers, A., Simpson, I. J., Shi, H., Smith, S. J., Steele, L. P., Thornton, B. F., Tian, H., Tohjima, Y.,
800 Tubiello, F. N., Tsuruta, A., Viovy, N., Voulgarakis, A., Weber, T. S., van Weele, M., van der Werf, G. R., Weiss, R. F.,
801 Worthy, D., Wunch, D., Yin, Y., Yoshida, Y., Zhang, W., Zhang, Z., Zhao, Y., Zheng, B., Zhu, Q., Zhu, Q., and Zhuang, Q.:
802 The Global Methane Budget 2000–2017, *Earth System Science Data*, 12, 1561–1623, [https://doi.org/10.5194/essd-12-1561-](https://doi.org/10.5194/essd-12-1561-2020)
803 2020, 2020.
- 804 Saunio, M., Martinez, A., Poulter, B., Zhang, Z., Raymond, P. A., Regnier, P., Canadell, J. G., Jackson, R. B., Patra, P. K.,
805 Bousquet, P., Ciais, P., Dlugokencky, E. J., Lan, X., Allen, G. H., Bastviken, D., Beerling, D. J., Belikov, D. A., Blake, D. R.,
806 Castaldi, S., Crippa, M., Deemer, B. R., Dennison, F., Etiope, G., Gedney, N., Höglund-Isaksson, L., Holgersson, M. A.,
807 Hopcroft, P. O., Hugelius, G., Ito, A., Jain, A. K., Janardanan, R., Johnson, M. S., Kleinen, T., Krummel, P. B., Lauerwald,
808 R., Li, T., Liu, X., McDonald, K. C., Melton, J. R., Mühle, J., Müller, J., Murguía-Flores, F., Niwa, Y., Noce, S., Pan, S.,
809 Parker, R. J., Peng, C., Ramonet, M., Riley, W. J., Rocher-Ros, G., Rosentreter, J. A., Sasakawa, M., Segers, A., Smith, S. J.,
810 Stanley, E. H., Thanwerdas, J., Tian, H., Tsuruta, A., Tubiello, F. N., Weber, T. S., van der Werf, G. R., Worthy, D. E. J., Xi,
811 Y., Yoshida, Y., Zhang, W., Zheng, B., Zhu, Q., Zhu, Q., and Zhuang, Q.: Global Methane Budget 2000–2020, *Earth System*
812 *Science Data*, 17, 1873–1958, <https://doi.org/10.5194/essd-17-1873-2025>, 2025.
- 813 Scarpelli, T. R., Jacob, D. J., Grossman, S., Lu, X., Qu, Z., Sulprizio, M. P., Zhang, Y., Reuland, F., Gordon, D., and Worden,
814 J. R.: Updated Global Fuel Exploitation Inventory (GFEI) for methane emissions from the oil, gas, and coal sectors: evaluation
815 with inversions of atmospheric methane observations, *Atmospheric Chemistry and Physics*, 22, 3235–3249,
816 <https://doi.org/10.5194/acp-22-3235-2022>, 2022.
- 817 Scarpelli, T. R., Cusworth, D. H., Duren, R. M., Kim, J., Heckler, J., Asner, G. P., Thoma, E., Krause, M. J., Heins, D., and
818 Thorneloe, S.: Investigating Major Sources of Methane Emissions at US Landfills, *Environ. Sci. Technol.*, 58, 21545–21556,
819 <https://doi.org/10.1021/acs.est.4c07572>, 2024.
- 820 Schiferl, L. D., Hallward-Driemeier, A., Zhao, Y., Toledo-Crow, R., and Commane, R.: Missing wintertime methane emissions
821 from New York City related to combustion, <https://doi.org/10.5194/egusphere-2025-345>, 19 March 2025.
- 822 Shi, Q., Ciais, P., Denier van der Gon, H. A., Schoenmakers, E. J., Engelen, R., Dou, X., Ke, P., Zhu, B., Liu, Z., Chevallier,
823 F., and Guevara, M.: Comparison of High-Resolution Gridded Emission Maps of Anthropogenic Carbon Dioxide in Europe:
824 GRACED & CAMS-REG, *Environ. Sci. Technol.*, 59, 4926–4937, <https://doi.org/10.1021/acs.est.4c07289>, 2025.
- 825 Soulie, A., Granier, C., Darras, S., Zilbermann, N., Doumbia, T., Guevara, M., Jalkanen, J.-P., Keita, S., Liousse, C., Crippa,
826 M., Guizzardi, D., Hoesly, R., and Smith, S. J.: Global anthropogenic emissions (CAMS-GLOB-ANT) for the Copernicus
827 Atmosphere Monitoring Service simulations of air quality forecasts and reanalyses, *Earth System Science Data*, 16, 2261–
828 2279, <https://doi.org/10.5194/essd-16-2261-2024>, 2024.
- 829 Srikanth, A., Stokes, S., Yang, S., and Ravikumar, A.: Understanding Trends in Methane Emissions from Landfills through
830 Repeat Aerial Surveys, <https://doi.org/10.26434/chemrxiv-2025-77s45>, 21 November 2025.
- 831 Stark, B. M., Tian, K., and Krause, M. J.: Investigation of U.S. landfill GHG reporting program methane emission models,
832 *Waste Management*, 186, 86–93, <https://doi.org/10.1016/j.wasman.2024.05.037>, 2024.
- 833 Sun, H., Gurney, K. R., Dass, P., Kato, A., Gawuc, L., and Aslam, B.: Assessment of Spatial Downscaling Used in Global
834 Greenhouse Gas Emission Estimates, <https://doi.org/10.22541/essoar.177135631.13214578/v1>, 16 January 2026.
- 835 United States Geological Survey: Annual National Land Cover Database (NLCD) Collection 1 Products (ver. 1.1, June 2025),
836 <https://doi.org/10.5066/P94UXNTS>, 2025.



- 837 TIGER/Line Shapefiles from the Geography program: [https://www.census.gov/geographies/mapping-files/time-](https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html)
838 [series/geo/tiger-line-file.html](https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html).
- 839 U.S. Code: 33 USC 1375: Reports to Congress; detailed estimates and comprehensive study on costs; State estimates, 1972.
- 840 U.S. EIA: Natural Gas Interstate and Intrastate Pipelines, 2025.
- 841 Clean Watersheds Needs Survey (CWNS) – 2022 Report and Data: [https://www.epa.gov/cwns/clean-watersheds-needs-](https://www.epa.gov/cwns/clean-watersheds-needs-survey-cwns-2022-report-and-data)
842 [survey-cwns-2022-report-and-data](https://www.epa.gov/cwns/clean-watersheds-needs-survey-cwns-2022-report-and-data), last access: 21 November 2025.
- 843 Table HH-3 to Subpart HH of Part 98—Landfill Gas Collection Efficiencies: [https://www.ecfr.gov/current/title-40/appendix-](https://www.ecfr.gov/current/title-40/appendix-Table%20HH-3%20to%20Subpart%20HH%20of%20Part%2098)
844 [Table%20HH-3%20to%20Subpart%20HH%20of%20Part%2098](https://www.ecfr.gov/current/title-40/appendix-Table%20HH-3%20to%20Subpart%20HH%20of%20Part%2098), last access: 29 March 2026.
- 845 GHGRP and the U.S. Inventory of Greenhouse Gas Emissions and Sinks: [https://www.epa.gov/ghgreporting/ghgrp-and-us-](https://www.epa.gov/ghgreporting/ghgrp-and-us-inventory-greenhouse-gas-emissions-and-sinks)
846 [inventory-greenhouse-gas-emissions-and-sinks](https://www.epa.gov/ghgreporting/ghgrp-and-us-inventory-greenhouse-gas-emissions-and-sinks), last access: 10 June 2025.
- 847 U.S. Global Change Research Program (USGCRP): Stat of the Carbon Cycle Report (SOCCR), Washington, DC, USA, 2007.
- 848 U.S. Global Change Research Program (USGCRP): Second State of the Carbon Cycle Report (SOCCR2), Washington, DC,
849 USA, 2018.
- 850 Varon, D. J., Jacob, D. J., Estrada, L. A., Balasus, N., East, J. D., Pendergrass, D. C., Chen, Z., Sulprizio, M., Omara, M.,
851 Gautam, R., Barkley, Z. R., Saldaña, F. J. C., Reidy, E. K., Kamdar, H., Sherwin, E. D., Biraud, S. C., Jervis, D., Pandey, S.,
852 Worden, J. R., Bowman, K. W., Maasakkers, J. D., and Kleinberg, R. L.: Seasonality and Declining Intensity of Methane
853 Emissions from the Permian and Nearby US Oil and Gas Basins, *Environ. Sci. Technol.*, 60, 425–435,
854 <https://doi.org/10.1021/acs.est.5c08745>, 2026.
- 855 Vollrath, C., Xing, Z., Hugenholtz, C. H., Barchyn, T. E., and Winter, J.: A review of methane emissions source types,
856 characteristics, rates, and mitigation effectiveness across U.S. and Canadian cities, *Environ. Res. Lett.*, 20, 083003,
857 <https://doi.org/10.1088/1748-9326/ade9e1>, 2025.
- 858 Weller, Z. D., Hamburg, S. P., and von Fischer, J. C.: A National Estimate of Methane Leakage from Pipeline Mains in Natural
859 Gas Local Distribution Systems, *Environ. Sci. Technol.*, 54, 8958–8967, <https://doi.org/10.1021/acs.est.0c00437>, 2020.
- 860 Wickham, H. and Bryan, J.: *readxl: Read Excel Files*, 2025.
- 861 Wickham, H., François, R., Henry, L., Müller, K., and Vaughan, D.: *dplyr: A Grammar of Data Manipulation*, 2023.
- 862 Williams, J. P., Ars, S., Vogel, F., Regehr, A., and Kang, M.: Differentiating and Mitigating Methane Emissions from Fugitive
863 Leaks from Natural Gas Distribution, Historic Landfills, and Manholes in Montréal, Canada, *Environ. Sci. Technol.*, 56,
864 16686–16694, <https://doi.org/10.1021/acs.est.2c06254>, 2022.
- 865 Zeng, Z.-C., Pongetti, T., Newman, S., Oda, T., Gurney, K., Palmer, P. I., Yung, Y. L., and Sander, S. P.: Decadal decrease in
866 Los Angeles methane emissions is much smaller than bottom-up estimates, *Nat Commun.*, 14, 5353,
867 <https://doi.org/10.1038/s41467-023-40964-w>, 2023.

868

869