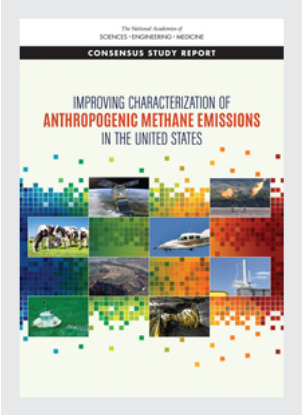

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IMPROVING CHARACTERIZATION OF **ANTHROPOGENIC METHANE EMISSIONS** IN THE UNITED STATES

Committee on Anthropogenic Methane Emissions in the United States: Improving Measurement, Monitoring, Presentation of Results, and Development of Inventories

Board on Atmospheric Sciences and Climate
Board on Agriculture and Natural Resources
Board on Earth Sciences and Resources
Board on Energy and Environmental Systems
Board on Environmental Studies and Toxicology

Division on Earth and Life Studies

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COMMITTEE ON ANTHROPOGENIC METHANE EMISSIONS IN THE UNITED STATES: IMPROVING MEASUREMENT, MONITORING, PRESENTATION OF RESULTS, AND DEVELOPMENT OF INVENTORIES

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This Consensus Study Report was reviewed in draft form by individuals chosen for their diverse perspectives and technical expertise. The purpose of this independent review is to provide candid and critical comments that will assist the National Academies of Sciences, Engineering, and Medicine in making each published report as sound as possible and to ensure that it meets the institutional standards for quality, objectivity, evidence, and responsiveness to the study charge. The review comments and draft manuscript remain confidential to protect the integrity of the deliberative process.

We thank the following individuals for their review of this report:

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Although the reviewers listed above provided many constructive comments and suggestions, they were not asked to endorse the conclusions or recommendations of this report nor did they see the final draft before its release. The review of this report was overseen by **Chris G. Whipple,** ENVIRON (retired), and **Spyros N. Pandis,** Carnegie Mellon University. They were responsible for making certain that an independent examination of this report was carried out in accordance with the standards of the National Academies and that all review comments were carefully considered.

Responsibility for the final content rests entirely with the authoring committee and the National Academies.

We thank our collaborating National Academies boards, including Elizabeth Eide (Board on Earth Sciences and Resources), John Holmes (Board on Energy and Environmental Systems), Robin Schoen (Board on Agriculture and Natural Resources), and Raymond Wassel (Board on Environmental Studies and Toxicology). We would also like to thank numerous people who provided input to the Committee throughout the study process (see the list of names in Appendix E). Additionally, we thank the following organizations and their staff for hosting the Committee on our various field trips: Anadarko Petroleum Company, Kinder Morgan, the University of California, Davis Department of Animal Science, and Southwestern Energy.

Preface

It is not the norm for scientists to describe an atmospheric gas as *intriguing*, but perhaps we should make an exception for methane, the subject of this report. Methane touches our lives in many ways, from significant climate impacts to multiple public health effects. And unlike many other important greenhouse gases, methane does not have a single dominant source, but rather a myriad of significant anthropogenic and natural sources, a situation that requires a broadly interdisciplinary approach to understanding the sources and impacts of, and controls on, this gas.

At the request of the National Aeronautics and Space Administration, National Oceanic and Atmospheric Administration, U.S. Department of Energy, and U.S. Environmental Protection Agency, the National Academies of Sciences, Engineering, and Medicine established the Committee on Anthropogenic Methane Emissions in the United States. This necessitated bringing together a group of experts in fields ranging from measurements and modeling of atmospheric gases, to petroleum and gas exploration, recovery, and distribution; enteric fermentation in farm animals; landfill gas production and gas recovery; management of animal waste on farms; coal mine gases; national and international policies on atmospheric pollutants and greenhouse gases; and environmental statistics.

We had to learn each other's languages, approaches, and views of the world of methane. Initially, like a team of blind people touching and describing different parts of an elephant, we stuck with our own parts and our own world, but quickly the team began to use a common language and describe together the greater, more complex whole that is anthropogenic atmospheric methane. Stepping out of individual comfort zones, the Committee formed a cohesive team that shared trips to a petroleum and natural gas facility and a cattle farm dedicated to quantifying methane emissions from cows and cow manure—complete with a visit to a large tent filled with barrels of decaying manure—and viewed many presentations from experts spanning the many sectors that interact with methane. It is safe to say that it was a learning experience for everyone, and the Committee hopes that this report, with its impressive breadth and depth, will be valuable to policymakers, those working in field sites across the United States, and scientists as well. The Committee hopes the report helps scientists, policy-

makers, and science communicators to more accurately convey the state of current understanding and relevance of future studies.

The Committee was charged with examining approaches to measuring, monitoring, presenting, and developing inventories of anthropogenic emissions of methane to the atmosphere. A major focus of this report is to examine the range of inventories and the approaches for developing those inventories, as well as the associated data requirements. The goal is to help federal agencies develop inventories with wider applications and improved accuracy and verifiability. Currently, the U.S. national Greenhouse Gas Inventory of methane emissions cannot be independently verified because both spatial and temporal attributes are missing, and thus expected atmospheric concentrations cannot be inferred. There are many benefits of building a strong link between atmospheric measurements of methane concentrations and methane emission inventories, including the discovery of missing sources or processes, improved confidence in the basic data that enter into decisions by companies and governments, and enhanced capability to detect trends over time. Other important elements of the charge, such as research to address key uncertainties, enhanced observing networks, and remote sensing techniques, are also considered.

In addressing its task, the Committee met five times from January to August 2017 to discuss the current understanding of U.S. anthropogenic methane emissions across dominant sectors, including key uncertainties and unmet research needs. The Committee also conducted an extensive review of the published literature on these topics, again with the aim of presenting conclusions and recommendations related to the primary U.S. anthropogenic sources of methane emissions in a common language and framework. Two of the meetings, in March and May 2017, were centered around open public workshops that gathered extensive input from scientists across academia, federal and state agencies, industry, and nongovernmental organizations, and included site visits to two operating petroleum and natural gas facilities and a livestock facility. Additional community and stakeholder input was gathered in a series of public webinars and in brief open sessions at meetings in January and July 2017.

On a final, more personal note, I would like to thank the Committee members, who gave so freely of their time and talent, and who were models of interdisciplinary listening and respect. Thanks also to the NAS staff, who organized us, melded our writings and thoughts, and were there with us in that manure-filled tent. And thanks to those who presented to the Committee and enriched this report in doing so, and to the reviewers who helped to sharpen and focus the report. The monitoring and verifica-

tion of methane emissions is a science that is, at least in part, still in early stages of development. But it is a large and very important task, one that we must take on to live sustainably and with resilience on this shared planet. The United States should take bold action now to match monitoring and measurement efforts to the importance of the task.

James W. C. White, *Chair*
Committee on Anthropogenic Methane Emissions
in the United States

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Summary

Understanding, quantifying, and tracking atmospheric methane and emissions are essential for addressing concerns and informing decisions that affect the climate, economy, and human health and safety. Atmospheric methane is a potent greenhouse gas (GHG) that contributes to global warming. While carbon dioxide is by far the dominant cause of the rise in global average temperatures, methane also plays a significant role because it absorbs more energy per unit mass than carbon dioxide does, giving it a disproportionately large effect on global radiative forcing. In addition to contributing to climate change, methane also affects human health as a precursor to ozone pollution in the lower atmosphere. Methane is also the dominant component of natural gas used as a source of energy. Its recovery via natural gas or petroleum wells and from landfills provides an economic benefit. Monitoring of methane emissions is a safety need for petroleum and natural gas exploration, recovery, and transport, as well as for coal mines and landfill sites. For petroleum and natural gas companies, methane inventories and monitoring may improve their operational efficiency and support cost-effective mitigation actions to keep natural gas within engineered systems for useful purposes.

Methane is emitted to the atmosphere by human activities across key sectors of the economy—including energy, agriculture, and waste disposal—and has several natural sources as well (Figure S.1). About 60 percent of total global methane emissions are thought to be from anthropogenic sources and about 40 percent from natural sources.[1] Livestock (through fermentation processes in their digestive systems that generate methane and manure management), rice cultivation, landfills, and sewage account for 55-57 percent of global anthropogenic emissions. Emissions from production of fossil fuels, including petroleum, natural gas, and coal, are estimated to account for 32-34 percent, with the remainder from biomass, biofuel burning, and minor industrial processes.

Current levels of methane in the atmosphere have been unprecedented over the past two millennia. As of December 2017, the global mean methane concentration was nearly triple that of preindustrial times (before 1750). Atmospheric observations show that methane levels rose sharply throughout the 20th century, leveled off around the

[1] These percentages are from top-down estimates.

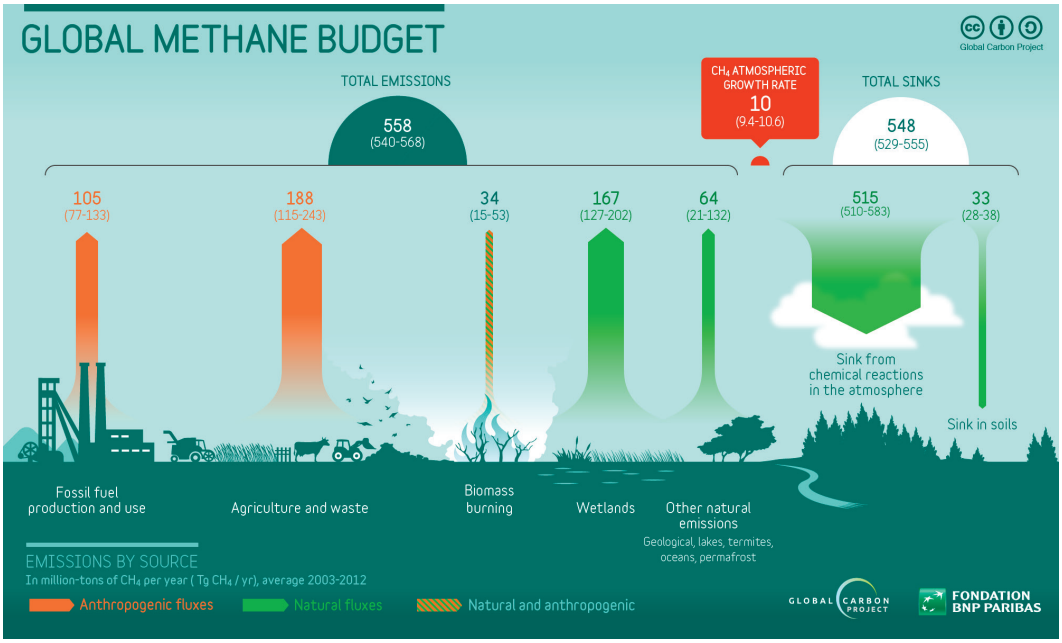


FIGURE S.1 Schematic of sources and sinks of methane globally. SOURCE: Global Carbon Project, http://www.globalcarbonproject.org/.

late 1990s, and have been steeply rising again since 2006 (Figure S.2). The underlying causes of these methane changes are not fully known.

MEASUREMENT APPROACHES

Measurements and emission estimates are made along a spectrum of spatial and temporal scales, from instantaneous measurements of methane emissions from individual emission sources to global assessments of annual methane emissions (Figure S.3; Chapter 3). There are two main approaches to estimating methane emissions. The bottom-up approach (typically used for emission inventory development) involves measuring and/or modeling emissions at the scale of individual methane emitters, such as petroleum and natural gas wells, landfills, and cattle farms, and then extrapolating those results to similar kinds of sources on regional and national scales. This approach involves use of emission factors, activity data, and process-based models. In contrast, the top-down approach estimates emissions using observations of atmospheric methane concentrations and models that account for atmospheric trans-

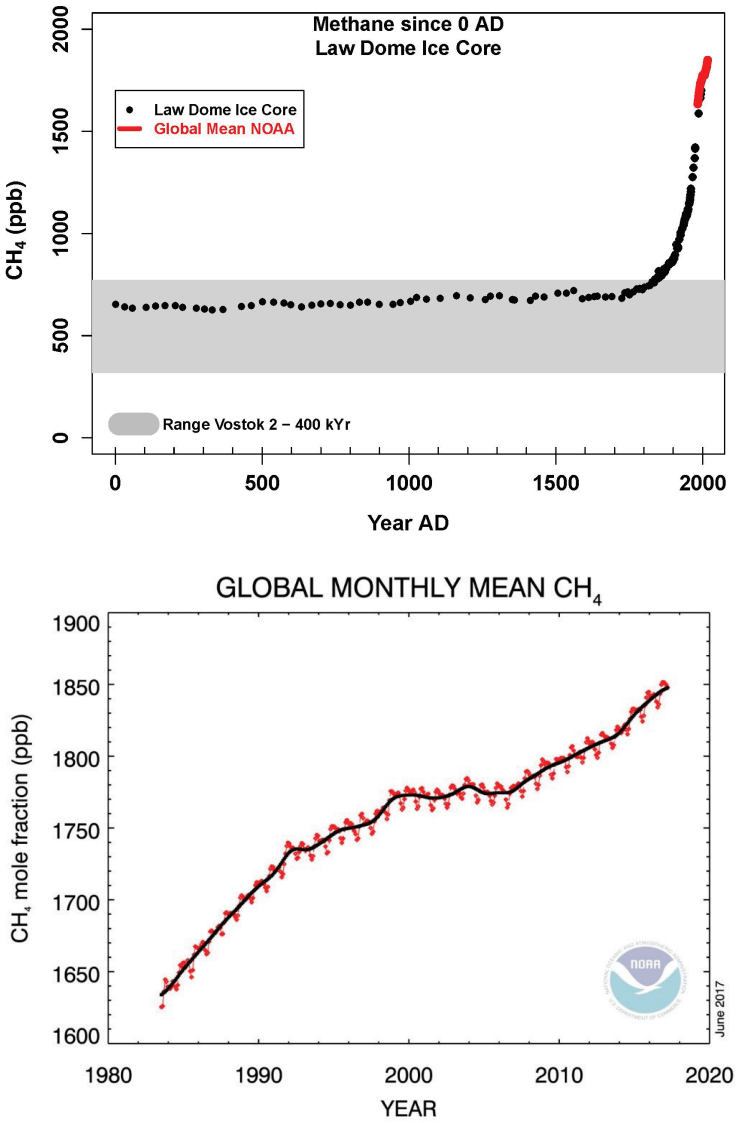


FIGURE S.2 Trends in global atmospheric methane concentration. (*Top*) Analysis of air bubbles trapped in ice cores show that current levels of methane in the atmosphere are unprecedented over the past two millennia. The grey shading shows the range of methane values from 2,000 to 400,000 years before present (data from the Vostok, Antarctica ice core). SOURCE: The Law Dome data are from Meure et al. (2006). The Vostok data are from Petit et al. (1999). (*Bottom*) Global monthly mean methane concentrations (red) from 1983 to 2017, with the running average (black). Global mean values are constructed using latitude-weighted surface sites. Uncertainties are 3 ppb or less, so error bars are very small. SOURCE: National Oceanic and Atmospheric Administration.

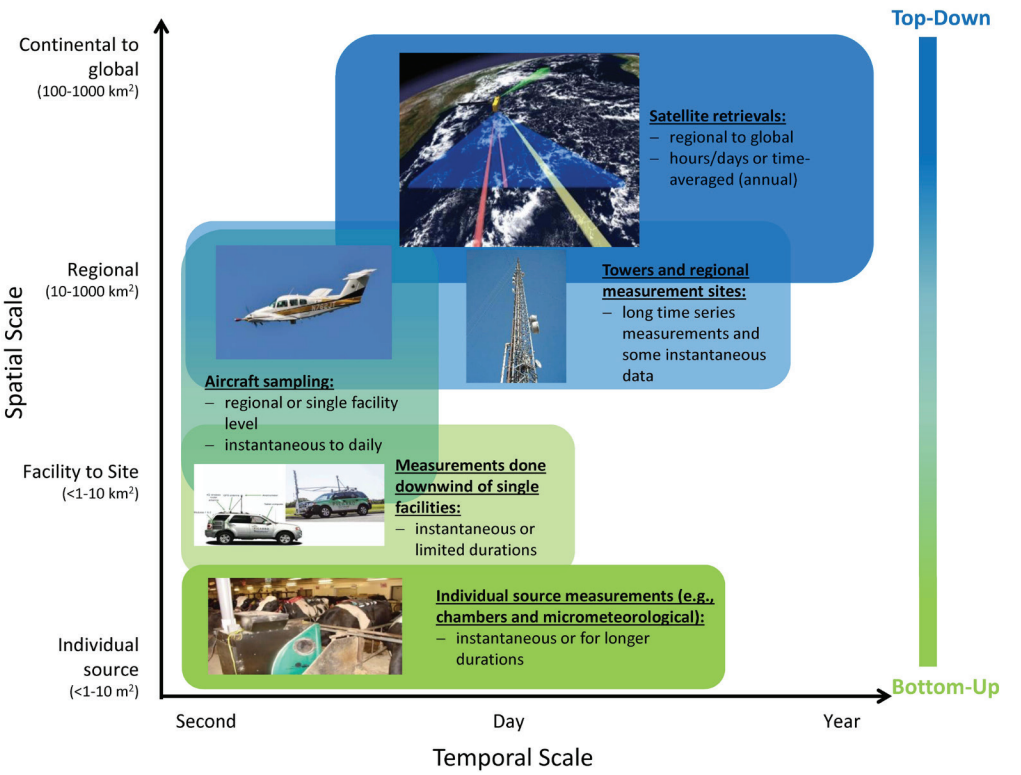


FIGURE S.3 Examples of methane measurement platforms operating across a variety of spatial and temporal scales.

port from the emitter to an observation location (e.g., tall towers and aircraft). Because atmospheric concentration measurements are combined with modeled transport to determine the forcing (emissions), the resulting top-down estimates of regional- to global-scale emissions are also referred to as "inverse models" or "inversions."

The distinction between top-down and bottom-up techniques is not always clearly defined. At intermediate spatial scales (e.g., total emissions from a large complex facility such as a natural gas processing plant, an animal feeding operation, or a large regional landfill), the emission estimation might be considered either top-down or bottom-up or both. Emissions from multiple sources or components within a facility may be aggregated like a top-down assessment. At the same time, the total facility emissions might be used to represent emissions from other similar facilities, like a bottom-up assessment.

Comparing estimates produced from top-down and bottom-up techniques has helped identify information gaps and research needs. In some cases, top-down estimates of emissions and bottom-up inventories have significantly differed, leading to reexamination of estimates from both approaches.

The National Academies of Sciences, Engineering, and Medicine established the Committee on Anthropogenic Methane Emissions in the United States in response to a request from the U.S. Environmental Protection Agency (EPA), U.S. Department of Energy (DOE), National Oceanic and Atmospheric Administration (NOAA), and the National Aeronautics and Space Administration (NASA). The Committee was charged with examining approaches to measuring, monitoring, presenting, and developing inventories of anthropogenic emissions of methane to the atmosphere (Box S.1).

The Committee's goal for this report is to summarize the current state of understanding of methane emission sources and the measurement approaches, evaluate opportunities for methodological and inventory development improvements, and inform future research agendas of various U.S. agencies, including NOAA, the EPA, the DOE, NASA, the U.S. Department of Agriculture, and the National Science Foundation. Fi-

BOX S.1
STATEMENT OF TASK

An ad hoc Committee will examine approaches to measuring, monitoring, presenting, and developing inventories of anthropogenic emissions of methane to the atmosphere. The geographic scope of this study is limited to the United States, although much of the Committee's report could be relevant internationally. Specifically, the Committee will

1. discuss how methane emission measurements, monitoring data, and inventories are used and usable for managing emissions, scientific research, and other purposes;
2. assess scientific understanding with respect to published inventories of U.S. anthropogenic methane emissions, including estimates of current emissions, recent trends, and projections of future emissions;
3. describe and evaluate approaches used to measure and monitor methane emissions;
4. recommend how to present results of methane emission studies to facilitate comparisons among studies and to ensure results are useful for policymaking;
5. describe and evaluate approaches used to develop inventories of past, present, and future methane emissions;
6. recommend best available approaches for addressing key uncertainties, areas of incomplete understanding, and technical challenges in developing methane inventories; and
7. recommend research needed to improve methane emission measurement, monitoring, and inventory development.

nally, the Committee believes that the recommendations in this report will enable the methane part of the U.S. Greenhouse Gas Inventory (GHGI)[2] to truly be transparent, consistent, comparable, complete, accurate, and widely applicable to science needs and policy applications.

INVENTORIES AND CURRENT U.S. METHANE EMISSIONS

Emission trends resulting from human activities can be tracked over time by constructing inventories that link emissions to key economic sectors. Inventories are developed using a combination of activity data (e.g., the number of emitters) and emission factors (e.g., the amount of methane per emitter) and/or sophisticated models, at various spatial and temporal scales. Inventories are developed for specific purposes and, in combination with observations of GHGs in the atmosphere, help policymakers assess the effectiveness of new policy initiatives (Chapter 2).

The GHGI is a national, annual inventory and is the main repository of emission information in the United States. The EPA is the lead agency for compiling emission data and coordinating development of the GHGI with input from other federal agencies, state agencies, research and academic institutions, nongovernmental organizations, industry trade associations and individual companies, and other experts. The GHGI is currently developed using methods from the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) and submitted annually to the United Nations Framework Convention on Climate Change (UNFCCC). These guidelines are highly standardized and carefully designed to be achievable by all nations of the world using tiered approaches. Other types of inventories have also been developed, such as state-level and gridded inventories with finer spatial and temporal resolution (e.g., $0.1° \times 0.1°$ grid with monthly resolution) than the GHGI's national annual resolution; see Figure S.4.[3]

According to the GHGI, the two largest source categories of U.S. anthropogenic methane emissions are enteric fermentation in domestic ruminant animals (such as cattle), and petroleum and natural gas systems (Figure S.5). Landfills, livestock manure management, and coal-mining operations are also significant sources. This report focuses on these predominant sources of U.S. anthropogenic emissions which are responsible for almost 94 percent of the total estimated U.S. anthropogenic methane emissions

[2] The GHGI reports anthropogenic emissions of seven gases or classes of gases (CO_2, CH_4, N_2O, hydrofluorocarbons, perfluorocarbons, SF_6, and NF_3), but the primary focus of this report is on the methane portion of the GHGI. In this report, when the Committee refers to the GHGI, it is referring to the methane portion.

[3] $0.1° \times 0.1°$ is roughly 100 km^2.

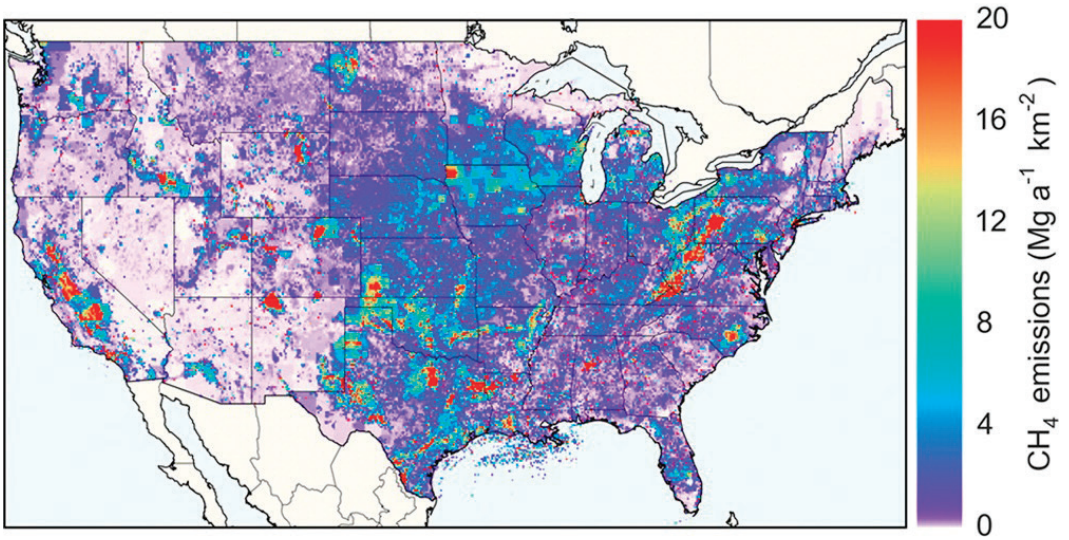


FIGURE S.4 Spatially and temporally resolved gridded inventory of the 2012 U.S. GHGI.
SOURCE: Maasakkers et al., 2016.

(excluding land use, land use change, and forestry[4]). Smaller U.S. sources—wastewater, rice cultivation, and other industrial and agricultural sources—are not discussed in detail in this report. In addition, some natural sources of methane such as wetlands and natural geological sources may be affected by human activities; these were not considered in detail by the Committee.

MEETING THE CHALLENGES OF CHARACTERIZING METHANE EMISSIONS

Recent advances in atmospheric observations and facility-scale measurements make it possible to significantly improve estimates of anthropogenic methane emissions. Top-down and bottom-up approaches provide complementary information about methane emissions (Table S.1). Top-down estimates include emissions from all sources (both natural and anthropogenic), but may have difficulty in attributing emissions to specific sources or source categories. In contrast, bottom-up methods provide information about the magnitudes and patterns of emissions from specific sources.

[4] Methane emissions resulting from the use and conversion of land use categories in the United States, for example, managed peatlands, coastal wetlands, and forest fires.

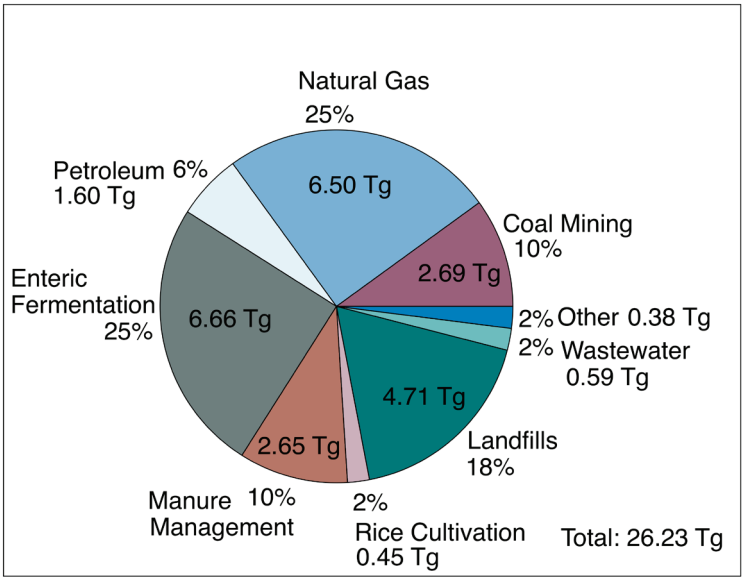


FIGURE S.5 Anthropogenic sources of methane emissions in the United States in 2015 according to the GHGI. "Other" includes other industrial and agricultural sources. SOURCE: EPA, 2017b.

TABLE S.1 Comparison of Top-Down and Bottom-Up Approaches to Estimating Methane Emissions

	Top-Down Data	**Bottom-Up Data and Inventories**
Spatial scale	Facility to global	Individual site level to global
Temporal scale	Instantaneous to annual or multiyear averages	Generally reported as annual averages for inventory purposes from limited time duration data collected at various temporal scales
Source attribution	Involves use of models and assumptions as well as molecular and isotopic tracers	Calculated from source-specific activity data
Potential for missing sources	Measurements reflect all sources that contribute to observed atmospheric concentrations	May not account for all sources in a given region

However, bottom-up inventories of emissions may not account for all sources, and the methods may have uncertain or inaccurate activity data and emission factors. The measurements used in both top-down and bottom-up approaches can also be spatially and temporally sparse. For example, when aircraft are used to obtain data, the flights are typically limited to just a few days, and the measurements are generally done in the midday when the atmosphere is well mixed. These measurements will not capture ways that these emissions differ at other times of day, or in other seasons, which limits direct comparisons with annual methane inventories such as the GHGI.

Building a strong link between atmospheric measurements of methane concentrations and methane emission inventories has many benefits, including

- more accurate estimates of methane emissions,
- better attribution of emissions to specific processes/sources,
- discovery of missing sources or processes,
- detection of trends in sectoral emissions,
- improved confidence in the basic data that enter into decisions by companies and governments, and
- better capability to detect trends over time.

This interlinking of top-down and bottom-up approaches involves strengthening both approaches, as well as developing a mechanism to integrate across these approaches[5] (Figure S.6).

Atmospheric Methane Observations and Modeling

Atmospheric observations are the foundation for understanding changes in methane concentrations. Long-term observations, together with atmospheric models that estimate methane emissions, are critical for detecting large-scale trends in methane emissions. Adequate observational coverage in space and over time is required to constrain emission estimates using inverse modeling at global, national, or regional scales. However, the current surface network is sparse and thus not able to capture the full spatial and temporal variability of methane emissions (Chapter 3). Until recently, there were only about 100 surface sites globally that measure atmospheric methane; many of these sites only measure weekly, with only a small number measuring continuously. New sites have been added, largely to support regional studies of major sources (e.g.,

[5] The Committee identifies agencies to implement the recommendations where possible, but recognizes that the list it provides may not be exhaustive, and that the agencies should have the flexibility to parse out the tasks as they think will best serve the interests and missions of their agencies and the country.

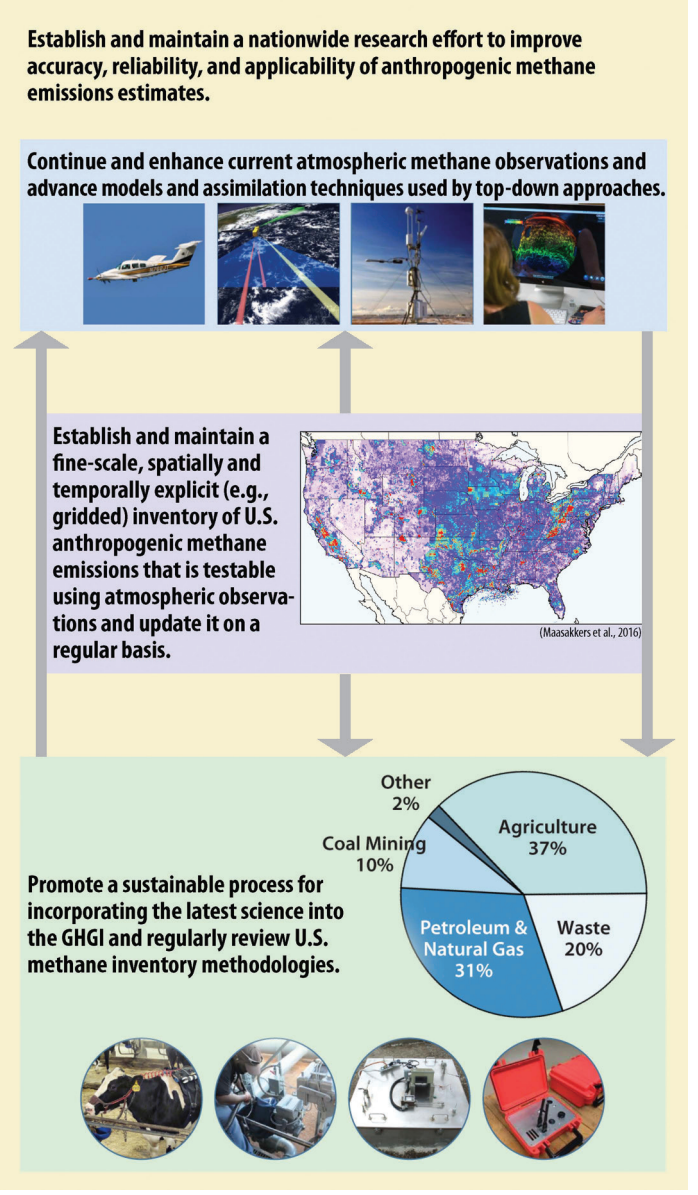


FIGURE S.6 Schematic summarizing the four major recommendations for improving characterization of anthropogenic methane emissions in the United States.

urban areas, petroleum and natural gas basins). Many of the original surface network sites have been selected to represent the background atmospheric concentrations. Thus they are remote from strong local sources, meaning that urban and regional sources are inadequately resolved by inverse models.

Uncertainties in current top-down methane emission estimates at global and continental scales are increased by sparse surface observation networks that do not capture the full spatial variability in emissions. The addition of new continuous observation sites offers the opportunity to develop strategic linkages between top-down and bottom-up approaches intended to assess, improve, and support the bottom-up method, so that extrapolations inherent in bottom-up inventories can be trusted. Studies are needed to identify measurements to close observational gaps that result in current ambiguities of our methane budget (sources and sinks), including observation system simulation experiments and intensive field experiments (Chapter 4).

In addition to investing in comprehensive monitoring of atmospheric methane and associated species, improvements to our ability to accurately simulate these data in models should be undertaken. **At all scales, uncertainties in top-down methane emission estimates arise due to uncertainties in atmospheric transport models.** A major source of variability among different top-down estimates is modeled atmospheric transport, which can change the emission source apportionment among regions. In particular, it is challenging to use current global models with relatively coarse spatial resolution to represent in situ point measurements. **Current global and regional atmospheric transport models being used for atmospheric inversions are likely unable to accurately represent small-scale processes. As a result, it is difficult for these models to accurately simulate observed methane at continental sites. Developing higher spatial and temporal resolution atmospheric transport models and approaches for evaluating these models would likely improve transportation simulations.**

More accurate transport models will likely require more computationally intensive models with finer spatial and temporal resolution.

In addition, **high-quality, long-term, multiscale surface- and space-based data records are necessary for quantifying and tracking changes in methane emissions on regional scales.** The existing U.S. and global background methane concentration observational networks need to be continued, with expansion of measurements across multiple scales. Multiscale observational strategies (e.g., aircraft, surface, tower, and satellite remote sensing) supply complementary information and can provide emission flux estimates from the facility through the local and regional scales, which can be compared with gridded inventories.

One of the primary challenges in using top-down analyses to estimate emissions is the difficulty of attributing emissions to specific sources. Measuring a suite of tracer species can provide additional information on the attribution of emissions and observations and should be expanded. Related species used to obtain insight into underlying source processes can include carbon monoxide, ethane, and multiple substituted (clumped) methane isotopes ($^{13}CH_4$, CH_3D, $^{14}CH_4$) (Chapter 4).

Recommendation 1: The National Oceanic and Atmospheric Administration and the National Aeronautics and Space Administration should continue and enhance current atmospheric methane observations and advance models and assimilation techniques used by top-down approaches.

Fine-Scale Spatially and Temporally Resolved Gridded Methane Emission Inventories

The national, annual GHGI has been formulated to meet the reporting requirements of the UNFCCC and provides an adequate resolution for evaluating long-term national emission trends. However, the goals for measuring and monitoring methane in the United States are broader than the UNFCCC objectives for which the GHGI was originally developed.

The publicly available GHGI is used by diverse communities for a variety of scientific and policy purposes. As the most frequently updated comprehensive inventory of anthropogenic methane emissions in the United States, the GHGI has increasingly been used for purposes for which it was not initially designed, including comparisons with top-down estimates of methane emissions in specific regions at specific times, thus attempting to merge and compare information collected at different spatial and temporal scales.

It is very challenging to test the GHGI against top-down estimates (i.e., verify the GHGI) owing to its high degree of spatial (national) and temporal (annual) aggregation, and thus it can be used to address only a limited range of science questions and policy issues. In a country the size of the United States, with many climate regimes and multiple emission source types mixed on the landscape, it is impractical to provide a meaningful check on the national-scale GHGI using top-down atmospheric measurements. Hence, the GHGI as currently configured cannot be tested by independent means in terms of the total emissions. However, verifiability is the bedrock upon which inventories should be built if they are to be widely applicable to policy needs. A new, spatially disaggregated (gridded) GHGI, with temporal resolution consistent with the temporal resolution of top-down observations, would be verifiable at regional scales,

gaining accuracy and allowing for a wider range of applications beyond meeting the reporting requirement to the UNFCCC.

Finer-scale, gridded inventories of national methane emissions provide significant value to the scientific community to better characterize and compare inventories and test against top-down emission estimates. Further, gridded inventories have the potential to inform mitigation action at spatial scales relevant to policymakers and industry. Improvements in the GHGI and state-level inventories will also support improvements in finer-scale gridded inventories.

To be most useful, a gridded inventory should be consistent with the GHGI for integrated total emissions per source and have sufficient documentation to allow the scientific and policy communities interested in regional methane emissions to adapt the inventory to meet their needs. The spatial and temporal resolution should be at as fine a scale as possible (e.g., $0.1° \times 0.1°$ or finer spatial resolution and monthly or finer temporal resolution), based on the data used to generate the inventory. Since some expected uses of the gridded inventory (e.g., comparison with top-down snapshots of diurnal emissions) require finer temporal resolution than the inventory would normally address, process-based field-validated models are also required to provide guidance on fine-scale temporal allocation of emissions.

Both the GHGI and the recommended gridded inventory should meet needs of different users and therefore should be viewed as complementary to jointly increase overall knowledge.

Recommendation 2: The U.S. Environmental Protection Agency in collaboration with the scientific research community, the U.S. Department of Energy, the National Oceanic and Atmospheric Administration, the U.S. Department of Agriculture, and the National Aeronautics and Space Administration should establish and maintain a fine-scale, spatially and temporally explicit (e.g., gridded) inventory of U.S. anthropogenic methane emissions that is testable using atmospheric observations and update it on a regular basis.

Methane Emission Inventory Development

Updating Inventory Approaches for Specific Sources

Targeted improvements to the GHGI (bottom-up approach) are needed, and as research evolves, there should be a sustainable process to incorporate the latest science into the GHGI. A significant source of uncertainty in estimating emissions

from various sectors is the scarcity of activity data. For example, there are numerous emission sources from petroleum and natural gas systems, yet relatively sparse activity data on which to develop estimates. In the agriculture sector, there is uncertainty about animal feed intake—particularly on pasture—and feed composition and a lack of data on the distribution of manure in different management systems. For landfills, activity data are uncertain for the mass of annual landfilled waste as well as emissions that may not be closely related to the mass of landfilled waste.

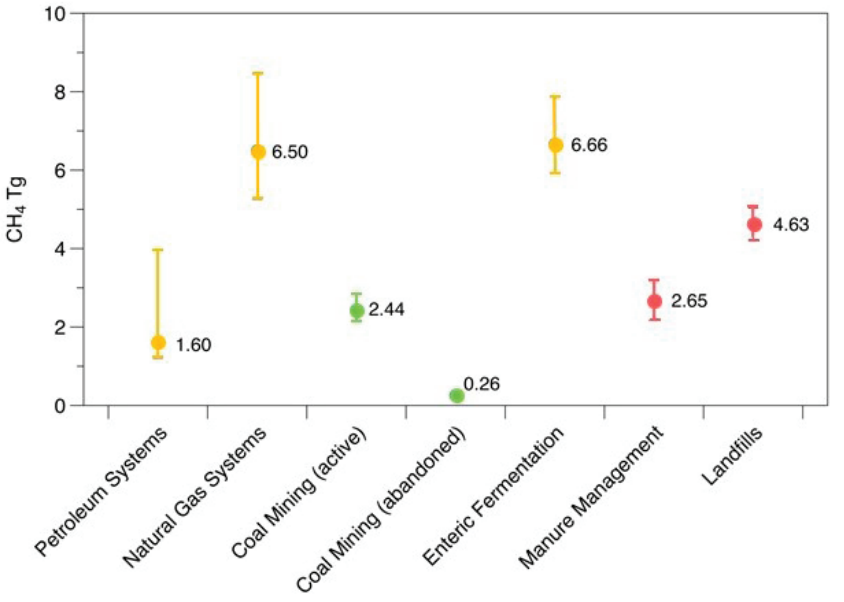
Inventory methodologies should be evolutionary to be consistent with the latest science and process-based models. However, as of 2018, IPCC Guidelines on inventory methodologies had not been updated since 2006.[6] Thus, they predate the last decade of field measurements and modeling. For example, for petroleum and natural gas, many of the emission factors that are used in developing methane emission inventories rely on a comprehensive study conducted by the Gas Research Institute and the EPA in the 1990s. For manure management, most of the equations in the IPCC (2006) methodologies were developed using data that are now more than 30 years old. The current methodology for landfills relies on 20 to 40-year-old assumptions and excludes the two major drivers for emissions: site-specific climate and operational factors.

Updating of emission estimation methodologies should prioritize inventory categories with the greatest uncertainties. The research literature for individual source categories typically indicates larger uncertainties than those reported in the GHGI. The Committee evaluated the reliability of the uncertainty estimates reported in the GHGI (Figure S.7; Chapter 4).

Each source category has a wide range of uncertainties for methane emission estimates; sparse activity data and limited emission measurements are the primary reasons for uncertainties in most source categories. Reducing these uncertainties will require collecting and reporting activity and emission data in a consistent and comprehensive manner and will be challenging because of cost, time, and technical limitations.

Priority anthropogenic sources for future research on methodological and data improvements are petroleum and natural gas systems, enteric fermentation, manure management, and landfills because of these sources' high uncertainties and/or overall high contribution to total anthropogenic U.S. methane emissions.

[6] The IPCC is in the process of developing a report to refine the 2006 IPCC Guidelines. This report is expected to be released in 2019.



Confidence Level	Description	Source
High	Uncertainty interval calculation uses available data and accounts for current known uncertainties. Uncertainty range would be reduced with increased measurement data. Uncertainty estimate can be improved by updates reflecting additional data and evolving scientific consensus of evaluation methodology.	Coal mining (active) Coal mining (abandoned)
Medium	Uncertainty interval calculation partially reflects known uncertainties, and is partially based on available measurement data. Further research identifying and quantifying uncertainties would improve uncertainty quantification.	Petroleum systems Natural gas systems Enteric fermentation
Low	Uncertainty-interval calculation does not reflect current known uncertainties, and there are insufficient measurement data from which to base calculations. Fundamental research identifying and quantifying uncertainties is needed.	Manure management Landfills

FIGURE S.7 Comparison of mean national methane emission estimates and their uncertainty ranges, as reported by the U.S. Environmental Protection Agency in the Greenhouse Gas Inventory for year 2015 (EPA, 2017b), indicated by vertical lines, with ranges representing variations of 95 percent confidence intervals as determined by the EPA, for major source categories. A Committee-assigned confidence level (CL) for each uncertainty value is also provided, with the descriptions and assigned source categories given for the CLs.

Missing ("Unaccounted-for") Methane Emissions and High-Emitting Sources

With numerous possible sources of methane emissions, bottom-up inventories can overlook some sources. Such "unaccounted-for" sources can include (1) known sources that may not be fully accounted for in inventories and (2) previously unknown sources that have been unrecognized because of their scale, complexity of attribution, or other factors and are not currently incorporated in the GHGI. An example of the latter includes previously unrecognized microbial coal-bed methane from active mining in the Four Corners region. Examples of the former include sources in certain natural gas end-use sectors such as residential and commercial operations, electric power plants, refineries, and high-emitting sources. **Identifying and quantifying unaccounted-for emissions through multiscale measurement campaigns is critical to addressing uncertainties in emission inventories and to improve understanding of methane emissions in general. Given that observations of unaccounted-for methane emissions are limited, any extrapolation to national totals needs to be done with caution.**

High-emitting sources (also known as "fat tails" or "super-emitters") are a small number of sites or equipment that dominate emissions and are a common element in many of the recent methane emission studies on natural gas. Some measurements of high emissions may be due to the size of the facility; however, the root causes of high-emitting sources are not well understood. Identifying and quantifying high-emitting sources remain major challenges. Incorporating high-emitting sources into the GHGI is also difficult because the GHGI is meant to represent annual average estimates of methane emissions, and high-emitting sources have significant temporal variability. For petroleum and natural gas, factors that cause certain subpopulations to become high emitters are not well known. Research is needed to gain a mechanistic understanding of high-emitting sources and establish appropriate estimation methods. Conducting campaigns in coordination with owners and operators of the facilities within the regions would help ensure the availability of contemporaneous information concerning operations.

A Process for Improving the GHGI

It can be a challenge to take the wealth of methane studies in the last decade and incorporate their results into the GHGI to improve the estimates. Additionally, the development of the Greenhouse Gas Reporting Program, a facility-level reporting program for larger GHG emitters from 41 industries across the United States, has provided a new source of emission information to improve the emission estimates for many key sectors.

In recent years, the EPA has periodically convened stakeholder webinars and workshops to discuss possible forthcoming changes to the methane GHGI, which provide an opportunity for any interested individual or stakeholder to offer feedback. In addition to these relatively informal workshops, **an advisory group could help guide how new science should be incorporated into improving the methane portion of the Greenhouse Gas Inventory. Such an advisory group could be facilitated by the EPA and NOAA and composed of experts from academia, industry, policy-making, other federal agencies, and nongovernmental organizations. Its goal would be to facilitate timely improvements in activity data and enhance characterization of emission sources and quantities.**

Such an advisory group could consider questions such as

- Is there sufficient new information available to justify updating an existing emission factor or activity data?
- What other types of research efforts may be necessary before including data in the methane inventory?
- Do the data reported using various aggregation levels, such as facility versus component level or information generated by the top-down networks, suggest that current methods should be updated?
- In general, will the new information reduce the uncertainty of the estimates?

Any changes to the GHGI resulting from these activities should be transparently described and clearly communicated to the public.

Recommendation 3: The U.S. Environmental Protection Agency, U.S. Department of Energy, National Oceanic and Atmospheric Administration, and U.S. Department of Agriculture should promote a sustainable process for incorporating the latest science into the U.S. Greenhouse Gas Inventory and regularly review U.S. methane inventory methodologies.

Research for Improving Characterization of Anthropogenic Methane Emissions

Improvements in the accuracy and precision of methane emission estimates will be maximized through the complementary use of both top-down and bottom-up measurements and linkage to field-validated process-based models at appropriate scales. While working toward this goal, consistency in measurement and modeling approaches and development of study protocols need to be transparent to the researchers involved in methane emission measurements. Furthermore, the methods

utilized for quantifying methane emissions, and the accuracy of those measurement methods, is not always clearly communicated to policymakers.

The complementary information provided by top-down and bottom-up methods offers the opportunity to combine their strengths in coordinated measurements. However, these coordinated measurements are challenging due to the different types of data they provide. Only a limited number of highly coordinated campaigns have been performed at square kilometer scales that utilize both types of methodological approaches, mainly in regions dominated by petroleum and natural gas emissions.

Coordinated, contemporaneous top-down and bottom-up measurement campaigns, conducted in a variety of source regions for anthropogenic methane emissions, are crucial for identifying knowledge gaps and prioritizing emission inventory improvements. Careful evaluation of such data for use in national methane inventories is necessary to ensure representativeness of annual average assessments.

When presenting results on methane emissions, clarity on the scope and spatial and temporal boundaries is essential to enable potential users of the data to interpret the results. Knowing the technical coverage (types of processes covered) informs understanding of the completeness and applicability of the results of a study. Clarity on the spatial and temporal resolution is important because emissions are not uniformly distributed across the United States or over time, and without clear understanding of the boundaries used for a study, there is a risk of misinterpretation of the results.

Recommendation 4: The United States should establish and maintain a nationwide research effort to improve accuracy, reliability, and applicability of anthropogenic methane emission estimates at scales ranging from individual facilities to gridded regional/national estimates.

Such a national research effort should include results from atmospheric observations, sustained spatial and temporal characterization of methane emissions for key sectors in the United States, and improvements in estimation techniques and validated process-based models. Results from such efforts could better support attribution of emissions to specific sectors or processes and trend detection.

The improved monitoring network (Recommendation 1) and recommended gridded national inventory (Recommendation 2) are necessary to conduct comparisons at the finest temporal and spatial scales that the data, models, and site access allow. The comparisons will enable stakeholders and the public to identify deficiencies in the gridded

inventory as well as the atmospheric observations, catalyzing Recommendation 3 for continual improvement in all aspects of methane inventory development. The improvements should be informed by a national research effort (Recommendation 4) for which the guiding goal should be (1) better quantification and attribution of methane emission rates and trends over time and (2) identification of knowledge gaps and guidance for resolving those gaps.

CHAPTER ONE

Introduction

Methane is emitted to the atmosphere from diverse anthropogenic sources in many key U.S. economic sectors, including energy, agriculture, and waste. Understanding and managing methane emissions requires a broad monitoring, modeling, and regulatory approach, with economic, health, and safety co-benefits that go far beyond understanding the role of methane in the Earth's climate system. This is a significant challenge; methane is readily transported, combusted as a fuel, chemically oxidized in the atmosphere, and biologically oxidized via both aerobic and anaerobic pathways.

WHY MONITOR, MEASURE, AND TRACK ATMOSPHERIC METHANE AND METHANE EMISSIONS?

The effects of increasing concentrations of global methane are diverse and profound. Understanding, quantifying, and tracking atmospheric methane and emissions of methane are essential for addressing concerns and informing decisions that affect the climate, economy, and human health and safety.

Climate Change

Global average temperatures have risen by 1.25°C (2.25°F) over the past century, with a significant contribution from increases in greenhouse gases (GHGs) and their associated radiative forcing (Hansen et al., 1997). While carbon dioxide is by far the dominant cause of this increase (Figure 1.1), methane also plays a significant role that is made more complex by the diversity of methane sources. Even though it has much lower atmospheric abundance than carbon dioxide, methane has a disproportionately large effect on global radiative forcing because it absorbs more energy per unit mass than carbon dioxide does, making it a powerful greenhouse gas. Although methane is a potent GHG, its relatively short lifetime in the atmosphere (9-10 years [Myhre et al., 2013]) compared to carbon dioxide means that reducing human-driven methane emissions now may reduce some near-term impacts of climate change. Furthermore, oxidation of methane provides almost half of the water vapor in the middle stratosphere, which acts as an important factor in the loss of stratospheric ozone, and as a source of radiative forcing of climate.

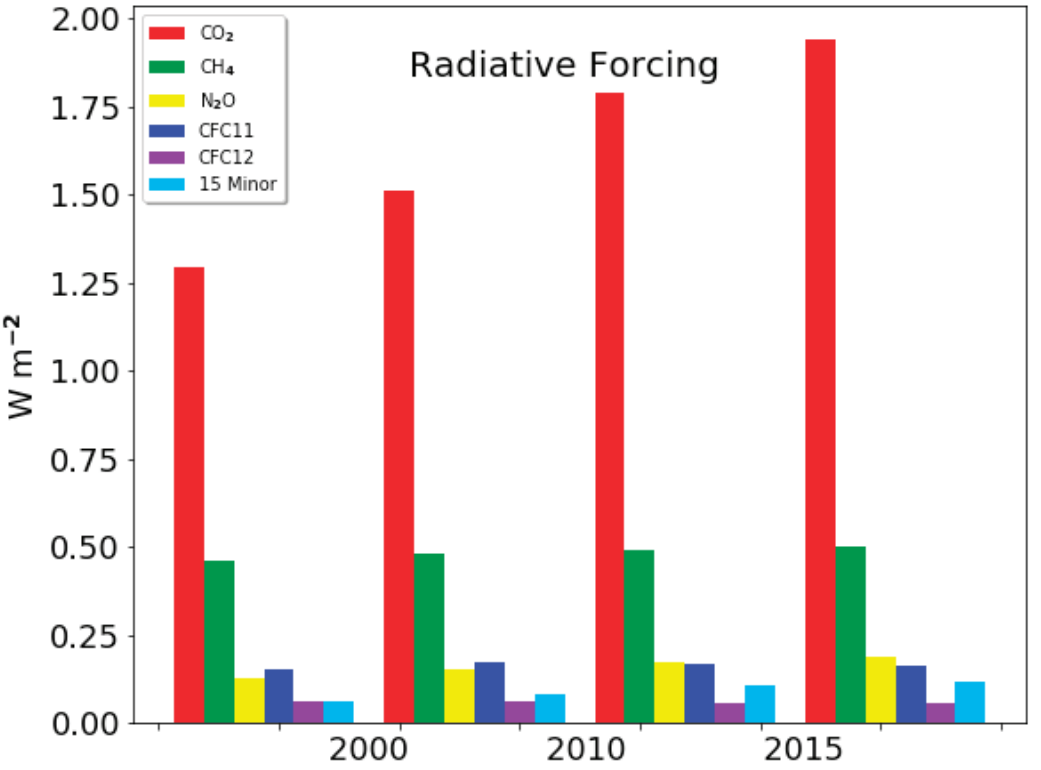


FIGURE 1.1 Radiative forcing (relative to 1750) due to major greenhouses gases (GHGs). The 15 minor GHGs include CFC-113; CCl_4; CH_3CCl_3; HCFCs 22, 141b, and 142b; HFCs 134a, 152a, 23, 143a, and 125; SF_6; and halons 1211, 1301, and 2402. Radiative forcing calculations are based on the National Oceanic and Atmospheric Administration Global Monitoring Division measurements of GHGs. This figure does not include indirect effects associated with increased ozone and water vapor. If such indirect effects are included, the positive radiative forcing attributed to methane is about 40 percent of the total positive radiative forcing (Myhre et al., 2013). Recent studies indicate that methane radiative forcing may be even higher (Etminan et al., 2016).

If GHG concentrations and associated global temperature continue to increase, widespread impacts on global climate are expected to occur, and some are already beginning to transpire (Cubasch et al., 2013; USGCRP, 2017). These impacts are expected to have broad implications for global food production, human health, and the habitability of coastal and arid regions. Being able to accurately quantify methane emissions and attribute emissions to specific sources is a critical component of addressing climate change.

Changes in the carbon cycle in response to anthropogenic methane emissions will likely be a reinforcing feedback that increases warming. The magnitude of the projected feedback is uncertain. There are many possible processes that can result in carbon cycle feedbacks that lead to both increases and reductions in warming. A warmer climate can lead to increased fires and droughts, including methane emissions from smoldering fires. Thawing frozen waterlogged soils in the Arctic will also lead to increases in methane (Isaksen et al., 2014). Many recent studies have explored the possible feedback between wetland methane emissions and climate change over the next century and have found the potential for significant increases as the climate warms (e.g., Zhang et al., 2017).

Climate Mitigation Policy

Accurate methane inventories enable policymakers to undertake science-based policy decisions and evaluate the effectiveness of mitigation policies. Because of methane's short atmospheric lifetimes relative to carbon dioxide, it has been proposed as a target for emission reduction in order to prevent the worst effects of climate change. Reduction of methane emissions, along with reductions in black carbon emissions, could reduce global mean warming by about a half a degree by 2050, with additional benefits for air quality and agricultural productivity (Shindell et al., 2012). However, reductions in methane (and other short-lived climate forcers) have short-term benefits and are not significantly beneficial for limiting maximum warming over the long term (i.e., beyond 2050; Rogelj et al., 2014).

Human Health and Safety

Increases in global methane since 1800 are believed to have led to higher levels of global tropospheric (or ground-level) ozone worldwide (Fiore et al., 2008). This pollutant reduces air quality and increases respiratory illnesses and mortality (West et al., 2006). Higher levels of ozone also lead to increases in radiative forcing and may reduce crop yields (e.g., Myhre et al., 2013; Shindell et al., 2012; West et al., 2006). There is an approximately linear relation between anthropogenic methane emissions and tropospheric ozone such that for every teragram per year decrease in methane emissions, ozone was found to decrease by 11-15 ppt (Fiore et al., 2008). Protection of human health and safety are also provided by monitoring methane where concentrations can be flammable and dangerous (e.g., in mines and from landfill sites).

Economic Factors

Monitoring for site-specific methane emissions in the energy, agriculture, and waste sectors can inform practices and maintenance that reduce losses or enhance recovery of a valuable product. Measuring methane emissions in sectors with relatively high emissions can also help to identify where the installation of capture and utilization technologies could be advantageous. For example, the International Energy Agency estimates that 40-50 percent of the current global petroleum and natural gas methane emissions could be mitigated at positive net present values (IEA, 2017). Methane inventories and monitoring may improve petroleum and natural gas companies' operational efficiency and support cost-effective mitigation actions to keep the product (natural gas) within the systems for eventual useful end-use purposes. Facility- or company-specific methane emission inventories are integral to corporate sustainability reporting. Methane emission inventories help assess the impact of mitigation strategies and may also help investors benchmark various companies and make informed investment and risk management decisions.

METHANE IN THE ATMOSPHERE

Analysis of air bubbles trapped in ice cores shows that current levels of methane in the atmosphere are unprecedented over the past two millennia (Loulergue et al., 2008). As of December 2017, the global mean methane concentration was nearly triple that of preindustrial times (before around 1750). Observations show that methane concentration levels rose sharply throughout the 20th century, then leveled off for a period of time beginning around 2000, and have again been steeply rising since 2006 (Figure 1.2). The underlying causes of these methane changes are not fully known. Global observations of the methane isotope $^{13}CH_4$ suggest that the recent growth in global methane is dominated by microbial sources, such as wetlands or agriculture (rice and livestock), and waste (Nisbet et al., 2016; Schaefer et al., 2016). However, it is difficult to reconcile the idea that agriculture is behind the recent methane growth with data that show only modest increases in the global livestock population.[1] A distinct possibility is that natural methane emissions are changing in response to global climate change, even though some studies based on space-based observations of inundated areas have suggested declines in wetland area (Poulter et al., 2017). Other studies suggest that at least some of the observed changes in the methane growth rate may be attributable to decreases in the abundance of hydroxyl radicals, which react with and break down methane, acting as the largest sink of atmospheric methane (Rigby et al., 2017; Turner et al., 2017). These studies have argued that isotope-

[1] See http://www.fao.org/faostat/en/#home.

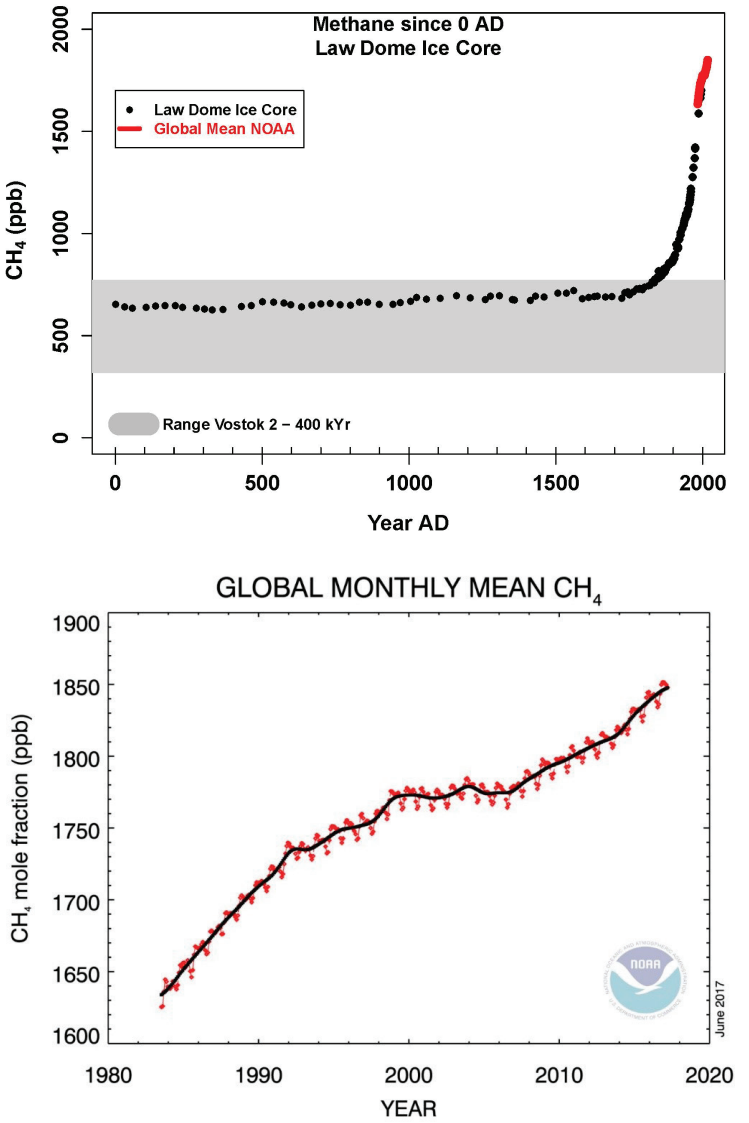


FIGURE 1.2 Trends in global atmospheric methane concentration. (*Top*) Analysis of air bubbles trapped in ice cores shows that current levels of atmospheric methane are unprecedented over the past two millennia. Atmospheric methane has increased threefold since preindustrial times. The gray shading shows the range of methane values from 2,000 to 400,000 years before present (data from the Vostok, Antarctica ice core). SOURCE: The Law Dome data are from Meure et al. (2006). The Vostok data are from Petit et al. (1999). (*Bottom*) Global monthly mean methane concentrations (red) from 1983 to 2017, with the running average (black). Global mean values are constructed using latitude-weighted surface sites. Uncertainties are 3 ppb or less, and so error bars are very small. SOURCE: National Oceanic and Atmospheric Administration.

based data are not a strong constraint on the global methane budget, in conflict with Schwietzke et al. (2016).

METHANE INVENTORIES

The U. S. Greenhouse Gas Inventory (GHGI) is the official national GHG emission information for the United States, and therefore assessment of the methods to develop the GHGI[2] is central to this report. The GHGI has been formulated to meet the reporting requirements of the United Nations Framework Convention on Climate Change and therefore the preparation of the GHGI follows the required protocols, which in turn are based on the three-tiered approaches of the Intergovernmental Panel on Climate Change (see Chapter 2). It is a bottom-up inventory, built by summing emissions from individual sources that are estimated using emission factors and activity counts. Emissions are reported at the national scale, rather than spatially distributed over the United States. The prescribed methods, particularly for non–carbon dioxide (CO_2) gases such as methane, mostly predate the last decade of field measurements and modeling, a period during which understanding of methane emissions and sources has significantly advanced.

Other types of inventories have emerged recently, such as inventory reports summarizing emissions from certain major emitting sources under the Greenhouse Gas Reporting Program regulations, the spatially explicit (gridded) inventory for methane developed by Maasakkers et al. (2016) or for livestock emissions (Hristov et al., 2017), and a process-based inventory methodology for site-specific landfill emissions that has been applied to California (Spokas et al., 2011, 2015).

SOURCES OF METHANE EMISSIONS

Current estimates place global annual emissions of methane at about 560 Tg methane yr^{-1} (Saunois et al., 2016), based in part on our best understanding of the global hydroxyl (OH) concentrations that determine removal rates from the atmosphere. Methane comes from numerous anthropogenic activities and natural processes (Figure 1.3), and notably, there is no single dominant source, but rather many significant sources. This configuration of sources forces a broader view of emissions for this gas, as opposed to many other significant GHGs whose anthropogenic sources tend to be dominated by a single source type such as from the combustion of fossil fuel.

[2] The focus of this report is on the methane part of the GHGI. In this report, "GHGI" refers to the methane part of the inventory unless otherwise noted.

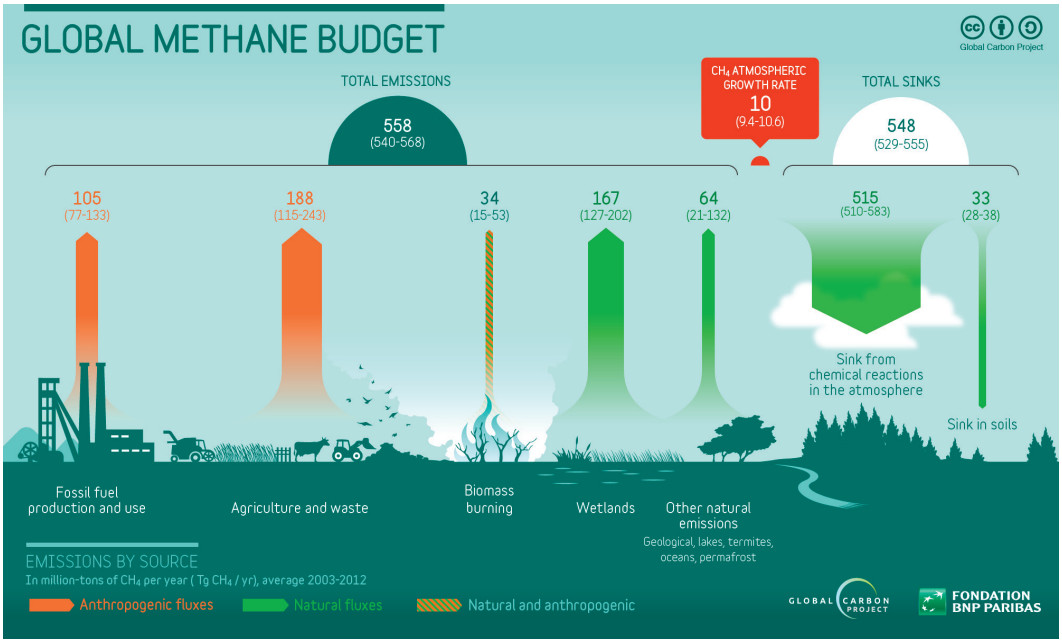


FIGURE 1.3 Schematic of global methane budget. SOURCE: Global Carbon Project, http://www.globalcarbonproject.org/.

The U.S. methane budget (emissions and removal processes) cannot be considered in isolation from the global methane budget because U.S. emissions account for only about one-tenth of global emissions. Consequently, atmospheric methane abundance over the United States is significantly influenced by sources located outside of the United States, even though there may be large responses due to strong local emissions. The atmospheric residence time for methane is about a decade; hence emitted methane is redistributed globally, and methane emissions from the United States influence global concentrations.

About 60 percent of total global methane emissions are thought to be from anthropogenic sources and about 40 percent from natural sources[3] (Saunois et al., 2016). Anthropogenic sources encompass a wide range of human activities, including food and energy production and waste disposal. Livestock (through fermentation processes in their digestive system that generate methane and manure management), rice cultivation, landfills, and sewage account for 55-57 percent of global anthropogenic

[3] These percentages are from top-down estimates.

emissions. Emissions from production of fossil fuels, including petroleum, natural gas, and coal, are estimated to account for 32-34 percent (Saunois et al., 2016), with the remainder from biomass, biofuel burning, and minor industrial processes.

Natural Sources of Methane Emissions

The main natural sources of methane emissions globally are from wetlands, with small contributions from enteric fermentation[4] in wild animals and insects, coastal oceans, and wildfires. About 10 percent of total methane emissions could come from geological sources, including seeps, hydrates, mud volcanoes, and geothermal systems (Etiope, 2015; Schwietzke et al., 2016). The relatively large contribution of methane from natural sources compels scientists to consider these sources when attributing methane measured via atmospheric samples to the various anthropogenic sources.

Wetlands and lakes are the largest and most uncertain natural sources of methane. For the United States (including Alaska; Chang et al., 2014; Potter et al., 2006), these emissions are estimated to be comparable to methane emissions from petroleum and natural gas use and production (Saunois et al., 2016) and are therefore not a negligible component of total U.S. methane emissions. Associated emissions are sensitive to saturated soil depth, as well as soil temperature and moisture, and lake depth, leading to significant seasonal and interannual variability in wetland emissions and to feedbacks between methane emissions and climate change. Wetland emissions are particularly difficult to quantify because they depend on both the details of microbial production and the distribution of wetlands. Although for some regions—such as the continental United States, Canada, and Europe—the distribution of wetlands may be well defined, for most of the world, the locations of wetlands are not well known. Recently, spaced-based observations of surface inundation have been used as a proxy for wetland locations (e.g., Poulter et al., 2017; Prigent et al., 2007); however, inundation may include water too deep for methane to reach the atmosphere before being consumed by microbes in the water column. Also, the inundation data likely miss shallow waters and areas where soil is saturated to the soil-air interface, the most methane-productive environments.

An important example of a potential feedback between climate and methane emissions is from permafrost thaw. Permafrost contains vast amounts of organic material that can decompose when thawed, resulting in the release of carbon (as either carbon dioxide or methane) to the atmosphere. Current understanding suggests that perma-

[4] The term "enteric methane" refers to methane produced by microbial fermentation-related activities in the gastrointestinal tract of ruminant or nonruminant animals (for more information on these processes, see Hristov et al., 2013).

frost carbon emissions will increase slowly over the next century (Schuur et al., 2015). This could lead to increased methane emissions from this source, which would contribute to further climate warming and more permafrost thaw as a feedback. Currently, there is no observational evidence that indicates that methane emissions have increased as a result of climate change, at least for the North Slope of Alaska (Sweeney et al., 2016), despite rapid Arctic warming. Wetland and lake emissions can also be affected by human activities such as agriculture and development. For example, drainage or restoration of wetlands and construction of reservoirs can affect wetland emissions.

Currently, enteric methane emissions from wild ruminants (e.g., bison, deer, elk, moose, antelopes), in the United States are low, around 4.3 percent of the total enteric methane emissions. Before the European settlement of the West, however, emissions from wild ruminants (predominantly bison) may have been comparable to emission from the current cattle population in the United States (Hristov, 2012).

Anthropogenic Sources in the United States

This report focuses on U.S. anthropogenic emissions, excluding land use, land use change, and forestry (LULUCF[5]), specifically the predominant sources that emit almost 94 percent of the total estimated U.S. anthropogenic methane, including agriculture (enteric fermentation and manure management), energy (petroleum, gas, and coal mining), and waste (landfills) sectors. Methane emissions from LULUCF are not included in this report because according to the GHGI, LULUCF is also a relatively minor source (approximately 1.7 percent).

Enteric fermentation in domestic ruminants such as cattle, sheep, and goats accounts for over 25 percent of U.S. methane emissions, excluding LULUCF (EPA, 2017b; Figure 1.4). Methane emissions from natural gas and petroleum systems are responsible for 25 and 6 percent of total methane emissions, respectively. Management of livestock manure accounts for another 10 percent. Waste, which includes landfills and wastewater, accounts for 18 and 2 percent, respectively. Coal mining operations account for 10 percent of U.S. methane emissions. Emissions from rice cultivation contribute 2 percent, and the remaining 2 percent is due to other primarily industrial (e.g., petrochemical industry), agricultural (e.g., field burning of agricultural residues), and waste treatment processes (e.g., composting). Although rice cultivation is a significant source of methane emissions globally, it is a relatively minor source in the United

[5] Methane emissions resulting from the use and conversion of land use categories in the United States, for example, managed peatlands, coastal wetlands, and forest fires.

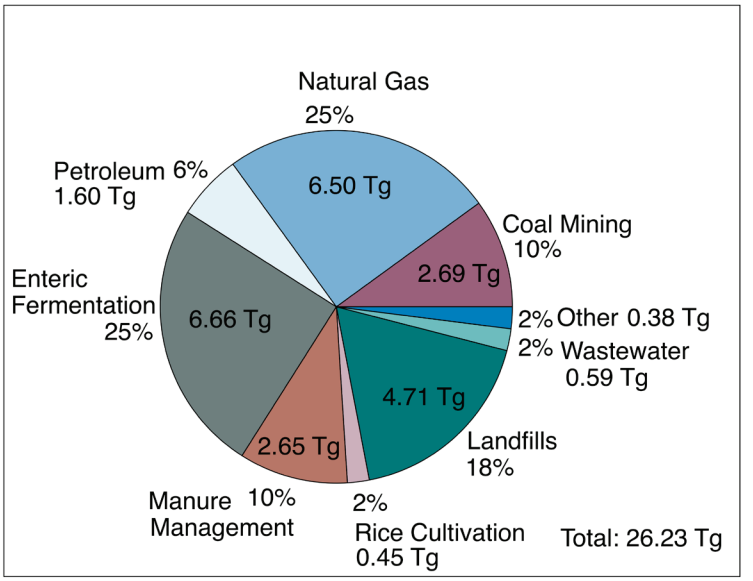


FIGURE 1.4 Anthropogenic sources of methane emissions in the United States in 2015, excluding land use, land use change, and forestry, according to the U.S. Greenhouse Gas Inventory. "Other" includes other industrial and agricultural sources. SOURCE: EPA, 2017b.

States, so was not covered in detail in this report. Wastewater is another relatively small source in the United States that was not addressed in detail here (for a brief discussion on these two sources, see Appendix C).

METHANE EMISSION ESTIMATION: THE TOP-DOWN AND BOTTOM-UP METHODOLOGIES AND MODELS

The bottom-up (or inventory development) approach involves measuring and/or modeling emissions at the scale of individual methane emitters, such as petroleum and gas wells, landfills, livestock operations, and developing representative emission factors (the estimated mean methane flux per emitter category) for the regional or national activity data (estimated emitter population) and then extrapolating the emissions to appropriate regional and national scales. In contrast, the top-down approach estimates emissions using observations of atmospheric methane concentration and models that account for transport from the emitter to the observation location. Because the atmospheric response (observations of methane concentration) is used

to determine the forcing (methane emissions), top-down techniques may also be referred to as "inverse models."

Measurements and emission estimates occur along a spectrum of spatial and temporal scales, from global assessments of annual methane emissions to instantaneous measurements of methane emissions from individual emission sources. At scales in between (e.g., total emissions from a large complex facility such as a natural gas processing plant or an animal feeding operation), the measurements might be considered either top-down or bottom-up.

Top-down and bottom-up approaches each have strengths and limitations (Chapter 3). The bottom-up approach allows for direct quantification of known sources or facilities and attributes emissions to specific sources, but it requires a comprehensive accounting of activity data, accurate emission factors, and an adequate sample size to represent the scaled-up population. The very large number of sources, which may significantly vary over time and space, poses a fundamental challenge to assembling accurate regional or national emission inventories. In addition, lack of comprehensive access to sources may not be possible. Top-down approaches include contributions from all sources, including any unknown or underestimated sources, but conversely have difficulty in attributing emissions to particular processes or activities, in part because sources are often intermixed across the landscape and limitations of detection capabilities to individual sources or facilities.

Both top-down and bottom-up approaches to regional or national emission estimation involve the use of models as well as measurements, and these models (Box 1.1) can also introduce uncertainties. In the case of top-down measurements, atmospheric transport models are used to "invert" observed methane concentrations into emission estimates. In the case of bottom-up emission estimates, models are used in a variety of ways, including converting operational and other data on methane emission sources into methane emission estimates (engineering process models), converting methane measurements distant from a source to emission measurements (atmospheric dispersion models), and converting emission measurements on a sampled population to comprehensive facility, regional, national, or global emission estimates (statistical models). Chapter 2 and Chapter 4 directly address the statistical models used in U.S. Environmental Protection Agency (EPA) and other methane inventories, while Chapter 3 addresses top-down atmospheric and bottom-up (sectoral) approaches and models.[6]

[6] Life-cycle analysis (LCA) models are used for generalized comparison of methane emissions from various societal and business practices. Because the LCA models are not directly applied to national inventory estimates, their detailed assessment is beyond the scope of this report.

BOX 1.1
BROAD CATEGORIES OF MODELS FOR ESTIMATING ANTHROPOGENIC METHANE EMISSIONS

- **Engineering and natural process models:** Models for predicting methane emissions from a source based on the operational parameters of that source. Examples include engineering models that describe specific process chain activities (e.g., pipeline blowdown frequency and pipeline blowdown volumes[a]) and process-based models that incorporate site-specific characteristics (e.g., landfill biogas recovery and climate-driven microbial methane oxidation in cover soils). These process models are of smaller scale than the atmospheric models discussed below and specifically target improved inventory methods for specific sources (e.g., use of annual soil carbon cycling models for methane emissions from field application of biosolids or manures).
- **Atmospheric transport models:** Models that describe the transport of methane emissions from a source to a measurement location. These transport distances range in scale from less than 1 meter to kilometers.
- **Large-scale atmospheric models:** Employed to calculate the concentration of methane at regional to global spatial scales. These models contain embedded models for engineering and natural processes (see above) that account for methane generation, transport, and emissions at various spatial and temporal scales.
- **Inventory models for extrapolating measurements to annual national emission estimates:** These models are used to generate regional to national emission estimates based on emission rates sampled from subpopulations (bottom-up emission estimates). Examples include EPA annual emission inventories for various sectors based on IPCC (2006).

[a] Blowdown is the intentional relieving or venting of pressure off of a piping system or the equipment in it.

Progress has been made in understanding methane emissions by using top-down and bottom-up techniques together. For example Miller et al. (2013) and Petron et al. (2014) found that in the petroleum, natural gas, and livestock categories, top-down methane emission estimates consistently exceeded bottom-up inventories by 50-200 percent or more. Discrepancies between top-down and bottom-up approaches have recently fueled discussion about how to improve inventory development as well as bottom-up and top-down measurement approaches. These discrepancies have also helped to identify information gaps and research needs (e.g., Bell et al., 2017; Brandt et al., 2014; Schwietzke et al., 2017; Zavala-Araiza et al., 2015; Zimmerle et al., 2016).

Table 1.1 shows a comparison between bottom-up and top-down estimates of contiguous U.S. methane emissions. Bottom-up estimates were compiled by the Global Carbon Project (Saunois et al., 2016) and include the GHGI (EPA, 2017b), Emissions Database for Global Atmospheric Research, and Greenhouse gas and Air pollutant Interactions and Synergies (Höglund-Isaksson, 2012) inventories. Top-down estimates

TABLE 1.1 Top-Down and Bottom-Up Estimates of Methane Emissions (Tg methane yr^{-1}) for the Contiguous United States

Source	Time Period	Anthropogenic	Fossil Fuels	Agriculture + Waste	Natural	Total (Anthropogenic + Natural)
Bottom-Up Estimates						
EDGAR 4.2FT	2000-2010	26	10	15	--	--
GAINS[a]	2000-2010	26	8	16	--	--
EPA GHGI[b]	2015	26 (24-31)	11	15	--	--
Top-Down Estimates						
Mean of global inversions[c]	2000-2010	30 (23-41)	12 (7-18)	18 (16-23)	12 (7-21)[d]	39 (30-63)
Miller et al., 2013	2007-2008	44 (±2)	--	--	3[e]	47 (±2)
Wecht et al., 2014a	2004 (July-August only)	30 (±1)	10 (±1)	20 (±1)	7 (±1)	37 (±1)
Turner et al., 2015	2009-2011	40-43	13-20	21-26	10-11	49-53

[a] Höglund-Isaksson, 2012.

[b] EPA, 2017b.

[c] Saunois et al., 2016.

[d] Includes wetland emissions and other natural sources.

[e] Prescribed using a wetland emission parameterization and not adjusted in the atmospheric inversion.

NOTES: Uncertainty ranges are in parentheses. Numbers may not add up due to rounding. EDGAR = Emissions Database for Global Atmospheric Research; GAINS = Greenhouse gas and Air Pollutant Interactions and Synergies; GHGI = U.S. Greenhouse Gas Inventory.

include multiple global inverse studies collected by the Global Carbon Project, along with several regional inverse modeling studies focused on the contiguous United States. The mean of the global inversion results for anthropogenic emissions is slightly higher than the bottom-up estimates. The inversion of Wecht et al. (2014a) agrees with the mean of the global inversions in its attribution of emissions to anthropogenic and natural sources, while the estimates of Miller et al. (2013) and Turner et al. (2015) fall in the high end of the range of global emissions for total U.S. emissions, and they are significantly higher for anthropogenic emissions. Miller et al. (2013) noted that emissions from petroleum and natural gas production could be underestimated in bottom-up inventories by a factor of 5 in the south central United States, while livestock emissions could be underestimated for the United States by a factor of 2. Turner et al. (2015) point out that source attribution is difficult and both fossil fuel and agricultural emissions could be underestimated by inventories. It is notable that the inversion of Miller et al. (2013) uses much lower natural emissions than the other inversions (~3 Tg methane yr^{-1}) and these emissions are not adjusted in their inversion. On a national scale, natural emissions contribute significantly to total U.S. emissions, and the lack of knowledge about these emissions can affect top-down estimates of U.S. anthropogenic emissions.

THIS STUDY AND THE COMMITTEE'S APPROACH

At the request of the U.S. Department of Energy (DOE), EPA, the National Aeronautics and Space Administration (NASA), and the National Oceanic and Atmospheric Administration (NOAA), the National Academies of Sciences, Engineering, and Medicine established the Committee on Anthropogenic Methane Emissions in the United States. The Committee was charged with examining approaches to measuring, monitoring, presenting, and developing inventories of anthropogenic emissions of methane to the atmosphere (see Box 1.2 for full Statement of Task). A major focus of this report is to examine the range of inventory approaches and products and the associated data requirements to help federal agencies develop a set of inventory products with wider applications and improved accuracy and verifiability. The report recommends enhancements to inventory methods, data collection, and products, as needed for the broad application of the inventories to societal needs and for verifiability. Other important elements of the charge, such as research to address key uncertainties, enhanced observing networks, and remote sensing techniques, are also considered.

In addressing its task, the Committee met five times during early and mid-2017 to discuss the current understanding of U.S. anthropogenic methane emissions across dominant sectors, including key uncertainties and unmet research needs. The Com-

BOX 1.2
STATEMENT OF TASK

An ad hoc Committee will examine approaches to measuring, monitoring, presenting, and developing inventories of anthropogenic emissions of methane to the atmosphere. The geographic scope of this study is limited to the United States, although much of the Committee's report could be relevant internationally. Specifically, the Committee will

1. discuss how methane emission measurements, monitoring data, and inventories are used and usable for managing emissions, scientific research, and other purposes;
2. assess scientific understanding with respect to published inventories of U.S. anthropogenic methane emissions, including estimates of current emissions, recent trends, and projections of future emissions;
3. describe and evaluate approaches used to measure and monitor methane emissions;
4. recommend how to present results of methane emission studies to facilitate comparisons among studies and to ensure results are useful for policymaking;
5. describe and evaluate approaches used to develop inventories of past, present, and future methane emissions;
6. recommend best available approaches for addressing key uncertainties, areas of incomplete understanding, and technical challenges in developing methane inventories; and
7. recommend research needed to improve methane emission measurement, monitoring, and inventory development.

mittee also conducted an extensive review of the published literature on these topics, again with the aim of combining conclusions and recommendations related to the primary U.S. anthropogenic sources of methane emissions in a common language and framework. Two of the meetings, in March and May 2017, were centered around open public workshops that gathered extensive input from scientists across academia, federal and state agencies, industry, and nongovernmental organizations and included site visits to operating petroleum, gas, and agricultural facilities. Additional community and stakeholder input was gathered in a series of public webinars and in brief open sessions at meetings in January and July 2017.

The Committee's goal for this report is to summarize the current state of understanding of methane emission sources and the measurement approaches, to evaluate opportunities for methodological and inventory development improvements, and to inform future research agendas of the United States, including NOAA, the EPA, the DOE, NASA, the U.S. Department of Agriculture, the National Science Foundation, and the National Institute of Standards and Technology. This information is also likely to be relevant to international agencies. This report could also inform future efforts to

develop emission inventories and regulatory approaches including assessment of emissions mitigation approaches. The Committee hopes the report helps scientists, policymakers, and science communicators more accurately convey the state of current understanding and relevance of future studies. Finally, the Committee believes that the recommendations in this report will enable the methane part of the GHGI to truly be transparent, consistent, comparable, complete, accurate, and widely applicable to science needs and policy applications.

REPORT ROADMAP

The report was written with a variety of audiences in mind, including funding agencies, regulatory agencies, climate policymakers and analysts, the research community, and the private sector. Chapter 2 synthesizes the current knowledge of methane emissions and inventory methods across all major methane-emitting human activities in the United States. Chapter 3 analyzes both top-down and bottom-up measurements, the models used to estimate emissions from top-down measurements, and compares top-down and bottom-up emission estimates and identifies strengths and weaknesses of each approach. Chapter 4 outlines the key uncertainties in estimating anthropogenic methane emissions and how these uncertainties can be reduced. Chapter 5 focuses on the presentation of methane emission data to facilitate comparisons among studies and to ensure that results are useful for policymaking. Chapter 6 concludes the report with the Committee's overarching recommendations for meeting the challenges of characterizing methane emissions. The major sources of U.S. anthropogenic methane emissions (enteric fermentation, manure management, petroleum and natural gas, landfill, and coal mining) are discussed extensively in Chapters 2, 3, and 4 through the lens of the corresponding chapter topic (inventory development, measuring and monitoring, and uncertainties, respectively).

CHAPTER TWO

Current Inventories of Methane Emissions

Development of greenhouse gas (GHG) emission inventories is necessary for estimating the relative significance of emissions from various sources and evaluating the effects of mitigation efforts. Inventories are developed for specific purposes and can provide emission estimates at many scales, from facility level, to urban, regional, national, and global scales.

INVENTORY OF U.S. GREENHOUSE GAS EMISSIONS AND SINKS

The United States, like all developed countries, submits a national, annual inventory of anthropogenic GHG emissions and sinks to the United Nations (UN) as part of its treaty obligations under the UN Framework Convention on Climate Change (UNFCCC).[1] The first Greenhouse Gas Inventory (GHGI) was submitted by the United States in 1994, covering the years 1990-1993 (EPA, 1994), and an inventory has been submitted every year since, with the latest submitted in 2017 and providing estimates for the years 1990-2015 (EPA, 2017b).

In developing the annual GHGI, the United States follows the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories (IPCC, 2006).[2] Key principles for development of the GHGI are inclusion of only anthropogenic GHG emissions, reporting of actual as opposed to potential emissions, ensuring full territorial coverage, and following a tiered methodological approach (Box 2.1) as contained in IPCC (2006) (see Appendix D for details). The GHGI of all developed countries is subject to an annual review by an international expert review team to ensure that each country follows the requirements in the relevant UNFCCC decisions and IPCC (2006). A final report of the review, which is coordinated by the UNFCCC secretariat, is made available online annually.[3]

[1] See http://unfccc.int/files/essential_background/background_publications_htmlpdf/application/pdf/conveng.pdf, Article 4, paragraph 1(a).

[2] The IPCC is in the process of developing a report to refine the 2006 IPCC Guidelines. This report is expected to be released in 2019. See https://www.ipcc-nggip.iges.or.jp/home/2019refinement.html.

[3] The latest review report of the U.S. GHG inventory can be found at http://unfccc.int/national_reports/annex_i_ghg_inventories/inventory_review_reports/items/9916.php.

BOX 2.1
2006 IPCC TIERED APPROACH FOR ESTIMATING GHG EMISSIONS

IPCC (2006) outlines a tiered approach for estimating GHG emissions from each source or sink of anthropogenic emissions. There are generally three tiers for estimating emissions for each category:

Tier 1 broadly relies on multiplying activity data (AD) by an international default factor representing emissions per unit of activity;
Tier 2 approaches generally involve the application of a country-specific emission factor to national- or regional-level AD;
Tier 3 approaches are more detailed, involving further stratification of the AD, plant-level (i.e., facility-level) emission estimates, direct measurement, or other equivalent country-specific approaches.

The basic Tier 1 methods are designed to be applicable for all countries, requiring only AD that are generally widely available. Use of higher tiered methods, including country-specific approaches, is encouraged for large sources of emissions in a country, because they are designed to better reflect national circumstances. Generally, the higher the tier, the more accurate the emission estimate, provided the method is well implemented and input data undergo appropriate quality control procedures.

A key feature of the GHGI reporting to the UNFCCC is providing estimates from 1990,[4] and accordingly, most countries have a base year of 1990 for reporting of methane emissions. Generally, recalculations of previously submitted GHGI estimates are made to reflect updated sources of information. These recalculations may be related to the use of a new emission calculation methodology, updated activity data, emission factors, or other parameters used for one or more years of the time series.

The U.S. Environmental Protection Agency (EPA) serves as the lead agency compiling and coordinating the inventory development, with input from other federal agencies, state agencies, research and academic institutions, industry trade associations, individual companies, and other experts (Appendix D). The EPA actively engages with the research and stakeholder communities to improve the GHGI. This has included multiple stakeholder engagements to improve the GHGI in recent years. The EPA also produces "memos"[5] to disseminate methodological or emission factor and activity data updates in the GHGI and has solicited stakeholder feedback on the same.

[4] See UNFCCC, Article 4, paragraph 2(b). http://unfccc.int/files/essential_background/background_publications_htmlpdf/application/pdf/conveng.pdf.

[5] See "Archives: Previously Posted Memos and Other Information on Stakeholder Engagement" at https://www.epa.gov/ghgemissions/natural-gas-and-petroleum-systems.

GREENHOUSE GAS REPORTING PROGRAM

Unlike the GHGI, which strives to develop a total, national-level estimate of GHG emissions and sinks by GHG and by sector, the GHG Reporting Program[6] (GHGRP) is a facility-level reporting program for larger GHG emitters from 41 industries across the United States and its territories. In general, facilities emitting ≥25,000 metric tons (or 0.025 Tg) of CO_2 equivalents[7] of GHGs (carbon dioxide, methane, nitrous oxide, and fluorinated gases) per year are subject to regulation under the GHGRP, thereby excluding reporting from smaller sources. As such, the total estimated GHG emissions reported within the GHGRP are lower than the GHGI. Facilities from several industries covered in this report are subject to reporting under the GHGRP, in particular, landfills, petroleum and natural gas operations, and underground coal mines. All of these operations are required to report their fugitive and combustion-related methane emissions, along with other GHGs. Methane emissions from enteric fermentation and manure management systems are not subject to reporting under the GHGRP. The program was designed to allow stakeholders to better track emissions and identify opportunities to reduce emissions, waste, and costs,[8] and although it may improve the estimation of national GHG emissions for specific categories, it was not designed to produce an inventory of national emissions. The GHGRP reports are generated by the industrial owner or operator following specific methods outlined in the regulations.

Overall, the GHGRP has been a valuable tool to improve methane estimates in the GHGI and to the scientific community in various methane measurement studies. Although coverage under the GHGRP is not complete, the methane data reported under the program can provide additional insight beyond what can be obtained from the national GHGI, because emissions are estimated using a higher-tiered method and provide specific plant- and component-level emission data for sources across the United States. The EPA uses the GHGRP data to update activity data and emission factors in the GHGI and refine national estimates and trends. After facilities submit information to the GHGRP, the EPA conducts several checks.[9] If potential errors are identified, the EPA will notify the reporter, who can resolve the issue either by providing an acceptable response describing why the flagged issue is not an error or by correcting the flagged issue and resubmitting their annual GHG report. Despite this process, data

[6] The EPA finalized the GHGRP on October 30, 2009, and codified the regulations under 40 CFR Part 98. See https://www.epa.gov/ghgreporting.

[7] GHGRP thresholds are based on the IPCC (2007) Fourth Assessment Report (AR4), 100-year global warming potential.

[8] See https://www.epa.gov/ghgreporting/learn-about-greenhouse-gas-reporting-program-ghgrp.

[9] See https://www.epa.gov/sites/production/files/2015-07/documents/ghgrp_verification_factsheet.pdf.

discrepancies have been noted in certain sectors (see sector-specific text in later section of this chapter for additional details).

STATE-LEVEL METHANE EMISSION INVENTORIES

Currently, methane inventories are generated by some states while others have methane reporting requirements only from certain industrial categories, similar to the GHGRP. The scope and coverage of categories varies from state to state, as does the frequency with which the state inventory is published. There are also many states that currently do not develop emission inventories.

The EPA has developed a "State Inventory Tool" (SIT)[10] that can be used by individual states to estimate methane emissions for key categories. The SIT provides a common framework developed in a manner consistent with the GHGI methodologies, but allowing for the use of state-specific activity data and emission factors where available. However, only a few states report methane emissions either through their state regulatory reporting program or employing the SIT to estimate their methane emissions.

Some states, such as California, have developed their methane inventories by using state regulatory reporting standards.[11] By maintaining consistency with IPCC methods, state-level inventories can generate state-level activity data and emission factors and provide useful data within their boundaries for continuous improvement of the national GHGI. These state-level inventories can also play an important role in the evaluation of state-level policies. For example, methane emission data for petroleum and natural gas systems are generally not collected at the state level, and there are significant regional differences in emissions (Allen et al., 2013; Lamb et al., 2015) due to differences in production practices (wet-gas versus dry-gas production), geology, infrastructure, and methane mitigation strategies. A state-level inventory can provide valuable information on state-specific activity data to reduce regional uncertainties.

States not currently developing a statewide methane inventory could use the EPA's State Inventory Tool (SIT) and complementary methodologies to provide valuable information, such as activity data and emission factors, for continuous improvement of the U.S. Greenhouse Gas Inventory.

[10] See https://www.epa.gov/statelocalclimate/download-state-inventory-and-projection-tool.

[11] See https://www.arb.ca.gov/cc/inventory/data/data.htm; https://www.arb.ca.gov/cc/reporting/ghg-rep/ghg-rep.htm.

GRIDDED METHANE INVENTORIES AND STUDIES

As noted previously, activity data in the GHGI are generally extrapolated to large regional scales (e.g., state or National Energy Modeling System regions from the Energy Information Administration) and emissions therefore are presented in similar spatial scales. Thus it is another challenge to verify[12] the GHGI because field measurement campaigns are mostly conducted at a subregional or site-specific scale. However, spatially resolved inventories are verifiable because spatial scales can be established at $0.1° \times 0.1°$ or finer resolution.[13] The GHGI is also strongly limited in the range of science questions and policy issues to which it can be applied because of its current large scale. Spatially and temporally resolved, verifiable inventories could inform the development of emission mitigation policies, and they also have the potential to direct appropriate mitigation programs at certain regional hotspots. Success in this regard requires "completeness" in the broadest sense, so that all major sources are included in the inventory. These goals require the ability to test the emission rates prescribed in the inventory and to accurately attribute emissions to particular source types using direct measurements. Verifiability is the bedrock upon which inventories must be built if they are to be widely applicable to societal needs. It is also important to ensure that the datasets and computer codes associated with development of the inventories are made publicly available to allow verification of the results or further analysis.

The GHGI reports estimated annual emissions for the United States, thus achieving adequate resolution for UNFCCC reporting on long-term national trends. However, the objectives for measuring and monitoring of methane in the United States are broader than the UNFCCC objectives for which the GHGI was originally developed. The EPA and other federal agencies, the states, and the U.S. scientific community are strongly motivated to better understand the geographic and temporal distribution of methane emissions.

Moreover, for the consideration of different spatial and temporal scales, alternatives to the GHGI may be more appropriate. For instance, field studies that quantify local- to regional-scale emissions may report daily or hourly averages. Discrepancies between these subnational values and those reported by the GHGI may be difficult to explain given the differences in estimation and measurement approaches, as well as the complex spatial and temporal dynamics of methane emissions from various source categories.

[12] In this report, "verify" means to test against top-down measurements.

[13] $0.1° \times 0.1°$ is roughly 100 km^2.

To address this challenge, several studies and entities have developed methane emission inventories at a finer spatial and temporal resolution than the GHGI. For example, the European Commission global dataset Emissions Database for Global Atmospheric Research (EDGAR)[14] estimates global emissions on a per country basis as well as a 0.1° × 0.1° grid and a temporal resolution of 1 month. EDGAR is frequently used by the scientific community for comparisons with top-down study results. The Greenhouse gas and Air pollutant Interactions and Synergies (GAINS)[15] model is used to evaluate cost-effective controls on greenhouse gases and other air pollutants to inform response strategies. This model is run at a global scale with a 0.5° × 0.5° spatial resolution and can produce annual and monthly estimates. GAINS distinguishes between 165 regions around the globe, including many countries. Maasakkers et al. (2016) published a spatially and temporally resolved gridded inventory of the 2012 GHGI (Figure 2.1). The motivation for developing this gridded inventory was to provide (1) a better a priori estimate (i.e., a first estimate of emissions to be improved by the application of inverse models) and (2) a better interpretation of the top-down inversion results relative to EDGAR. Furthermore, most of the dozens of published top-down studies from the last 5 years construct their own "downscaled" inventory to compare bottom-up inventory results to their atmospheric observations. A consistently generated gridded inventory will provide a standard baseline against which to compare top-down atmospheric results. Maasakkers et al. (2016) designed a national gridded inventory to address these issues. They disaggregated the GHGI data into a spatial resolution of 0.1° × 0.1° with a monthly temporal resolution of the emissions using data from various sources. Importantly, the inventory also provided an error characterization that was unavailable in the commonly used EDGAR.

The Maasakkers gridded inventory could be updated to later years as activity data become available. Comparisons with other gridded inventories suggest that revisions would be beneficial. When compared with EDGAR, the Maasakkers et al. (2016) gridded inventory results for the United States are about 2.6 Tg yr^{-1} higher and the distributions are different. Large spatial differences in emissions from petroleum and natural gas systems and manure management were also observed between the two inventories, suggesting that evaluating emissions using different spatial and temporal scales can influence estimates.

Hristov et al. (2017) produced a gridded 0.1° × 0.1° inventory of livestock methane emissions for the contiguous United States. Their analysis yielded total average livestock methane emissions of 8.916 Gg yr^{-1} (or ~0.01 Tg yr^{-1}) for 2012 that were compa-

[14] See http://edgar.jrc.ec.europa.eu/.

[15] See http://www.iiasa.ac.at/web/home/research/researchPrograms/air/GAINS.html.

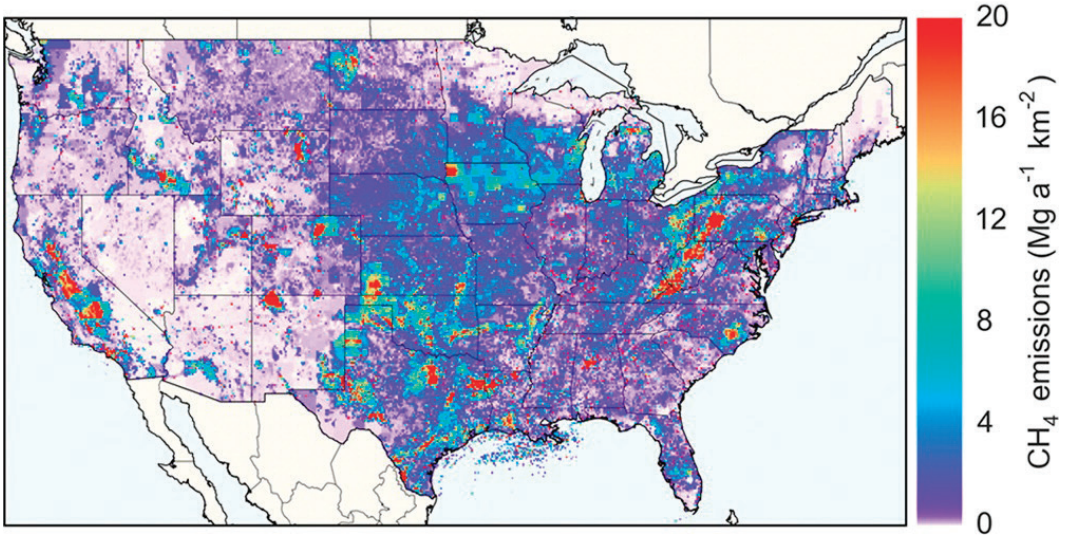


FIGURE 2.1 Total methane emissions in the gridded EPA inventory for 2012. SOURCE: Maasakkers et al., 2016.

rable to 2012 estimates from both the GHGI and EDGAR of 9.044 Gg yr^{-1} (~0.01 Tg yr^{-1}) and 8.657 Gg yr^{-1} (~0.01 Tg yr^{-1}), respectively. However, the spatial distribution of emissions differed significantly from that of EDGAR.

The differences in enteric emission estimates between the Hristov et al. (2017) and Maasakkers et al. (2016) studies are mainly due to different emission factors for the various subcategories of cattle (Figure 2.2). These comparisons (although only for methane emissions from livestock) demonstrate that discrepancies in source attribution still exist in current bottom-up gridded inventories. As an example, methane emissions from livestock in Texas and California (highest contributors to the national total) in the Hristov et al. (2017) study were 36 percent lower and 100 percent greater, respectively, than estimated by EDGAR. Compared with the Maasakkers et al. (2016) analysis, total livestock emissions in the Hristov et al. (2017) study for these two states were 12 percent lower and 4 percent higher, respectively. Differences in spatial distribution will likely have a strong impact on posterior (i.e., following inverse modeling adjustment) emissions estimated by top-down approaches, within the contiguous United States, even if the overall magnitudes of these estimates are consistent.

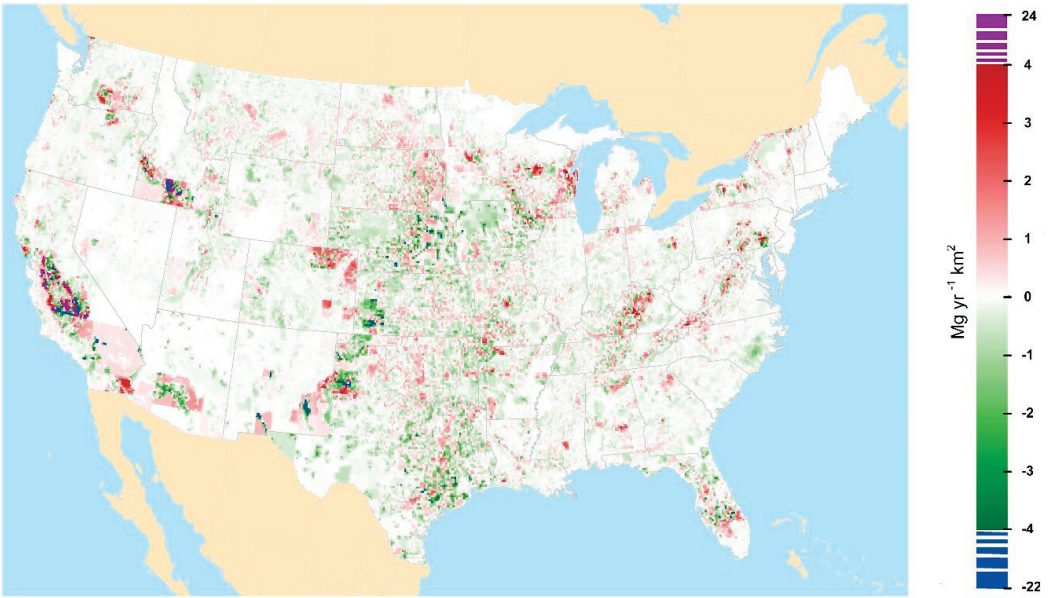


FIGURE 2.2 Gridded difference in livestock enteric methane emissions (Mg yr^{-1} km^2) between two bottom-up approaches, Hristov et al. (2017) minus Maasakkers et al. (2016).

Another example of a gridded inventory is the World Resources Institute's (WRI) Climate Analysis Indicators Tool (CAIT),[16] which is a state-level gridded allocation that uses some of the same principles as Maasakkers et al. (2016). CAIT is an online analytical tool that provides GHG emissions, including methane, and projected emission data across different source categories across the world. CAIT U.S. State GHG Emissions (CAIT-US) rely on EPA data, including the SIT tool.[17] However, it does not include methane emissions from key petroleum and natural gas segments and from industrial wastewater. This tool helps users understand which states have the highest methane emissions and identify potentially relevant policies for the methane sources within these states (Figure 2.3).

The development of a gridded version of the national GHGI can aid policymaking by providing greater clarity on where emissions are occurring. The national GHGI and the gridded version meet different user needs. In general, policymakers, media, and indus-

[16] CAIT Climate Data Explorer available at http://cait.wri.org.

[17] See http://cait.wri.org/docs/CAIT2.0_US_Documentation.pdf. CAIT uses data from the GHGI published in 2015 for calendar years 1990-2013.

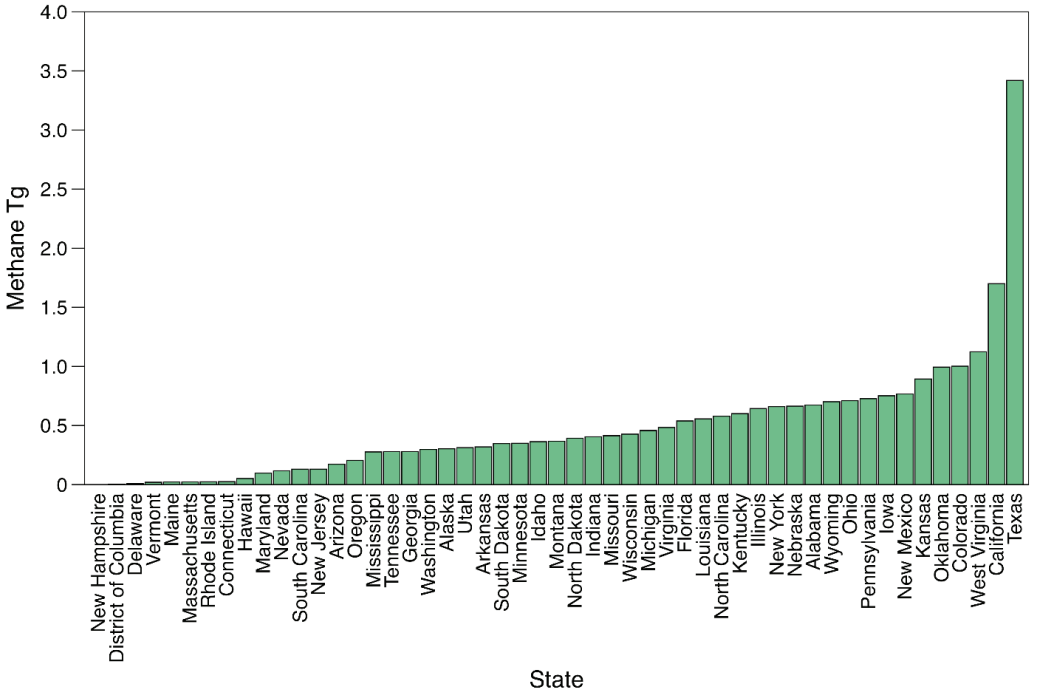


FIGURE 2.3 Estimated anthropogenic methane emissions from each state for year 2011. SOURCE: WRI, 2014.

try have tended to focus historically on the central (average) emission estimates provided in the national GHGI, while researchers also focus on the associated uncertainties and the finer resolution offered by the gridded inventory. While meeting different user needs, the various methane inventories can be complementary and, together, increase overall knowledge.

Finer-scale, gridded inventories of national methane emissions provide significant value to the scientific community to better characterize and compare inventories and test against top-down emission estimates. Further, gridded inventories have the potential to inform mitigation action at spatial scales relevant to policymakers and industry. Improvements in the GHGI and state-level inventories will also support improvements in finer-scale gridded inventories.

OVERVIEW OF METHANE EMISSIONS IN THE UNITED STATES FROM KEY SOURCE CATEGORIES

According to the latest GHGI (EPA, 2017b), total methane emissions in the United States in 2015 were estimated to be 26.23 Tg excluding land use, land use change, and forestry (LULUCF), and 26.68 Tg including LULUCF. Overall, between 1990 and 2015, total anthropogenic methane emissions reported by the EPA in the GHGI decreased by 16.0 percent (excluding emissions from LULUCF). However, trends differed among source categories. The values below are according to EPA (2017b) using current methods unless otherwise noted. Uncertainties related to emission estimates from these sources are discussed in detail in Chapter 4.

- **Enteric fermentation** was the largest source of methane emissions in 2015, an increase of 1 percent from 1990 despite declining cattle population.
- **Manure management** methane emissions have increased by 78 percent since 1990, resulting partially from a shift from smaller dairies and swine production facilities to larger facilities and increasing use of liquid manure systems for both swine and dairy cows, which have higher methane emissions than solid storage or application to pasture, range, and paddock.
- **Natural gas system** emissions reflect the vented, fugitive, and flared emissions from hundreds of thousands of individual sources. Overall, methane emissions from this category have decreased by 16 percent since 1990, with the increase in emissions from field production offset by decreases in emissions from natural gas processing, transmission and storage, and distribution driven largely by reductions in emissions from compressors in the transmission and storage segment and replacement of cast iron and steel pipelines with plastic pipeline in the distribution segment.
- **Petroleum system** methane emissions stem from numerous small and large sources. Between 1990 and 2015, methane emissions decreased by 28 percent due in large part to a decrease in the venting and flaring of associated gas from petroleum wells.
- **Landfills** are the third largest source of methane emissions, exhibiting a decline of more than 35 percent since 1990 as a result of increased use of landfill biogas collection systems (879 landfill sites in 2015 according to the June 2017 GHGRP). Moreover, commercial biogas utilization has been installed at over 600 sites, primarily for onsite electrical generation.[18] In addition, diversion of garden waste from landfills (required in 25 states) and, increasingly, food waste (in more than 180 communities) has resulted in greater than 17.63 Tg

[18] See Landfill Methane Outreach Program (LMOP), https://www.epa.gov/lmop (June 2017).

annually diverted to more than 4,900 composting operations (Goldstein et al., 2014). These decreases were partially offset by increasing waste generation from an increased U.S. population.

- **Coal-mining** methane emissions result predominantly from degasification and ventilation systems at underground coal mines (66 percent of the total) with a lower contribution from surface mines (13 percent) and post-mining activities at underground and surface mines (11 percent). Abandoned mines were responsible for 9 percent of emissions from this category. Overall, methane emissions from coal mining have declined by 35 percent since 1990 due in part to the decline in the number of active mines that, becoming abandoned and sealed, emit significantly less methane.

Methane Emissions from the Agriculture Sector

The main sources of methane emissions from U.S. agriculture are generated by enteric fermentation in livestock, manure management including composting, rice cultivation, and field burning of agricultural residues. In 2015, it is estimated that these activities collectively contributed 9.77 Tg of methane emissions, or about 37 percent of anthropogenic methane emissions in the United States, excluding LULUCF (EPA, 2017b). This section discusses the two largest sources within the agriculture sector: enteric fermentation and manure management. Rice cultivation is discussed briefly in Appendix C.

Enteric Fermentation

Beef cattle are the largest contributor of enteric methane emissions (they accounted for 71 percent of 2015 emissions), followed by dairy cattle (26 percent), and the remaining emissions are from horses, sheep, swine, goats, American bison, mules, and asses (EPA, 2017b). Enteric methane emissions represent about 2-11 percent of dietary gross energy consumed by livestock (Moraes et al., 2014), and methane is a natural by-product of microbial fermentation of carbohydrates and amino acids in the rumen and the hindgut of farm animals (Hristov et al., 2013).

The amount of enteric methane emissions largely depends on the type of digestive system (ruminants versus nonruminants, with ruminants producing much more methane), feed intake (greater feed intake leads to more methane production), and feed composition, particularly the amount of fiber and lipid in the diet (Appuhamy et al., 2016). Feed intake is positively correlated with methane emissions and productivity (e.g., milk or average daily gain). Attempts to quantify enteric methane emissions show

that feed intake alone can account for most of the variability in enteric methane emissions (e.g., Hristov et al., 2013; Kebreab et al., 2008; Moraes et al., 2014).

For GHGI reporting, national estimates have relied on the IPCC (2006) methodologies to calculate enteric methane emissions based on type of livestock. The majority of the enteric methane emissions are from cattle, and so a more detailed approach (i.e., IPCC Tier 2) is applied for cattle, while a less detailed approach (i.e., IPCC Tier 1) is used for other livestock. The IPCC Tier 2 approach (IPCC, 2006) requires detailed information on livestock subcategories (e.g., calves, stockers, and cows) and feed intake estimates in each subcategory. In the Tier 2 methodology, animal performance and diet data are used to estimate feed intake as the daily amount of energy (gross energy intake [GEI], MJ day^{-1}) that an animal needs for maintenance and for activities such as growth, lactation, and pregnancy (IPCC, 2006) considering feed digestibility. Annual cattle population data are obtained from the U.S. Department of Agriculture's National Agricultural Statistics Service QuickStats database (USDA-NASS, 2016). Diet characteristics are estimated by region for dairy, beef cattle on pasture (i.e., cow-calf operations), and feedlot beef cattle. These diet characteristics are used to calculate digestible energy (DE) values. Enteric methane emissions are then calculated as a percentage of GEI.

The default emission factors (Y_m) for cattle in the United States are 3 ± 1 percent for feedlot cattle (fed high-grain diets) and 6.5 ± 1 percent for dairy cows (cattle that are primarily fed forages, concentrate feeds, low-quality crop residues, and by-products) and grazing cattle (IPCC, 2006). However, because of the availability of detailed diet information for different regions and animal types in the United States, DE and Y_m values that are unique to the specific regions have been developed. Diet characterizations and estimation of DE and Y_m values are based on information from state agricultural extension specialists, a review of published forage quality studies and scientific literature, expert opinion, and modeling of animal physiology. A simulation using a process-based ruminant digestion model was used to estimate Y_m for each diet evaluated from the literature, and a function was developed to adjust regional values over time based on the national trend (Kebreab et al., 2008). For feedlot animals, the DE and Y_m values used have been continuously updated from the literature for 1990-2007 (EPA, 2014). For grazing beef cattle, Y_m values are based on specific diet components, and the values have been continuously updated with weight and weight gains for cattle taken from the literature and expert opinion.

Most of the equations for calculating GEI in the IPCC (2006) guidelines were developed as an average for world conditions (not only the United States) using data that are

now over 30 years old.[19] Recent research suggests that estimates could be improved by updating methodologies to reflect the current state of science. For example, the net energy requirement for maintenance during lactation used in the IPCC (2006) is greater than estimates from Moraes et al. (2015) commonly used for Holstein cows in the United States. The equation to calculate net energy requirement for lactation does not include protein, which can be variable in milk. Moreover, the Y_m value for dairy cattle in the United States has been reported to be 12 percent lower than IPCC (2006) recommendations (e.g., Appuhamy et al., 2016). In addition to updating the methodologies, research is needed to define the probabilities of updated emission factors, given that, from a statistical perspective, emissions factors should follow certain probability distributions.

In an effort to evaluate IPCC Tier 2 recommendations and improve methodologies for estimating methane emissions from enteric fermentation, an international team of animal scientists (Global Network[20]) compiled a large database of available information on this topic. They reported that models that used dry matter intake (DMI) or DMI and fiber concentration had accuracy in predicting enteric methane emissions from lactating dairy cows similar to models that included a greater number of animal and feed-related variables. These findings suggest that enteric methane emissions can be predicted with a single or a few variables, which can be relatively easily generated for various animal categories and production systems. Further, it suggests that the existing, rather complicated Tier 2 methodology could be simplified without increasing uncertainty of estimations.

DMI of cattle can be estimated using extant models. Using such estimates in models predicted enteric methane emissions well in dairy cattle (Appuhamy et al., 2016). However, beef cattle are the main contributors to enteric methane production, and predicting enteric methane emissions from beef cattle on range and pasture is highly uncertain. This is mainly due to difficulty in measuring actual intake while cattle are on rangeland or pasture as well as changes in digestibility of forages in different seasons of the year. The Global Network is working to develop models to predict enteric emissions from beef cattle and, similar to dairy, DMI and fiber content of diet are the primary determinants of emissions. Therefore, better estimation of intake and forage quality is required to improve predictions. The analysis from the Global Network also indicated that the average Y_m value for nonfeedlot dairy was around 7.1 percent of GEI, which is an increase of about 9 percent compared to IPCC (2006) recommendations.

[19] The IPCC is currently revising methodologies for both the enteric and manure management sections.

[20] The Global Network is a multinational collaborative effort funded by national governments. For more information, see http://animalscience.psu.edu/fnn/current-research/global-network-for-enteric-methane-mitigation.

Updating and simplifying existing Tier 2 equations, including emission factors, based on synthesis of recent scientific studies would improve the methodology for estimating methane emissions from enteric fermentation. Additional research focused on predicting dry matter intake estimates for cattle on rangeland and pasture based on animal and feed characteristics could significantly improve emission estimates for this livestock category.

Manure Management

Estimated 2015 manure management methane emissions reported by the GHGI totaled 2.65 Tg, with the dairy (52 percent) and swine (37 percent) being the two largest contributors (Figure 2.4). Manure from livestock is managed in various systems, using practices that contribute to methane emissions. These include storing manure in pits under housing areas, manure treatment (e.g., solids separation, anaerobic digestion, and composting), and manure transport and storage in tanks, lagoons, static piles, etc. (Key et al., 2011; Leytem et al., 2013; MacDonald et al., 2007). National GHGI reporting for manure management is based on the IPCC (2006) methodologies with some modifications to account for variable methane conversion factors (MCFs) on a

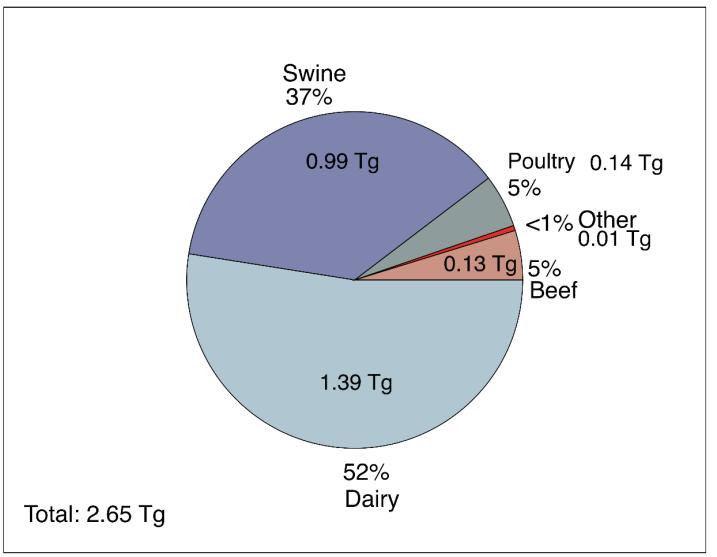


FIGURE 2.4 Percentage and amount of manure management methane emissions from each major livestock category in 2015 as reported by the GHGI (EPA, 2017b).

state basis. The overall estimation is derived from the amount of volatile solids (VS) that is stored for each livestock category (beef cattle, dairy cattle, swine, etc.) in each manure management system (anaerobic lagoon, static pile, etc.) along with a maximum methane generation potential (B_o) for each manure type (swine, dairy, etc.) and an MCF. The sum of all livestock categories over each manure management system provides the final national GHGI estimate for manure emissions.

The VS excreted for each livestock category are estimated utilizing feed intake and digestibility, while B_o and MCF (which are based on regional average temperatures) values were derived from the literature, when available, or the expert opinion of the IPCC (2006) authors and are largely unverified using on-farm data. Therefore, there is great uncertainty as to whether estimated emissions are representative of actual on-farm emission rates. For example the B_o values for anaerobic lagoons used in the IPCC methodologies were derived from research on the biological activity of methane digesters (Bryant et al., 1977; Hashimoto, 1983; Hashimoto et al., 1981; Morris, 1976), which may not be representative of a typical anaerobic lagoon. Research suggests the broader microbial community, longer residence times, and lower loading rates of uncovered anaerobic lagoons may lead to higher VS degradation rates than those found in anaerobic digesters (Lory et al., 2010). In addition, methane emissions from liquid systems are greatly influenced by manure temperature. Although the MCFs attempt to account for changes in emissions due to regional average temperatures, they were based on very limited data that may not accurately capture these relationships.

Comparisons of on-farm emission data with EPA inventory estimates have indicated that in some instances, the EPA methodology underestimated emission from liquid manure systems in North America by approximately 50 percent (Baldé et al., 2016; Leytem et al., 2017). In addition, activity data are difficult to obtain, as there is little information available that accurately portrays the amount of manure VSs that are handled and stored in each manure management system.

Presently, manure VS distribution within manure management systems is assigned based on farm size, which has not been validated. Therefore, improvements in both activity data and methodologies are needed to improve manure emission estimates.

More accurate methane emission estimates from manure management could be achieved by collecting more accurate activity data related to the distribution of manure in different manure management systems, updating the maximum methane potential for the various manure groups and methane conversion factors (via taking into account the effect of temperature and storage time on emissions), as well as evaluating the accuracy of assigning manure distribution based on farm size.

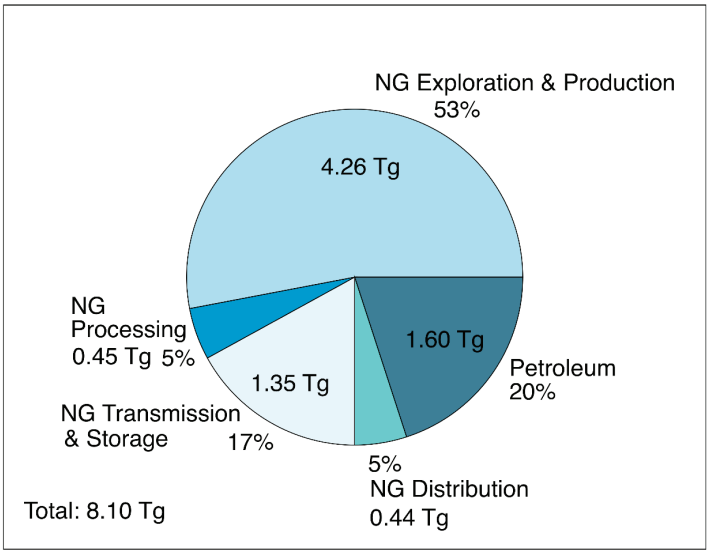


FIGURE 2.5 Methane emissions in 2015 (as reported) from the various segments of petroleum and natural gas (NG) systems in the United States. SOURCE: EPA, 2017b.

Methane Emissions from Petroleum and Natural Gas Systems

Emissions of methane from the petroleum and natural gas systems are estimated in the 2015 EPA GHGI (EPA, 2017b) to total 8.10 Tg. This includes petroleum and natural gas supply chain sources from production to distribution (Figure 2.5), but does not include emissions associated with fuel use (e.g., unburned methane from electricity power generation) or end-use emissions (i.e., residential, commercial, industrial, or transport). Petroleum and natural gas emission estimates are generally based on multiplying estimated or actual counts of specific devices (e.g., wells, compressors, and pneumatic controllers) and operations (e.g., compressor blowdowns and well completions) by an average emission rate (or emission factor) for the equipment type or operation.

The major emission source categories for which methane measurements are estimated in the petroleum and natural gas category include (Figure 2.6)

- **Natural gas well sites:** Sources of emissions at well sites are inventoried at the equipment level for the national inventory. Sources include but are not limited to pneumatic devices, liquid unloadings, and tanks. Pneumatic devices, primarily pneumatic controllers, use gas pressure to open and close control valves, typically on sites that do not have electrical power. Liquid unloadings remove

accumulated liquids from well bores; some liquid unloadings result in venting to the atmosphere. Tanks are used in storage of petroleum, condensate, and produced water and can vent methane.

- **Natural gas gathering and boosting stations:** These stations collect gas from multiple wells and perform some combination of compression, dehydration, and treatment; national emissions are inventoried at the facility level.
- **Gas processing plants:** These facilities receive gas from gathering and boosting stations and create pipeline-quality natural gas, removing contaminants and separating natural gas plant liquids (NGPLs, primarily ethane, propane, and butane) into separate NGPL sales streams; national inventories are performed at the facility level.
- **Transmission facilities:** Reciprocating and centrifugal compressors of various sizes, used at multiple points along the natural gas supply chain, are the primary sources of emissions during transmission. National inventories are performed at both the facility and component levels.
- **Petroleum production well sites:** Equipment and operations at petroleum well sites that are the largest sources of inventoried emissions include pneumatic devices, flares, and tanks. Flares are used to combust gases that might otherwise be vented, such as gases generated during well completions or

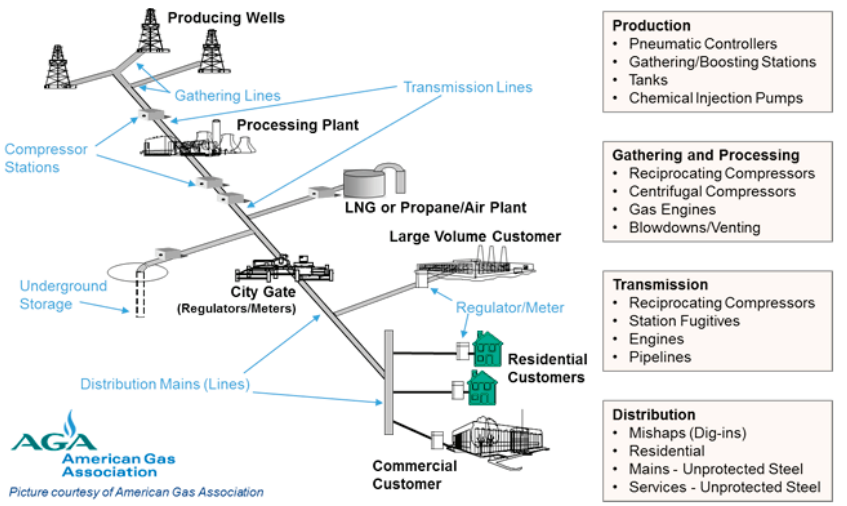


FIGURE 2.6 Segments of the natural gas industry, including production, gathering and processing, transmission, and distribution, and top methane emission sources for each category. SOURCE: American Gas Association.

gas produced in association with petroleum production (associated gas) that cannot be delivered to a pipeline system. Offshore platforms are inventoried separately from onshore well sites.

Studies have demonstrated that a significant fraction of the emissions from the petroleum and natural gas industry originate from a relatively small fraction of outlying sources with higher-than-expected emission factors, that some specific sources responsible for the emissions may change over time (including daily), and that the relative frequency of these high-emitting sources varies between petroleum and natural gas production regions. Additional discussions about specific methods, uncertainties, and unaccounted-for emission sources related to petroleum and gas inventories are discussed in Chapters 3 and 4.

The six highest-emitting sources within the natural gas systems collectively contribute over 68 percent of the total emissions from natural gas (Table 2.1). The emission factors for pneumatic controllers, normal fugitive emissions, gas engines, exhaust vents in production, and transmission segments are based on a comprehensive study by the Gas Research Institute and the EPA (Harrison et al., 1996). Emission estimates from these top six categories can be improved by conducting additional field studies at petroleum and gas production sites, natural gas gathering and boosting (G&B) stations, and natural gas transmission compressor stations. Recent studies by Marchese et al. (2015) and Zimmerle et al. (2015) have contributed to improvements in emission estimates from the G&B subsegment and also to updates to the transmission station emissions. The emission factors for other key sources such as pneumatic controllers, normal fugitives in the production sector, and gas engine exhausts can be improved by conducting additional studies and assessing incorporation of recent measurement studies by Allen (2014), Allen et al. (2015a,b), Prasino Group (2013), and Thoma et al. (2017). Fugitive emission factors might be improved by reviewing relevant data collected by leak detection and repair programs under state (e.g. Colorado), federal (New Source Performance Standard OOOOa), and voluntary programs (EPA Methane Challenge). Employing activity data from the 2017 GHGRP would improve the emission estimates for the largest emission source, G&B stations, as well as other key sources.

Recent measurement campaigns in the Barnett Shale in Texas (Zavala-Araiza et al., 2015) and Fayetteville Shale petroleum and gas production regions in Arkansas (Zimmerle et al., 2016) as well as measurements in the San Francisco Bay Area (Fischer et al., 2017) have demonstrated the importance of carefully designed, tiered-measurement campaigns incorporating and complementing the strengths of bottom-up and top-down approaches in improving the characterization of methane emissions from petroleum and natural gas supply chains. The emission factors for key emission

TABLE 2.1 Total Emissions and Basis of Emission Estimation for the Top Six Emission Sources Within the Natural Gas Systems

GHGI Emission Source	Sector	2015 Emissions, Tg	Basis for Emission Estimation
Gathering & boosting (G&B) stations	Production	1.97	G&B emission factors are based on Marchese et al. (2015) (53,066 standard cubic feet day^{-1} (scfd) methane per G&B station, or 1,503 cubic meters day^{-1} (scmd) which relies on emission measurements by Mitchell et al. (2015) at 114 G&B stations).
Pneumatic controllers[a]	Production	1.02	Pneumatic controller emission factors are based on Gas Research Institute (GRI)/EPA data (EPA, 1996b), but adjusted for methane content and operating hours from GHGRP Subpart W[b] data reported in 2014.
Pneumatic device vents, intermittent bleed (IB)		0.90	The IB emission factor is based on 323 scfd (9 scmd) whole gas. This factor is taken from GRI/EPA. As indicated above, the EPA adjusts the GHGI factor based on the average methane content and operating hours reported for the GHGRP Subpart W in 2014.
Pneumatic device vents, high bleed (HB)		0.09	The HB emission factor is based on 896 scfd (25 scmd) whole gas. This factor was derived from GRI/EPA study data split between HB and LB based on 6 scfh (0.2 scmh). The derivation is provided in Table B-14 of the American Petroleum Institute Compendium (API, 2009). The EPA adjusts the GHGI factor based on the average methane content and operating hours reported for the GHGRP Subpart W requirements in 2014.
Pneumatic device vents, low bleed (LB)		0.03	The current LB emission factor is based on 33.4 scfd (0.9 scmd) whole gas. This factor was derived from GRI/EPA study (EPA, 1996b) data split between HB and LB based on 6 scfh (0.2 scmh). The derivation is provided in Table B-14 of the American Petroleum Institute Compendium (API, 2009). The EPA adjusts the GHGI factor based on the average methane content and operating hours reported for the GHGRP Subpart W requirements in 2014.

continued

TABLE 2.1 Continued

GHGI Emission Source	Sector	2015 Emissions, Tg	Basis for Emission Estimation
Transmission station total emissions	Transmission and storage	0.57	The emission factors are based on the Zimmerle et al. (2015) analysis of the Subramanian et al. (2015) measurements at 37 transmission stations in 16 states.
Normal fugitives	Production	0.34	Normal fugitives consist of fugitive emissions from gas wells and well-pad equipment. Emission factors are based on the EPA/GRI, methane emissions from the natural gas industry (EPA, 1996a).
Gas engines (compressor exhaust vent)	Production	0.23	The compressor exhaust emission factor is based on the EPA/GRI methane emissions from the natural gas industry (EPA, 1996a).
Engines (compressor exhaust in transmission)	Transmission and storage	0.25	The compressor emission factor is based on EPA/GRI methane emissions from the natural gas industry (EPA, 1996a).

[a] Devices used in petroleum and natural gas systems to regulate liquid levels, valves, and gas pressure. Controllers powered by natural gas pressure when open, release methane (EPA, 2016b).

[b] Subpart W refers to the section in the *Code of Federal Regulations* that outlines the regulations related to the calculation, monitoring, and reporting of GHG emissions from petroleum and natural gas facilities under EPA's Greenhouse Gas Reporting Program. The *Code of Federal Regulations* is divided into 50 titles; Subpart W is contained in Title 40, Chapter 1, Subchapter C, Part 98.

sources such as pneumatic controllers and engine exhaust emissions still rely on factors that were generated over two decades ago. In many cases, these emission factors do not represent the population of emission sources or the current facility designs or work practices. The Gas Research Institute (GRI)/EPA 1996 factors were largely developed at the component level within a facility (e.g., number of high-bleed, low-bleed, and intermittent-bleed pneumatic vents).

In the petroleum and natural gas industry, there are thousands and in some cases millions of individual emission components. Obtaining accurate activity data at such a granular component level is a significant challenge. This is a leading cause of uncertainties with the petroleum and natural gas industry methane estimates (Chapter 4),

and updated counts have caused revisions to prior estimates and methods as part of the annual recalculation process within the GHGI. It is expensive to conduct national-scale, component-level bottom-up measurement campaigns that have enough samples to represent an industry that is complex and spatially and temporally varying and that comprises potentially hundreds of thousands of discrete components nationwide (Chapter 3). Although the EPA publishes the activity data associated with the GHGI, some of these data conflict with other agencies' data. For example, in the 2015 GHGI, the EPA lists the number of active gas wells in the United States as 421,893, while the Energy Information Administration (EIA) lists the same as 574,530. Similarly, the EPA identifies 668 natural gas processing plants in the 2014 GHGI, while the EIA identifies 551 such plants.[21] Hence, a publicly available, consistent, and centralized repository, similar to the National Oil and Gas Gateway,[22] of key facility-level and component-level activity data at an appropriate spatial scale could improve national methane emission estimates while supporting improved gridded inventories.

The EPA has in recent years employed activity data reported through the GHGRP to improve the emission estimates for some of the emission sources in the GHGI. For example, component-level emission factors and activity data have been improved in recent years due to the GHGRP reports by individual facilities by essentially scaling up the reported activity data for certain emission sources to a national total for use in the GHGI (EPA, 2017a,c). As noted earlier, the GHGRP reports emissions from a subset of the national total emission sources, generally considered as larger facilities or facilities with higher throughput. For example, Zimmerle et al. (2015) estimated that the 2012 GHGRP reported emissions from 25 percent of transmission and storage facilities, accounting for about 15 percent of the modeled emissions from the study. The 2015 total GHGRP methane emissions reported is only about 35 percent of the 2015 GHGI estimates for the petroleum and natural gas industry. However, the activity data are generated independently by each reporting facility and therefore provide a finer-resolution estimate than was possible prior to the availability of GHGRP data, which strengthens the value of this information. Although this new information is an improvement, uncertainties related to data errors have been noted.[23] For example, the 2015 total volume of natural gas produced at wells for all facilities reporting to the GHGRP exceeds volumes reported by the EIA.[24] Other data errors include data incon-

[21] Natural Gas Annual Respondent Query System (EIA-757 Data through 2014).

[22] See http://www.noggateway.org/.

[23] The issues identified here are not based on a comprehensive review of all of the GHGRP data available through Envirofacts, but rather are an illustration of issues identified in conducting various data analysis activities. As a result, there may be additional issues that are not included here.

[24] EIA reports 32,894,727 million cubic feet (931,466 million cubic meters) in 2015.

sistencies where reported hours of operations exceeded the total operating hours in a year. Further, since the GHGRP facilities are a subset of the total national population, the use of GHGRP activity data or developing national-level emission factors from the GHGRP for the entire population of emission sources needs to be done with caution.

Component-level estimation methods support granular-level component or subcomponent-level (e.g., different types of storage tanks or pneumatic controllers or different types of meters/regulators) emission inventory development. Therefore, year-to-year change in emissions profiles can be better explained by component-level estimates. Some recent methane studies, namely Marchese et al. (2015) and Zimmerle et al. (2015), report methane emissions from various segments of the petroleum and natural gas industry, presenting facility and subfacility levels instead of discrete component-level estimates. The results have now been incorporated into the GHGI calculations, reflecting EPA efforts to improve methodologies based on new information, when information is presented in a format that allows for incorporation. In addition to providing facility-level estimates, these methods could also potentially be used to provide a mechanistic understanding of emissions (i.e., using operational data and parameters along with observed emissions from the facility to characterize the temporal and spatial profile of the resulting emissions). Along with site access and data, a mechanistic understanding allows scientists to characterize and explain the emissions associated with the specific time duration of the study and the top-down and bottom-up emission estimation differences, thus negating the need to draw statistical assumptions related to frequency of emission events from limited observations (e.g., Bell et al., 2017; Schwietzke et al., 2017; Zimmerle et al., 2016, 2017).

Top-down studies also have crucial value in evaluating whether improvements to component-level emission estimates actually capture the bulk of total facility emissions. Recent studies have indicated that there may be unaccounted-for categories in current, component-level inventories (e.g., the GHGI), implying that component-level inventories may be incomplete (see further discussion on unaccounted-for emissions later in this chapter). These unaccounted-for emissions may be due to inaccurate activity data or high-emitting sources that are not accounted for in current emission factors; they may also be due to missing emission source categories. Prior unaccounted-for emissions from gathering and boosting stations now form the single largest emission source from natural gas systems, accounting for about 30 percent of the total natural gas emissions.

Littlefield et al. (2017) employed the term "unassigned" emissions to define the difference between observed or measured emissions at the facility level and the sum of component-level measurements (i.e., observed but unassigned to specific emission

components) at natural gas production sites. Using data from one petroleum and gas production area (Barnett) in the United States, Littlefield et al. estimated these unassigned methane emissions to be about 19 percent of the entire natural gas supply chain emissions. Similarly, Zavala-Araiza et al. (2017) concluded that there is a 52 percent difference between site-based estimates from the Barnett and component-based methane estimates of the petroleum and gas production sector due to existence of high-emitting sources (also known as "super-emitters"; see Box 2.2 and Chapter 3 for more details) due to abnormal conditions. Zimmerle et al. (2015) found that while the study model estimate (SME) of 1,237 Gg yr^{-1} [range = 950 to 1,680] (or 1.24 Tg yr^{-1}) was lower and not statically different from the 2012 GHGI estimates from transmission and storage facilities (1,805 Gg yr^{-1} [range = 1,460 to 2,350], or 1.81 Tg yr^{-1}), the author

BOX 2.2
HIGH-EMITTING SOURCES

A variety of terminology has been used to describe the subpopulations that dominate emissions, including high emitting, super-emitters, and fat tails. The Committee chose to refer to these subpopulations as "high-emitting sources."[a] High-emitting sources generally fall into the following categories (Munnings and Krupnick, 2017):

1. **Routine or "chronic" high-emitting sources:** These are sources that *always* emit at higher rates relative to "peers" in a sample. These may be large facilities (e.g., uncombusted methane emissions from a large compressor station, or flaring with incomplete combustion from a large petroleum field) or large emissions caused by poor design or operational practices. These high-emitting sources do not have temporal difference in their absolute emissions or methane intensities.
2. **Episodic high-emitting sources:** These emission sources are typically large in nature and are generally intentional releases from known maintenance events at a facility. The operator typically is aware of the event and plans such maintenance activities during normal working hours, and some of these emissions (e.g., blowdown of a known volume of pipe) can be readily quantified. Examples of potential high-emitting episodic events include liquid unloadings and compressor station or pipeline blowdowns. These high-emitting sources have very high methane emission intensity over very short time periods, even minutes.
3. **Malfunctioning high-emitting sources:** These sources can occur due to malfunctions and poor work practices. Examples include malfunctioning pneumatic controllers (Allen et al., 2015b; Thoma et al., 2017) or valves that isolate separators and liquid storage tanks that do not seal (a.k.a. stuck dump valves). Although not routine, these malfunctions have the potential to cause high emissions. These high-emitting sources, depending on the nature of the malfunction, may have high emission rates for prolonged periods (until the malfunction is addressed), or may be intermittent.

[a] The term "heavy tails" may still be referenced in this report when referring to the distribution of available data for statistical purposes.

estimated that about 23 percent of the SME attributable to such high-emitting sources resulted from abnormal events that are not accounted for in the GHGI.

More recent studies (Bell et al., 2017; Schwietzke et al., 2017; Zimmerle et al., 2016) provide a mechanistic understanding of the emission differences and indicate that finer temporal and spatial contemporaneous measurements, along with site access and activity data, can explain discrepancies between observed "peak emissions" (existence of a diurnal cycle with maximum emission intensity during mid-day) and annual average emissions, the latter being what forms the basis of the GHGI.

The need for component-level inventory estimates is justified mainly to support methane mitigation actions. Component-level methods provide better characterization of changes in emissions and therefore support appropriate operational and policy methane mitigation actions. The GHGRP's Subpart W is designed to provide facility-scale estimates by aggregating the component-level estimates at a facility that relies on multiple methods ranging from engineering estimates using default activity or emission factors to estimates from direct measurements. However, facility-level methods have the advantage of providing "completeness" of inventories by reducing uncertainties associated with activity data counts in the petroleum and gas industry, and are able to employ multiple measurements (satellites, aircrafts, towers, mobile vans, tracers) to verify and characterize facility-level emission factors.

The extensive network and complex composition of petroleum and natural gas infrastructure in the United States warrants careful consideration of how emission factors and activity data are developed and aggregated for use in inventories. Priority emission subcategories for improvement are those whose emissions estimation primarily relies on activity data and/or emission factors that originated from the 1996 EPA/Gas Research Institute study, including pneumatic controllers, fugitive emissions, and engine exhaust emissions through comprehensive data measurement and analysis.

Employing additional research to investigate the benefits and accuracy resulting from the use of facility- versus component-level emission data would further the development of national-scale emission inventories for petroleum and natural gas sources.

Methane Emissions from Landfills

Estimated 2015 waste sector methane emissions reported by the GHGI totaled 5.30 Tg. The dominant source was landfill methane (87 percent) with small estimated contribu-

tions from wastewater and the composting of garden and food waste. Current methodologies for the GHGI and GHGRP for all three sources have high uncertainties (IPCC, 2006). This section focuses on landfilling as the major source of methane from the waste sector (see Appendix C for a brief discussion of wastewater emissions). As discussed below, current methodologies (i.e., IPCC, 2006) assume a primary dependency for landfill emissions on the mass of landfilled waste that is not supported by current literature.

Biogenic methane in landfills is the end product of anaerobic microbial decomposition of paper products, garden, and food waste via methanogenic pathways. Most small, marginally engineered landfills closed in the mid-1980s prior to the implementation of EPA Subtitle D (Resource Conservation and Recovery Act) engineering and operational standards. Thus, at present, U.S. landfills are highly engineered and highly regulated facilities requiring monitoring and control of liquids and biogas. In addition, quarterly gridded sitewide surveys are required to detect and remediate elevated surface concentrations of methane. Engineered biogas recovery is routinely mandated at larger sites under Clean Air Act regulations to mitigate emissions of nonmethane organic compounds, which are trace components of landfill biogas. The recovered gas is either flared or, depending on site-specific economics, utilized for local energy needs. The commercial use of landfill biogas in the United States began in 1975 (Palos Verdes, California landfill). Encouraged by renewable energy tax credits, other incentives, and the EPA Landfill Methane Outreach Program (LMOP), utilization now occurs at more than 600 U.S. sites, primarily for onsite electrical generation and sale to the local grid.[25] Larger landfills must also report to the GHGRP, which as of 2015, included 879 sites with engineered biogas recovery systems to capture and combust methane and nonmethane organic compounds. Importantly, emissions of methane are also reduced via oxidation of methane to carbon dioxide + water vapor in landfill cover soils by indigenous methanotrophic microorganisms. Oxidation and net emission rates can vary greatly depending on site-specific cover soils and seasonal climate (Chapter 3).

The IPCC (1996, 2006) methodologies have historically been used for both GHGI and GHGRP estimates for landfill methane emissions. At the time of IPCC (1996), there were few comprehensive field measurements for landfill methane emissions (see discussion in Spokas et al., 2011, 2015). The IPCC (2006) revisions added calculation tools and defaults but did not fundamentally alter the underlying first-order decay (FOD) model, a first-order kinetic equation for estimation of methane generation from landfilled waste as the starting point for estimating emissions. In general, because of the necessity to consider complex soil gas transport and microbial methane oxidation

[25] See https://www.epa.gov/lmop.

processes, simple "emission factor" multiplied by "activity data" (i.e., landfilled waste) calculations are inappropriate for landfill methane emissions. Moreover, based largely on 1990s science prior to most field measurement campaigns, the current IPCC (2006) methodology includes several assumptions of questionable validity, as discussed below.

Modeling of Methane Generation Using First-Order Kinetic Equation

The IPCC (2006) methodology relies on a single first-order kinetic equation (termed the FOD model) to estimate methane generation at all engineered landfills worldwide. In this model, the kinetic constant (k, $1/t$) is assumed to be related to climate (i.e., highest value for warm humid sites). Also, biogas generation from a given mass of buried degradable carbon is assumed to peak in the year of disposal and decline exponentially thereafter. This approach is based on the assumption that a landfill functions like an anaerobic digester and was specifically based on an empirical model originally applied to biogas generation at a single California landfill (e.g., Scholl Canyon Model, EMCON Associates, 1980). Validation for the original IPCC (1996) methodology was limited to a comparison of modeled biogas generation to measured biogas recovery (*not* emissions) at nine Dutch landfills (Oonk and Boom, 1995; Van Zanten and Scheepers, 1995). A simple mass balance is then applied to derive the emitted methane; for engineered landfills, this is assumed to be equal to 90 percent of the modeled methane generation minus the measured or assumed methane recovery. The 90 percent allows for 10 percent annual oxidation in cover soils and has often been coupled in the United States (e.g., California GHG reporting) with an assumption of 75 percent biogas recovery "efficiency." Concerns with this approach include the reliance on limited data, the 10 percent annual oxidation (discussed below), global application of the FOD model (also discussed below), and the lack of field validation. Historically, the United States has also not compiled site-specific data on landfilled waste mass; thus, national, regional, and state data have typically been used as the basis for GHGI reporting to the UNFCCC.

Use of Historic U.S. Landfilled Waste Estimates for GHGI Reporting

There has been a long-recognized discrepancy between two disparate estimates for annual U.S. waste generation that are the current basis for estimating landfill emissions. These are the EPA material flow model approach developed in the 1970s by Franklin and Associates and the much larger (greater than 50 percent) annual values reported in periodic *Biocycle Magazine*/Columbia University "State of Garbage" reports

compiled from state-level reporting.[26] Recently, 2012 landfilled waste (summed from specific sites for the U.S. GHGRP) was documented to be more than double the number reported by the EPA (Powell et al., 2016). In general, the differences have to do with inclusion of landfilled construction and demolition debris (which generally does not lead to significant methane emissions) as well as other waste streams not captured by the current EPA estimates. For the future, harmonization of U.S. waste generation and management data, including annual statistical summaries for various subsources (i.e., household, construction, business/commercial, industrial, and forestry) could greatly improve tracking of national and regional trends for waste generation, recycling, and disposal. Moreover, achieving consistency and coordination with Eurostat's waste data methodology[27] could also be a desirable strategy to eventually achieve waste data harmonization among the United States, Europe, and other highly developed countries. At a minimum, more rigorous accounting of diverse waste generation and management activities could enable better local tracking of biodegradable waste diversion from landfills (typically to composting and anaerobic digestion; e.g., Brown, 2016); this is hampered by the high uncertainties associated with current national methods.

IPCC (2006) Assumption of 10 Percent Soil Oxidation

Many factors influence temporal soil oxidation rates; thus, relying on a fixed value is not appropriate. The 10 percent annualized value in IPCC (2006) was derived from the first study in the literature (Czepiel et al., 1996a,b) and was appropriate only for the specific New Hampshire study site. Realistically, methanotrophic oxidation rates in landfill cover soils are related to soil temperature and moisture variations over an annual cycle in each site-specific cover soil (e.g., Spokas et al., 2015, Fig. S9; see also Bogner et al., 2011; Scheutz et al., 2009; Spokas and Bogner, 2011; Spokas et al., 2011). Thus, soil oxidation is a climate-related feedback on landfill emissions. Overall, cover-specific oxidation and "net" emission rates on a unit area basis (e.g., grams of methane per meter per day) can vary by five to six orders of magnitude. Soil oxidation rates can range from negligible (too hot or cold, too wet or dry) to greater than 100 percent of the methane transport rate from the anaerobic zone (e.g., net uptake of atmospheric methane by cover soils with high oxidation capacities). Optimal soil temperature for oxidation is about 35°C with optimal soil moisture potential near the water-holding capacity (about 10 kPa) (Spokas and Bogner, 2011).

[26] See https://www.biocycle.net/2010/10/26/the-state-of-garbage-in-america-4.

[27] For example, europa.eu/eurostat/statistics-explained/index.php/Waste_statistics.

Assumed Dependency of Methane Emissions on Mass of Landfilled Waste

The direct application of IPCC (2006) at the facility level can result in a robust linear correlation between waste in place (WIP) and estimated emissions. To give one example, for 2011 California emissions (372 sites), plotting 2011 estimated emissions from the California Air Resources Board versus WIP (using 75 percent recovery efficiency and 10 percent soil oxidation), this regression indicates 191 Mg CH_4 emitted per Tg WIP ($r^2 = 0.88$) (Spokas et al, 2015; see Chapter 4, Figure 4.2, for highest-emitting sites using IPCC methodology). This means that large sites cannot reduce their reported emissions below a certain threshold as defined by this relationship, regardless of additional mitigation measures such as increased density of biogas recovery wells, installation of horizontal collectors concurrent with filling, or construction of thicker cover soils. This is not realistic and tends to stifle site-specific mitigation strategies because no measurable emission reductions can be derived using the IPCC (2006) method.

Conversely, a simple linear dependency for methane *generation and recovery* from a given mass of landfilled waste can now be readily demonstrated using 2010 data from 129 California landfill sites inclusive of small/large, new/old, open/closed sites from all climatic regions of California. Measured site-specific methane recovery was simply and linearly related to the mass of WIP at the rate of approximately 125 Nm^3 hr^{-1} methane recovered per Tg WIP ($r^2 = 0.85$) (Spokas et al., 2015).[28] This indicates demonstrable steady-state methane generation based on a large California dataset spanning more than half a century of controlled landfilling practices, in contrast to the FOD assumptions of IPCC (2006) where methane generation and emissions peak shortly after waste deposition. This is a surprising finding, given the diversity of California landfill sites, and requires further investigation. However, a similar relationship can be derived from the 2015 GHGRP database containing 879 sites with biogas recovery (96 Nm^3 hr^{-1} methane recovered per Tg WIP; $r^2 = 0.59$). In general, this suggests that landfill processes are longer term and more akin to (controlled) geological burial of organic carbon than the "anaerobic digester" analog assumed by the current FOD model.

Increased Complexity of Recent GHGRP Calculations

In recent years, the GHGRP has also applied IPCC (2006) for site-specific methane emission estimates for reporting sites. However, there are four different sets of re-

[28] "N" is for normal conditions of 0°C temperature and 101 kPa pressure used globally.

ported emissions (equations HH-5 through HH-8 in 40 CFR Part 98). These calculations depend on (1) whether biogas collection is considered and (2) what assumptions are made for biogas "collection efficiency," as well as (3) variable assumptions for percent oxidation from negligible to 35 percent (generally representative of average oxidation in the literature, e.g., Chanton et al., 2011). These more complex estimation methods have never been field validated for site-specific application and, in general, tend to magnify rather than reduce the shortcomings of the FOD method for the GHGI, as discussed above.

Need for a Field-Validated Process-Based Emission Model

The shortcomings of the current methodology indicate that a bottom-up process-based model is needed that can specifically address cover-specific methane emissions inclusive of site-specific climate. One such model has been developed and field validated, both for California and internationally, during the last decade. California Landfill Methane Inventory Model (CALMIM) 5.4[29] requires minimal site-specific data for inventory purposes and incorporates both the known dependencies for landfill methane emissions (soils, operational factors) with 0.5° × 0.5° U.S. Department of Agriculture climate models. It is also compatible with IPCC Tier 3 guidelines, has already been applied to a revised 2010 inventory for California (Spokas et al., 2015), and is being further evaluated in a current California research project by California Polytechnic State University and the University of California Irvine, supported by the California Air Resources Board and Department of Resources Recovery and Recycling (Calrecycles). See additional discussion in Chapters 3 and 4 as well as further information available in Bogner et al. (2011, 2014), Spokas and Bogner (2011), and Spokas et al. (2011, 2015). As discussed in Chapter 3, the GHGI and GHGRP might investigate an improved methodology focusing on the processes now known from literature to control emissions, for example, site-specific climate and operational factors (cover soil area, thickness, and composition; extent of engineered biogas recovery). A primary focus on site operational data as well as site-specific measurements for critical variables (e.g., WIP, average annual biogas recovery rate, and average annual methane concentration) has the potential to greatly improve and harmonize inventory calculations with the recent scientific literature. For example, de la Cruz et al. (2016) recently determined that IPCC (2006) can result in methane emission estimates ranging from several times to as much as 30-fold too high.

National harmonization and statistical analysis of waste generation, diversion,

[29] See ars.usda.gov.

processing, and disposal data are needed to better quantify national trends for consistency with international norms (i.e., Eurostat).

The current landfill methane U.S. Greenhouse Gas Inventory methodology based on IPCC (2006) was never field validated for emissions, relies on the mass of waste in place as the major driver for emissions, assumes that methane generation rates peak in the year following disposal, and does not directly consider major mitigation strategies such as increased density of biogas recovery wells or increased seasonal oxidation in thicker cover materials. Utilizing a field-validated, process-based model for inventory development has the potential to inform and incentivize improved landfill design and operational strategies to yield quantifiable reductions of landfill methane emissions.

Methane Emissions from Coal Mines

In 2015, total U.S. methane emissions related to coal mining (including abandoned mines) were estimated to be 2.69 Tg (EPA, 2017b). The United States was the second largest coal producer in the world in 2015, producing 812 Tg, following only China (EIA, 2016). In 2015, there were 834 coal mines in the United States: 529 surface and 305 underground (EIA, 2016; see Figure 2.7). Methane is emitted to the atmosphere from three types of coal-mining–related activities: underground mining (active and abandoned), surface mining, and post-mining activities (e.g., coal handling). Active underground mines are the largest source of coal methane emissions, responsible for approximately 66 percent of total emissions from this category in 2015 (Figure 2.8). Surface mines account for a large fraction of coal production in the United States (66 percent in 2015) but, due to the typically lower gas content of shallow surface-mined coals compared to deeper coals mined underground, were responsible for just 13 percent of emissions. Post-mining activities (surface plus underground) and abandoned underground mines make smaller contributions to emissions (11 and 9 percent, respectively, in 2015) (EPA, 2017b; see Figure 2.8). The EPA estimates of methane emissions from coal mines discussed below follow the 2006 IPCC Guidelines.

Underground Mines

Methane emissions from underground mines come from two sources: (1) ventilation systems and (2) degasification systems. Emissions from active underground mines are estimated based on data collected in individual mines. If methane is recovered and utilized (which occurs at some gassy mines), then recovered volumes are subtracted

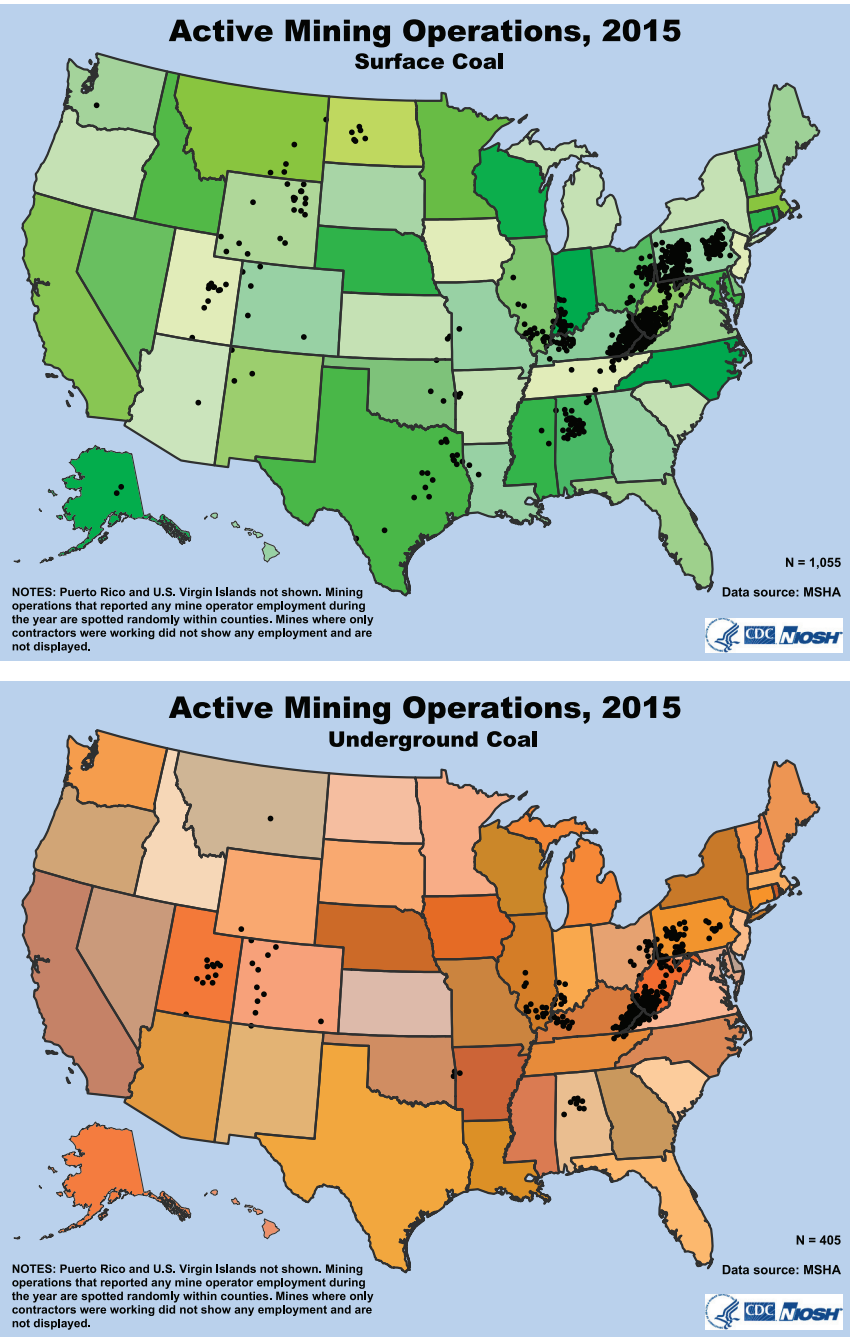


FIGURE 2.7 Distribution of active surface (*top*) and underground (*bottom*) coal mines (black dots) in the United States. The different shadings of the states are for visual purposes only. SOURCE: MSHA, 2015.

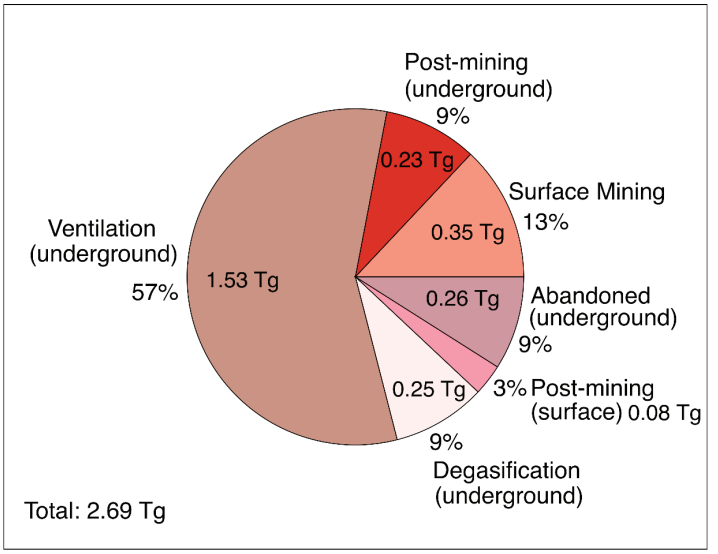


FIGURE 2.8 Estimated methane emissions from U.S. coal mines in 2015. SOURCE: EPA, 2017b.

from the total, resulting in the estimate of net emissions to the atmosphere. Ventilation systems are responsible for the majority of coal mine emissions (Figure 2.8), even though the methane is not highly concentrated from this source. In contrast, degasification systems release highly concentrated gas, and often in large volumes, but because they are used only in selected gassy mines, their total national emissions are much lower than those from the ventilation systems.

Ventilation-system methane emissions in the GHGI are estimated using information from the GHGRP, the U.S. Mine Safety and Health Administration (MSHA), and occasionally from site-specific sources (e.g., state gas production databases; EPA, 2017b). Since 2011, the gassiest mines (that emit more than about 36,500,000 cubic feet [or 1,033,565 cubic meters] of methane per year) report their emissions to the GHGRP and have the option of employing their own measurements or using measurements collected by the MSHA as part of required quarterly inspections. Currently, the GHGI estimates from this source are based on GHGRP data obtained from underground mines that report the emissions and quarterly measurement data obtained from MSHA for the remaining mines. For ventilation systems, methane emission calculations rely on the measurements of the flow rate and the methane content in the ventilation

air. Both of these measurements come from underground observations in entries connected to the ventilation shafts. Because the emission assessment relies on individual measurements in the entries rather than the total output on the surface, accurate reporting can be obtained by visiting and measuring all entries. Usually, there are no measurements conducted at the surface to confirm the values obtained underground, yet such measurements are needed to verify the current techniques.

Degasification systems are composed of wells drilled from the surface to the mine or boreholes drilled inside the mine that remove mine gases before, during, or after mining. Gassy underground mines report weekly measurements on the emissions from degasification systems to the GHGRP, and these data are summed to obtain yearly emission estimates (EPA, 2017b). For the 16 mines that have methane recovery and use projects, the amounts of methane recovered or destroyed (by flaring or thermal oxidation) is subtracted from the total volume of degasification system emissions.

For underground mines, measurements conducted at the surface are needed to verify the values obtained underground.

Surface Mining and Post-Mining Activities

Methane emissions in the GHGI from surface mining and post-mining activities[30] are estimated by multiplying basin-specific surface mine coal production by basin-specific gas content of the surface-mined coal (occurring up to about 76 meters deep) and by one emission factor for the United States. Basin-specific in situ gas content data used come from relatively outdated compilations by Rightmire et al. (1984) and Diamond et al. (1986). Including additional gas content data collected from various coal basins over the last 30 years is needed to decrease uncertainties. The emission factor currently used in the United States is based on 150 percent of the in situ gas content of the coal (EPA, 2017b) because mine-specific data are not available. This approach is limited in that it cannot account for variations in methane content of coal across different coal basins and different mines.

Post-mining activities utilize basin-specific coal production multiplied by basin-specific gas content and an emission factor of 32.5 percent of the in situ gas content of the coal (EPA, 2017b) to account for emissions during coal transportation and storage, based on a study of British coals (Creedy, 1993). For comparison, a 20 percent factor is used by Australia, after data by Williams et al. (1993). Similar to surface mines, because of variations in gas content between coals within the same basin (e.g., Strąpoć et al.,

[30] The GHGRP does not include reporting from operations at surface mines or post-mining activities.

2008), both basin-specific gas content and an emission factor of 32.5 percent can be sources of significant uncertainties in methane estimates from post-mining activities.

Updated and expanded information on coal gas content at mined depth for individual mines would allow for the development of more precise and representative methodologies for estimating surface coal mine methane emissions.

Abandoned Underground Coal Mines

Methane emissions from abandoned underground coal mines vary depending upon many factors including gas content of the coal, mine flooding, presence of conduits, the quality of mine seals, and the time since mine closure. The EPA produced a comprehensive inventory of abandoned underground coal mines in the United States (EPA, 2004) and developed a methodology to evaluate their methane emissions, which was subsequently incorporated into the 2006 IPCC Guidelines. The EPA classifies abandoned underground mines into three categories: venting mines, flooding mines, and sealed mines, with the estimation methods modified for each category to reflect different emission levels. Emission estimates from abandoned underground mines take into account the emissions during the active phase of the mine and use emission rate decline curves that have been developed for abandoned coal mines. These decline curves are used to evaluate gas emission potential and duration (Karacan et al., 2011). For the mines where venting is reduced because of mine flooding, decline curves are adjusted based on field measurements, and the modified equations are used to calculate gas flow rates (EPA, 2004). For mines with very good seals, the emission predictions are similar to the vented mines, but using lower initial rates dependent on the degree of sealing (high, middle, or low values; EPA, 2004). The main challenge with the estimation of methane emissions from the abandoned underground mines is generation of an accurate decline curve. Methane adsorption isotherms, coal permeability, and pressure at mine abandonment are needed to establish a reliable decline curve, and typically, there is uncertainty in all three parameters.

Unaccounted-for Methane Emission Sources in the GHGI

Although several methane emission sources are already accounted for in inventories, recent studies indicate that for certain end-use sectors, certain discrete emission sources may be missed or underestimated in the current GHGI (Fischer et al., 2017;

Lamb et al., 2016; Lavoie et al., 2017; McKain et al., 2015; Mehrotra et al., 2017).[31] Broadly, these unaccounted-for sources could be divided into two groups.

The first group is known sources that may not be fully accounted for in inventories. Examples include high-emitting sources (Box 2.2) and sources in certain natural gas end-use sectors such as residential and commercial operations, power plants,[32] refineries,[33] and transportation.[34] Recent research indicates that some source categories may not fully account for emissions from all sources within these facilities (Clark et al., 2017; Fischer et al., 2017; Lamb et al., 2016; Lavoie et al., 2017; McKain et al., 2015; Mehrotra et al., 2017). Lavoie et al. (2017) presented the first facility-scale methane measurements from three natural gas power plants (NGPPs) and three petroleum refineries. Their estimates were larger than the GHGRP submittals for these facilities by factors of 21 to 120 (NGPPs) and 11 to 90 (refineries), pointing to potential methane sources unaccounted for in the GHGRP and the GHGI. The authors scaled up these emissions to annual methane emissions of NGPPs and refineries and estimated that these sources contribute about 0.61 ± 0.18 Tg methane yr^{-1} to the United States. In another study, Fischer et al. (2017) estimated methane emissions for three refineries in California and suggested that the GHGRP estimates were underreported by a factor of 14. In the transportation sector, Clark et al. (2017) estimated "pump-to-wheels" (PTW) methane emissions from the heavy-duty transportation sector fueled by natural gas. Although the study does not compare results to the GHGI or GHGRP, it does indicate that engine crankcase and tailpipe emissions contribute to about 70 percent of the total PTW emissions.

Another example of another known and likely not fully accounted-for source is the dispersed, diffuse emissions occurring in urban areas. In addition to the more familiar "street leaks" from pipelines in the distribution system (Lamb et al., 2016; McKain et al., 2015; von Fischer et al., 2017), these emissions may also arise "after the meter," that is from leaks in homes and commercial buildings due to unburned gas from appliances or venting of pressure regulators, or due to equipment such as ovens and hot water heaters (Fischer et al., 2017; Mehrotra et al., 2017).

[31] The GHGI does not account for abandoned petroleum and natural gas wells within the petroleum and natural gas system inventories. EPA (2017b) acknowledged this limitation and has proposed revisions in June 2017 for incorporation in the 2018 GHGI to account for abandoned petroleum and natural gas wells.

[32] The methane emissions from fossil fuel combustion at power plants in the 2015 GHGI were estimated to be about 0.02 Tg (EPA, 2017b).

[33] The 2015 methane emissions from petroleum refining were estimated to be approximately 0.03 Tg in the GHGI or 0.3 percent of the total estimated emissions from petroleum and natural gas systems (EPA, 2017b).

[34] The 2015 total methane emissions from the transportation sector were estimated to be about 0.08 Tg, according to the GHGI (EPA, 2017b).

Urban settings are particularly challenging areas in which to assess methane emissions because of the presence of a multitude of commercial and residential sources. Many of these are of small scale, and their pattern of emissions is difficult to predict. In such settings, a multifaceted approach is especially desired to identify the sources and find a linkage between sources and emissions. McKain et al. (2015) analyzed data from a long-term measurement network consisting of four measurement tower sites in eastern Massachusetts and estimated an annual average methane emission rate from the study area to be two to three times higher than the Massachusetts state inventory. The authors attributed the difference between the study estimates and other inventories to unaccounted-for methane emission sources "downstream of customer meters" at industrial, residential, and commercial end-use facilities; however, they did not provide an estimate of such emissions. In another example, Fischer et al. (2017) measured methane emissions at single-family homes in the San Francisco Bay Area, California. They found methane leakage at nearly every home, even when the natural gas appliances were not used. Extrapolating these results statewide, the authors estimated unaccounted-for methane emissions from the residential sector to be about 0.2 percent of residential natural gas consumption. These emissions would add an additional 10 percent to the petroleum and gas methane emissions currently reported in the California state inventory.

The second group of unaccounted-for sources is previously unknown sources that have been unrecognized because of their scale, complexity of attribution, or other factors and are not currently incorporated in the GHGI. An example is previously unrecognized microbial coal-bed methane from active mining identified as part of a study in the Four Corners region (e.g., Arata et al., 2016).

All of these methane sources contribute to underestimating of bottom-up emissions, and their presence creates emission uncertainties. Though these studies of unaccounted-for emissions are limited in sample size to develop national emission factors or extrapolate to develop a national estimate, these studies suggest that further research is necessary to better characterize emissions from these sources. Increased, comprehensive research and methane measurement and monitoring could provide important insights and evaluation of the magnitude of these emissions for potential inclusion of these emission sources in future methane inventories, in particular, the GHGI (Chapter 4).

Additional research to better characterize emissions from unaccounted-for emission sources would likely further the incorporation of these sources into the U.S. Greenhouse Gas Inventory and other methane inventories. Given that observations of unaccounted-for methane emissions are limited, any extrapolation to national totals needs to be done with caution.

RECALCULATIONS IN THE GHGI

As indicated earlier in this chapter, the United States and other countries must use 1990 as a base year when estimating methane emissions for submission to the UNFCCC. Emission estimates from previous years are often recalculated in the GHGI based on new information so as to ensure that observed trends in emissions are real and not an artifact of the use of different data sources and methods. New information to better estimate emissions is becoming available due to the GHGRP and several methane measurements and activity data studies conducted recently which supports recalculations of methane emissions for certain sources. In general, recent revisions to the GHGI are more accurate than previous estimates and are therefore encouraged. The requirement to recalculate emissions back to 1990 using consistent data source and methods, however, poses distinct challenges for the United States (and other countries) to accurately estimate methane emissions. New research and estimation techniques may provide a more robust estimate of methane emissions. However, application of current emissions and activity data to develop a consistent time series back to 1990 can be difficult if the updated activity data and emission factors are not available for the entire time series or if new emission factors are not applicable to earlier years due to changes in technology and/or practices in the industry.

In addition to the technical challenge of developing a consistent time series of data, there is a challenge in communicating the results of such recalculations. Use of updated data can result in significant revisions in estimates for any given year when recalculated using new information. Figure 2.9 illustrates this, showing, for instance, that estimated emissions for 1990 were reported to be higher when calculated using information available in 2017 when compared to information available in 1998. Drawing inferences related to changes in emissions from key categories from prior years should be done with caution. Improvements in emission factors and activity data are encouraged and revisions reflect the use of updated technical data.

Although the 1990 baseline has remained for the UNFCCC and therefore GHGI development, recent global and U.S. policy commitments have used either 2005[35] or 2012[36] as a base year for emission reduction strategies.

The challenge of recalculating emissions back to 1990 should not be a barrier for utilizing the most up-to-date methodologies and information in developing

[35] U.S. Nationally Determined Contribution under the Paris Agreement. http://www4.unfccc.int/ndcregistry/PublishedDocuments/United%20States%20of%20America%20First/U.S.A.%20First%20NDC%20Submission.pdf.

[36] The Obama administration adopted a 40-45 percent reduction from 2012 levels by 2025. This commitment is also shared by Canada and Mexico.

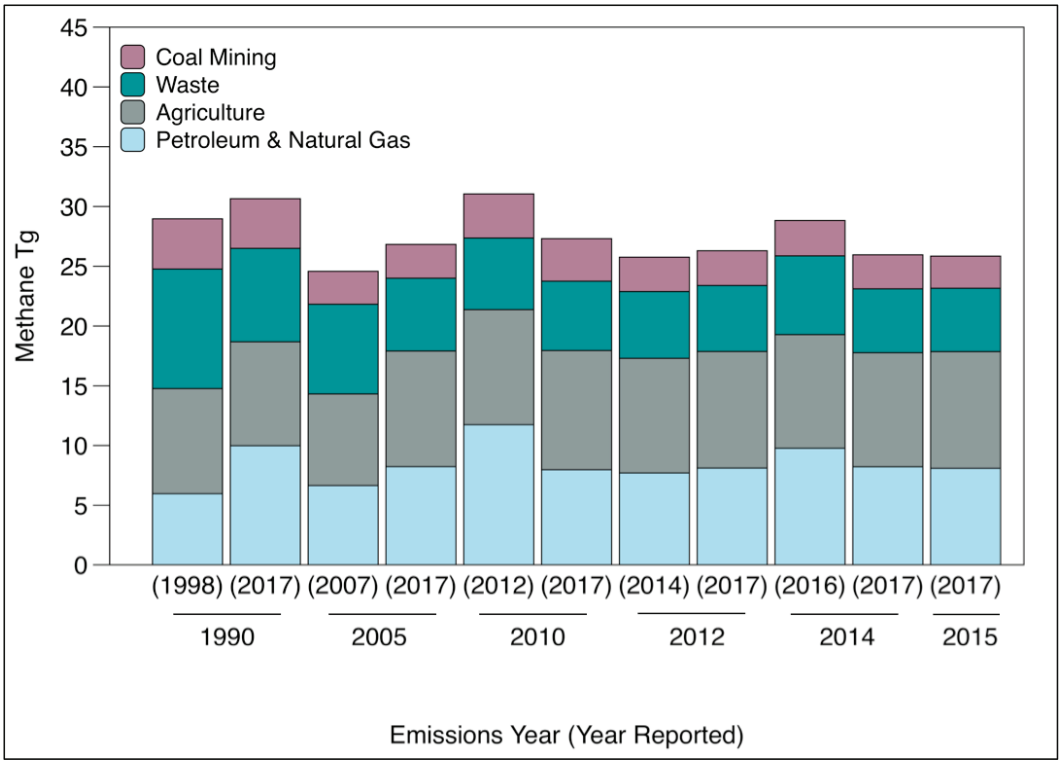


FIGURE 2.9 Reported emission estimates can vary for a given year when estimates are recalculated using new information. Methane emissions in teragrams from coal mining, waste, agriculture, and petroleum and natural gas for select years (the years not in parentheses) as originally reported in the EPA GHGI (and reported in 1998 for 1990) and in 2017 (reporting years in parentheses). Coal mining includes abandoned mines.

the U.S. Greenhouse Gas Inventory. The United States and the broader international community could consider adoption of the use of an alternative base year or period for reporting of national GHG inventories consistent with more recent national and international policies and commitments.

FUTURE U.S. METHANE EMISSIONS

Projecting future methane emissions is extremely challenging. Accurate projections of anthropogenic methane emissions are a key foundation for planning national policies or goals, but these projections are dependent on many factors that are difficult to

predict, including future energy and agricultural policies, methane mitigation policies, development of natural resources, population migration, etc. Unlike projections of carbon dioxide, which are strongly correlated with fuel combustion, methane emissions stem from several sources across various segments of the economy and are influenced by many distinct factors. As previously described in this report, many challenges and knowledge gaps remain in quantifying current emissions, adding complexity to future projections. Finally, climate change during the next few decades will also directly affect future methane emissions from several sources.

The United States reports sectoral projections through its National Communications[37] every 4 years, and every 2 years through its Biennial Reports issued by the U.S. Department of State to the UNFCCC. The reporting guidelines specify that countries should report projections (1) by gas and by sector, (2) without mitigation measures, (3) with measures (encompasses currently implemented and adopted policies and measures), and (4) with additional measures (also includes planned measures). However, the guidelines do not specify a method for projecting these emissions. U.S. projections are based on the methods outlined in *Methodologies for U.S. Greenhouse Gas Emissions Projections: Non-CO_2 and Non-Energy CO_2 Sources* (EPA, 2013). Emission estimates are calculated by scaling the most recent GHGI with macroeconomic data (e.g., population and gross domestic product), projections of activity data (e.g., natural gas production from the Energy Information Administration), and current mitigation policies and programs (e.g., Landfill Methane Outreach Program, Natural Gas STAR, Clean Air Act, and Clean Fuels Programs, as well as state-level programs). The most recent national projections are presented in the 2016 Biennial Report (DOS, 2016), which includes projections of total U.S. methane in 2020 (26.80 Tg methane), 2025 (26.96 Tg methane), and 2030 (27.28 Tg methane), as well as emissions by major source category. The 2025 and 2030 values are about 1 to 2 percent lower than 2015 emission values.

The quality of these national projections can only be as good as the quality of the most recent inventory estimates combined with the emission factors and activity data applied for future estimates. Moreover, activity data represented in the EPA 2015 GHGI (for calendar year 2013) projections which were employed in the last biennial report may not be sufficiently robust. As noted in earlier sections, methane inventories have been recalculated in recent years to account for improved activity data, emission fac-

[37] See http://unfccc.int/national_reports/items/1408.php. The last U.S. biennial report was submitted in December 2015 and employed the GHGI published in April 2015 covering emissions from 1990 to 2013 (EPA, 2016a).

tors, and methods. This illustrates the added uncertainty of using current inventories to develop future methane projections to 2030 and beyond.

The current methods established for projecting methane emissions from key categories may not be the best predictor of future emissions. For example, while the trends in emissions from livestock generally follow changes in cattle populations (e.g., Alemu et al., 2011), cattle population trends alone cannot be a predictor for enteric methane emissions. Animal live weight and feed dry matter intake have been steadily increasing. Both of these factors result in greater enteric emissions. Animal productivity (milk or daily gain) has also been increasing, which results in decreased emission intensity (i.e., emission per unit of product). Similarly, petroleum and natural gas emissions have significant regional variability with regard to technological improvements and voluntary actions, resulting in variable emission projections and activity data correlations. For the waste sector, improvements in the collection and statistical analysis of relevant waste data are needed (including waste generation from households and businesses, internal diversions/recycling/reuse within sectors, and the mass of biodegradable waste disposed to landfill), as are improvements to current methodologies discussed in this chapter.

For several sources where methane is generated, transported, and/or oxidized in soils and sediments, future climate is also an important determinant for future emissions at specific global locations. Sources include methane emissions due to subsurface leakages from petroleum/gas piping, land application of manures, some coal-bed leakages, and seasonally variable emissions from landfill cover soils. Subsurface methane transport to the atmosphere can be largely diffusive (from higher to lower methane concentrations) with both methane transport and soil oxidation rates dependent on transient soil temperature and moisture. Future climate could be factored into future emission estimates using a combination of climate projections and field-validated process-based modeling for specific sources.

Activity data and emission factors that serve as proxies for projecting future methane emissions, as well as current inventory methodologies, need to be robustly investigated regarding correlations to measured emissions from key categories. Such investigations could include updating the EPA report *Methodologies for U.S. Greenhouse Gas Emissions Projections: Non-CO_2 and Non-Energy CO_2 Sources* in collaboration with experts from federal and state agencies, municipalities, industry, and the research community. Future climate projections also need to be factored into future emission estimates for sources where methane is generated, transported, and oxidized in soils and sediments.

CHAPTER THREE

Methane Emission Measurement and Monitoring Methods

Measurements of emissions and monitoring of methane are essential for the development of robust emission inventories as described in Chapter 2. Field measurement of emissions from various sectoral sources can provide improved understanding of processes that lead to emissions, which contributes to the development of process-based emission models as well as regional- and urban-scale mitigation strategies. Furthermore, atmospheric monitoring of methane concentrations is also needed to detect regional trends in emissions and enable rigorous comparisons to bottom-up approaches.

Methane measurements and emission estimates occur along a spectrum of spatial and temporal scales (Figure 3.1), from large-scale global assessments of annual emissions to small-scale measurements of emissions from individual sources over short timescales (e.g., instantaneous). At larger spatial scales (e.g., global, continental, and regional), atmospheric methane concentrations can be transformed, using a variety of modeling tools, to estimate methane emissions from broad geographic areas. These emission estimates, which aggregate emissions from multiple sources, are defined by the Committee as top-down assessments. At smaller spatial scales, measurements from single processes, individual sources, or components within a facility are extrapolated to larger scales (regional, national, global). These bottom-up assessments are intended to be representative of broader categories of emissions. At spatial scales in between an individual source and a source region (e.g., total emissions from a large complex facility such as a natural gas processing plant, an animal feeding operation, or a large regional landfill), emission estimation might be considered either top-down or bottom-up or both. At these intermediate scales, emissions from multiple sources or components within a facility may be aggregated like a top-down assessment. At the same time, the total facility emissions might be used to represent emissions from other similar facilities, like a bottom-up assessment.

In addition to various spatial scales, both top-down and bottom-up approaches have varying temporal scales. Single-source measurements may be done on either short (hour/daily) or longer (monthly/annual) timescales depending on the techniques

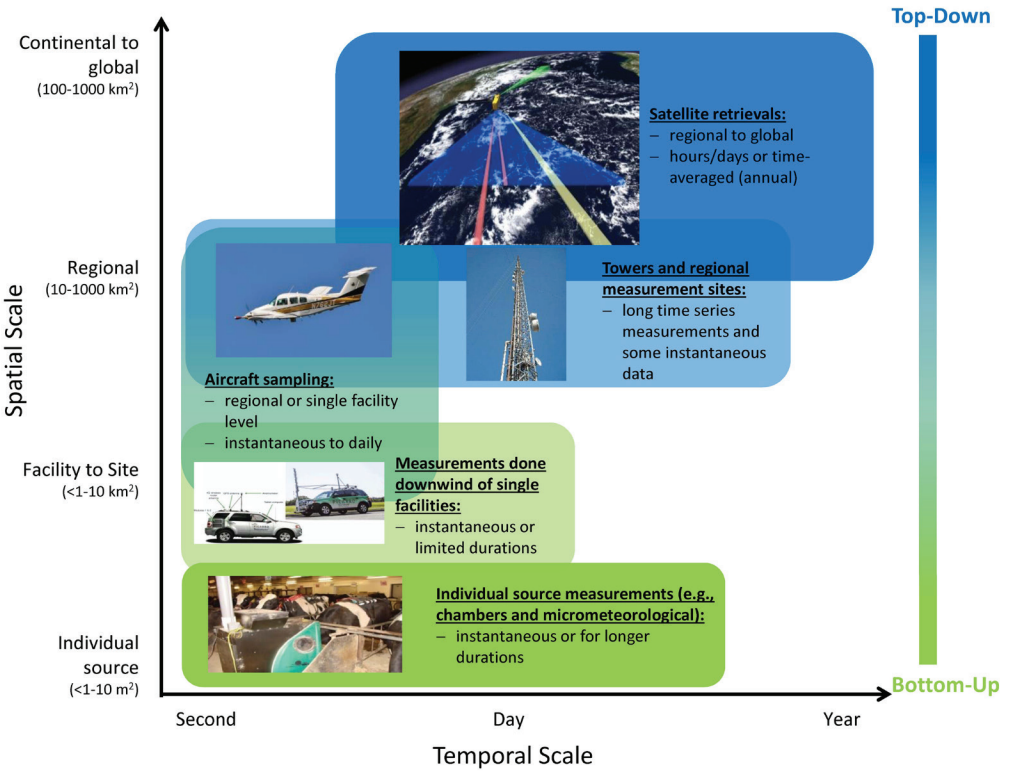


FIGURE 3.1 Examples of methane measurement platforms operating across a variety of spatial and temporal scales.

employed. Chamber techniques, vehicle-mounted sensor techniques, and aircraft sampling tend to capture snapshots of emissions over shorter time periods. Some micrometeorological techniques and high-tower monitoring may provide information from days to years. Satellite retrievals that cover regional to global scales may provide instantaneous snapshots or be time averaged to provide longer-term measurements.

This chapter describes global-, continental-, and regional-scale atmospheric methane measurements, along with the models used to estimate emissions from these top-down measurements. Bottom-up approaches are also described, and recent measurement techniques used for specific source categories are reviewed. The strengths and weaknesses of various top-down and bottom-up approaches are summarized in Tables 3.1 and 3.2. These tables do not explicitly address uncertainties; however,

TABLE 3.1 Bottom-Up Techniques for Measuring Methane Emissions

Technique	Method	Advantages	Disadvantages
Point-source measurements	• Measurement of emissions from fixed points based on flow rate and methane composition.	• Measures total methane emissions from individual point sources (e.g., stacks, animal). • Captures temporal trends if deployed for extended time periods.	• Limited number of methane sources are emitted as point sources. • Labor intensive to quantify spatial and temporal variability (requires a large number of individual measurements to capture variability). • Often limited to measurements from "normal" operations or where there are no safety concerns.
Enclosure (chamber) techniques	• Direct measure of emissions from small area (or number of animals). • Static chambers quantify emissions by multiplying the change in methane concentration over short monitoring periods by the chamber volume/area ratio. • Dynamic chambers quantify emissions by the use of inlet/outlet methane concentrations with an external flux gas known rate.	• Quantifies diffusive emission rates from a small source area (typically 1 m^2 or less) during daytime or nighttime conditions. • Accurately measures emissions from individual or small groups of animals in a controlled environment. • Does not rely on atmospheric modeling to derive fluxes. • Quantifies rates for soil oxidation of atmospheric methane (i.e., "negative" emissions resulting from high soil oxidation capacities).	• Labor intensive to measure the variability of emissions over large source areas (requires geostatistical techniques, a large number of chamber measurements, and ancillary information). Provides an instantaneous measurement that must be repeated to capture temporal trends. • Single enclosures may not capture all variability in emissions.

continued

TABLE 3.1 Continued

Technique	Method	Advantages	Disadvantages
Micrometeorological techniques	• Tower-based vertical measurements of gas concentrations and atmospheric parameters with standard modeling approaches to calculate fluxes. • Examples include flux gradient, integrated horizontal flux, eddy covariance, etc.	• Measures total methane emissions from individual sources/small open source areas. • Measures continuously over time to capture temporal trends in emissions. • Measures uptake of atmospheric methane (i.e., negative emissions).	• Difficult to measure the variability of the emissions depending on the ratio of the technique's footprint to the overall source area (i.e., smaller ratios), and therefore may over- or underestimate emissions. • Appropriate topographic and meteorological conditions are necessary for technique to work properly. • Nighttime measurements are a challenge.
Perimeter facility line measurements	• Measurement of path-integrated methane along boundaries of a source area (i.e., ppm methane-m) along with wind characteristics to estimate an emission rate.	• Measures total methane emissions from variable-sized source areas. • Allows long-term continuous monitoring to capture temporal trends in emissions.	• Difficult to isolate the different sources in source area depending on distribution and meteorological conditions. • Appropriate topographic and meteorological conditions are necessary for technique to work properly. • Difficult to determine the area contributing to flux.

TABLE 3.1 Continued

Technique	Method	Advantages	Disadvantages
External tracer	• Release of tracer gas (C_2H_2, N_2O) at known rate from source area. • Measurement of methane and tracer concentrations across well-mixed downwind plumes to derive emission rate.	• Measures total methane emissions from source area. • Measures complex sources or quantifies the uncertainty in the emission estimate (multiple tracers).	• Difficult to isolate individual sources within source area depending on layout and meteorological conditions. • Appropriate meteorological conditions are necessary for technique to work properly. • Vulnerable to bias if the locations of tracer release differ significantly from the location of methane release. • Labor intensive to measure the spatial and temporal variability of emissions over many sources.
Inverse dispersion modeling	• Measurement of downwind methane concentrations with estimated or measured meteorological parameters to estimate the flux rate from point and area sources.	• Estimates total methane emissions from point and area sources. • Estimates temporal trends when measurements are made continuously.	• Difficult to isolate various sources within the source area depending on source layout and meteorological conditions. • Reliant on modeled meteorological conditions, which may differ from reality and/or limited field measurements. • Regional-scale methods are not fully developed. • Accuracy may vary depending on the source to be measured.

continued

TABLE 3.1 Continued

Technique	Method	Advantages	Disadvantages
Facility-scale in situ aircraft measurements	• Multiple vertical measurements of atmospheric methane and wind-speed gradients above a source area to derive an emission rate.	• Remotely measures total methane emissions from a source area/facility regardless of the operational status or safety conditions at the facility. • Captures temporal trends with repeated overflights.	• Generally cannot isolate individual sources within source area unless useful source-specific tracers can be co-quantified. • Appropriate meteorological conditions (sufficient vertical mixing of surface emissions at flyover elevations, typically midday conditions) are necessary. • Requires multiple flights to capture temporal trends in emissions. • Generally limited to higher-emitting sources (lower detection limits are much higher than point-source techniques). • Labor intensive to measure the spatial and temporal variability of emissions over many sources.

TABLE 3.2 Top-Down Techniques for Measuring Methane Emissions

Technique	Method	Advantages	Disadvantages
Remote observatories	• Atmospheric methane by infrared spectrometry at precise infrared wavelengths for "pristine" sites remote from population centers. • Other radiatively active gases and hydrocarbon gases are also measured.	• High precision • Consistent measurements across multiple sites • Long time series	• Limited spatial coverage.
Towers	• Methane by infrared spectrometry at precise infrared wavelengths. • Time-series measurements of concentrations, analyzed by eddy covariance or by inverse modeling.	• High precision • Consistent measurements across multiple sites • Long time series	• Sparse spatial coverage, potential small-sensitivity footprint.[a] • Methods are not fully developed. • Challenging to apply to individual facilities and distinguish confounding sources.
Aircraft mass balance measurements	• Measurements upwind and downwind of source region. • High-time-resolution instruments. • Infrared spectrometry at precise infrared wavelengths.	• Ability to target specific emission source regions and obtain vertical profiles of methane concentrations. • Analyzed using simple flow-through models and/or sophisticated inversion modeling.	• Limited spatial coverage; temporal coverage limited to a snapshot. • Challenging to account for transient plumes through the "box." • Labor intensive to measure the spatial and temporal variability of emissions.
Aircraft remote sensing measurements	• Absorption spectroscopy using reflected sunlight or thermal emissions.	• Ability to map methane plumes at the 1-5-m scale, direct source attribution.	• Limited spatial and temporal coverage. • Not as accurate as in situ data.

continued

TABLE 3.2 Continued

Technique	Method	Advantages	Disadvantages
Satellite	• Absorption spectroscopy using reflected sunlight (sensitive to entire atmospheric column) or thermal emissions (less sensitive to boundary layer).	• Global, complete spatial coverage, frequent revisit time with a single instrument (TROPOMI).	• Coarse spatial resolution with current instruments (>10 km). • Not as accurate as in situ data, emissions not cleanly resolved. • Limited to sunlit, cloud-free, snow-free scenes.

[a] The sensitivity footprint of an observation at a tower is the region over which emissions can be sensed at that tower. Sensitivity footprints can change with meteorological conditions, and near-field, upwind signals are usually most heavily represented.

NOTE: TROPOMI = TROPOspheric Monitoring Instrument.

uncertainties in top-down and bottom-up methods are addressed in detail later in this chapter and in Chapter 4.

BOTTOM-UP TECHNIQUES FOR MEASURING METHANE EMISSIONS

Bottom-up emission inventories, as discussed in Chapter 2, have historically been developed by multiplying activity data (e.g., numbers of livestock, natural gas operations, landfilled waste) by emission factors (e.g., emissions per head of livestock, emissions per natural gas facility). However, for some anthropogenic sources of methane (e.g., landfills, manure), such simple calculations are generally inappropriate. Emissions from such sources are microbially driven or are subject to significant differences in equipment or operating practices, and as such, they are subjected to large temporal and spatial variability. This requires better temporal and spatial coverage when conducting measurements.

Site-specific research projects have applied multiple field techniques to measure methane emissions. While the nature and sources of activity data vary among sources, many source categories rely on similar methods to measure emissions as the basis for emission factors. In general, the bottom-up techniques described below have application in all source categories discussed in this report. Thus, rather than describe each of these techniques separately for each source, the general methodologies are described first, followed by those more specific to individual source categories.

Overview of Bottom-Up Measurement Methodologies

Methane emissions can be quantified from point sources and area sources using a wide variety of bottom-up techniques, ranging from the direct determination of methane concentration and flow rate at a single leaky valve to aircraft-based mass balance techniques applied to a facility. In between those extremes are

- chamber techniques that use a time series of methane concentrations to determine diffusive soil fluxes at square meter scales or emissions from single or small groups of animals;
- whole-building mass balance approaches to quantify livestock emissions;
- micrometeorological methods to derive emissions from the turbulent transfer of gases over hundreds of square meters at the base of the atmospheric boundary layer; and
- perimeter facility line measurements, inverse dispersion modeling, and external tracer methods to derive atmospheric methane transport rates over square kilometer scales.

Point-Source Measurements

Some emission sources have discrete, well-defined emission points (i.e., valves), and emission rates can be determined directly from the composition and flow rate of the gas at that point. Stack sampling at combustion exhaust points is a common application, but other types of discrete, well-defined emission points also exist. For example, coal mine ventilation systems can release methane through stacks; pneumatic valves and multiple discrete sources in both the petroleum and natural gas supply chains can emit methane as they operate. One approach for measuring point sources is the use of "calibrated bags" where the sample bag, when fully inflated, contains a known volume of gas collected over a known time period. Also, for ruminant animals, enteric methane emissions for individual cows can be measured using an internal tracer technique (Zimmerman, 1993). In other applications for industrial point sources, measurement devices sampling at a known flow rate attempt to capture the entire emission stream—the methane emission rate is calculated by multiplying the sampling rate by the methane concentration minus the background air concentration.

Enclosure (Chamber) Techniques

Emissions of methane from surfaces can be directly determined using small chambers placed on top of the source (e.g., soil surfaces and manure storage surfaces). For static

chambers, diffusive methane emissions are quantified directly from the change in methane concentration over a short time series multiplied by the chamber volume/area ratio (Rolston, 1986). Dynamic chambers (flux gas flowing through a chamber at a known rate) measure emissions based on the difference between the inlet and outlet methane concentration and the flow rate of the flux gas (Eklund, 1992). The chamber approach has been used for quantifying emissions from landfills and above pipelines, water surfaces (using floating chambers) in manure management lagoons, individual or small groups of animals, and multiple other applications. Chambers for surface measurements typically enclose 1 m^2 or less and are useful to quantify the variability of emissions; however, they are a labor-intensive technique which can be partly mitigated using automated chamber systems and specialized chambers with volumes >1 m^3. Importantly, static chambers can also directly quantify uptake of atmospheric methane by soil methanotrophs with high oxidizing capacities (e.g., negative flux [Bogner et al., 1997] for landfill soils).

Micrometeorological Techniques

If emissions from a source area cannot be enclosed or captured, there are several micrometeorological techniques that can estimate methane emissions using towers with fast-response methane sensors and wind speed/direction sensors, combined with atmospheric transport modeling. Measurements made at a particular site and height represent the conditions of the underlying surface upwind of the sensor. This area of influence is called the "footprint" and is dependent on factors such as measurement height, roughness height, stratification, the standard deviation of the lateral wind component, and wind velocity. Therefore, to accurately assess source emissions, the footprint must cover a large enough area of the source to capture the spatial variability of emissions. The flux gradient technique determines the vertical flux of a gas at a given height as a product of the gas's turbulent diffusivity and the concentration gradient at that height (Laubach and Kelliher, 2004). The integrated horizontal flux technique depends on a mass budget equation, simplified for two-dimensional flow (Laubach and Kelliher, 2005). A micrometeorological mass balance method can be utilized by measuring all input and output gas emissions within a given volume of air around the source with the emission rate calculated by subtraction of output and input fluxes (Harper et al., 2011; Ryden and McNeill, 1984). The eddy covariance technique calculates fluxes from rapid measurements of the vertical wind speed and gas concentrations (Harper et al., 2011; Prajapati and Santos, 2017). See Harper et al. (2011) for other micrometeorological techniques.

Perimeter Facility Line Measurements

Perimeter facility line measurements are conducted by equipping a site with open-path spectrometers (infrared, tunable diode laser), which measure average methane concentrations per meter distance on the upwind and downwind sides of a site. The emission rate is then estimated by multiplying the difference between upwind and downwind concentrations by the ventilation rate across the site. Some measurement systems use open-path spectrometers with reflectors at multiple elevations to obtain cross sections of the methane plume (e.g., Childers et al., 2001; Goldsmith et al., 2012).

External Tracer

Measurement of methane emissions from area sources (e.g., landfills, livestock housing areas, and natural gas well sites) can also be accomplished by utilizing an external tracer. In this approach a tracer gas not emitted by the facility (often nitrous oxide or acetylene) is released at a known rate at or near the source area of interest. Downwind measurements are made of the tracer and methane, and the methane emission rate is estimated by multiplying the tracer release rate by the concentration ratio of methane to tracer observed downwind (e.g., Dore et al., 2004; Harper et al., 2011; Lamb et al., 1995). The estimated emission rate relies on the assumption that methane and the tracer undergo equivalent atmospheric dispersion between the source and the measurement location. This assumption can break down if some portion of the emissions from a site are buoyant (e.g., partially unburned methane in combustion exhaust) (Vaughn et al., 2017) and the tracers are not similarly buoyant or if the source contains a mixture of buoyant and nonbuoyant tracers. The assumption can also break down if some emissions are released from elevated locations (e.g., from the top of a storage tank) while others are at ground level. To address these issues, some investigators (e.g., Herndon et al., 2013) have used multiple external tracers for a single source measurement, locating one type of tracer release at an elevated release point and other tracer releases near ground level. When colocated, multiple tracers can also be used to provide a quantitative estimate of the extent to which the tracer and the targeted emissions do not undergo equivalent dispersion.

Inverse Dispersion Modeling

Methane emissions from point and area sources can also be determined utilizing inverse dispersion modeling by making downwind measurements of methane alone (without an external tracer), along with measurements of background methane concentration

and wind speed, wind direction, and air turbulence. Those data are then coupled with dispersion modeling to estimate an emission rate. Similar to micrometeorological techniques, in order to accurately assess source emissions, the footprint must cover a large enough area of the source to capture the spatial variability of emissions.

Downwind concentrations can be measured in a variety of ways. One approach is to measure methane concentrations at a consistent height above ground level downwind of the source on a moving platform, often a vehicle. If the vehicle drives along a path that is perpendicular to the wind direction, the horizontal extent of the plume can be determined. Typically, the observed concentrations and their variability across the plume are fitted to a dispersion model to estimate an emission rate (Brantley et al., 2014; Flesch et al., 2005). Because of the high spatial and temporal variability of diffusive emissions from landfill surfaces, generally poor matches are observed between predicted and measured downwind methane concentrations using standard dispersion models. Some investigators have outfitted vehicles with the ability to measure concentrations at multiple heights above ground level, improving the characterization of the plume and the precision of the emission estimate. Other investigators have used techniques that measure an integrated methane concentration in the entire atmospheric column above the vehicle rather than at specified heights (Mellqvist et al., 2016). Downwind concentration measurements can also be made at a stationary point or over a fixed distance using open-path instruments, along with the three-dimensional wind statistics, and fitted to a dispersion model to estimate an emission rate (Flesch et al., 2005; Leytem et al., 2011).

The accuracy of this method depends on the situation in which it is used. For example, several validation studies using a backward Lagrangian stochastic inverse dispersion technique to measure emissions from livestock report errors of less than 20 percent, likely because these emissions are relatively uniform (e.g., Gao et al., 2010; McGinn et al., 2009; Ro et al., 2013). However, for measuring methane emissions from petroleum and natural gas, which tend to be more variable, errors may be much higher. A recent analysis of emission estimates based on dispersion modeling downwind reports error bounds of +117/−46 percent (Robertson et al., 2017).

Facility-Scale In Situ Aircraft Measurements

Aircraft-based measurements can be used to estimate emissions from individual facilities (e.g., an animal feeding operation, a landfill, or a natural gas processing facility). A typical approach is to fly concentric closed flight paths at multiple altitudes around a source while continuously measuring methane concentrations, wind speed, and wind

direction. Emission rates are estimated using a mass balance approach; the concentration differences between the upwind and downwind portions of the flight paths are multiplied by the ventilation rate for the volume enclosed by the flight paths to arrive at the emission estimate (e.g., Conley et al., 2017; Gvakharia et al., 2017). These techniques have been applied to a variety of methane sources in urban areas (e.g., Cambaliza et al., 2015; Mehrotra et al., 2017). This approach is at a relatively early stage compared to other methods (e.g., tracers), and there are several limitations that need to considered. For example, facility aircraft measurements tend to be successful only under restricted conditions, when there are no confounding sources close to the facility and when aircraft can fly nearly to the bottom of the emission plume. In addition, this approach can only detect emissions that are encountered at flight elevations at the flight radial distance. It is uncertain that the extrapolation from the bottom flight level to the ground is robust for a close-to-ground emission (e.g., a leaking blowdown vent).

Bottom-Up Techniques for Measuring Methane Emissions from Major Sources

Agriculture Sector

There are two sources of methane emissions from livestock: enteric fermentation (predominantly in the digestive tract of ruminant animals) and manure management (methane produced by methanogenesis during manure storage). For some ruminant production systems (e.g., beef or dairy cattle on pasture), enteric fermentation is by far the main source of methane emissions. In ruminant production systems in which manure is handled as liquid (e.g., flush dairy barns, where manure is flushed from the barn with water), methane emissions from manure management can be as high as or even higher than emissions from enteric emissions. For nonruminant production systems (e.g., swine, poultry), methane generated from manure storage is the main source of methane emissions. Methane emissions from livestock are microbially driven and therefore can have large spatial and temporal variability, because microbial activity is governed by the substrate available as well as other conditions. Therefore, care must be taken to ensure that temporal, spatial, and animal (enteric) variability in emissions is captured in order to accurately portray emissions from any given source category.

Enteric Methane

The term "enteric methane" refers to methane produced by microbial fermentation-related activities in the gastrointestinal tract of ruminant or nonruminant animals (for more information on these processes, see Hristov et al., 2013). Ruminant animals are

the largest contributor to methane emissions from agriculture. Nonruminant farm animals, however, also emit methane through fermentative activities in their hindgut.

Enteric methane can be emitted by ruminants through eructation, expiration, or flatulence. Earlier (Murray et al., 1976) and more recent (Muñoz et al., 2012) data have unequivocally shown minimal contribution of methane (2-3 percent) emitted through flatulence, compared with methane emitted through expiration (exhaling) or eructation (belching). A significant portion of methane produced in the rumen, the largest organ of the digestive tract of the ruminant animal, is absorbed into the bloodstream (12 percent in a study by Reynolds et al., 2013). Most of this methane, however, is exhaled through the lungs (Ricci et al., 2014).

Methods for measuring enteric methane from livestock include enclosure chambers, tracer techniques, "sniffer" techniques, and handheld laser methane detectors.[1] The "gold standard" for measuring enteric methane emissions from farm animals (ruminants and nonruminants) is the respiration chamber. The main principles of dynamic respiration chambers are to measure incoming and exhaust airflows, concentration of gases of interest in that air, and initial and final gas concentrations in the chamber. A detailed discussion on the design and operation of respiration chambers was provided in the *Technical Manual on Respiration Chamber Designs,* published by the Global Research Alliance (Pinares-Patiño and Waghorn, 2012). Animals are usually placed in chambers for several days (recommendations are for at least 3 days), during which they are fed and milked (if lactating), and manure is removed from the chamber. The animals have to acclimatize to the chamber environment before measurements take place. The main advantage of respiration chambers is that (1) they are accurate when properly calibrated and operated, (2) all methane emissions, including from the anus, are captured, and (3) measurements take place continuously over several days, accounting for diurnal variation in methane emissions. The results of a recent ring test of respiration chambers in the United Kingdom demonstrated the importance of calibration for the accuracy and precision of respiration chambers (Gardiner et al., 2015). The drawbacks of respiration chambers are that (1) animals are placed in an "unnatural" environment, which in many cases results in stress and decreased feed intake and/or milk production; (2) chambers cannot be used to measure emissions from a large number of large animals concurrently (which is important for genetic selection of low-methane emitters); and (3) they are expensive and require extensive training and operational skills.

[1] A comprehensive review of enteric methane measurement techniques was recently published by an international team of scientists (Hammond et al., 2016) as part of the Global Network project (http://animalscience.psu.edu/fnn/current-research/global-network-for-enteric-methane-mitigation). Materials from the Hammond et al. (2016) review were extensively used in the preparation of this section.

While chamber systems can be utilized to measure emissions from ruminants and nonruminants, there are a variety of other techniques available to measure enteric methane emissions from ruminant animals. A widely used technique is the sulfur hexafluoride (SF_6) tracer method (Figure 3.2). Originally developed by Zimmerman (1993) and first used by Johnson et al. (1994), the method was recently modified and improved by Deighton et al. (2014). The technique is based on using a tracer gas, SF_6, which is continuously released at a known rate from a permeation tube placed in the reticulum (one of the compartments of the complex ruminant stomach) and mixed with rumen gases. Eructated and expired gas is continuously sampled around the nostrils of the animal into an evacuated container and the gas is analyzed for SF_6 and methane. The ratio of the two gases and the SF_6 release rate are used to calculate the methane emission rate. The technique is less costly compared with the investment to build and operate respiration chambers, and has been widely used by research groups around the globe. Variability with the SF_6 technique has been notoriously high (Clark,

FIGURE 3.2 Simultaneous measurement of enteric methane emissions from dairy cows using the GreenFeed® system (C-Lock Inc., Rapid City, South Dakota) and the SF_6 technique (courtesy of A. N. Hristov, The Pennsylvania State University).

2010; Pinares-Patiño and Clark, 2008; Pinares-Patiño et al., 2010), but the modifications by Deighton et al. (2014) addressed the most important sources of error, and the modified technique produces methane measurements with accuracy similar to measurements using respiration chambers. Unlike chambers, the SF_6 technique can be used to measure methane emissions from a large number of animals and in their natural environment. The technique does not account for methane generated in the hindgut and excreted through the rectum. Detailed guidelines for using the technique have been published by Berndt et al. (2014).

Several important conditions have to be met to reduce variability in the methane measurement data when the SF_6 technique is used. These include (1) high release rate of SF_6 from the permeation tube, (2) at least five consecutive measurement days, and (3) low concentrations of SF_6 and methane in background air (i.e., using the technique in enclosed barns is not recommended, unless there is adequate ventilation throughout the measurement period; Hristov et al., 2016). When these conditions are met, the SF_6 tracer technique can produce accurate methane emission data from a large group of animals.

More recently, an automated head chamber system, GreenFeed® (GF), was developed for spot sampling of exhaled and eructated gases (Zimmerman and Zimmerman, 2012). Comparisons with respiration chambers or SF_6 have established that when properly used, GF is a reliable technique for measuring enteric methane emissions from ruminant animals (Dorich et al., 2015; Hammond et al., 2015; Hristov et al., 2016). Similar to the SF_6 technique, the GF system can be used to monitor methane emissions from a group of animals in their natural environment. The technique is based on attracting the animal to the GF head chamber and keeping it there for at least 5 minutes at each sampling event while eructated and exhaled gases are captured and directed to gas sensors.

An important prerequisite for using the GF system is that all animals visit the unit at all times of the day and night. Methane emissions have a clear diurnal pattern, related to feed intake (usually lower at night) and therefore, for accurate daily emission estimates, animal visits have to be spread out over a 24-hour feeding cycle. Best results with the GF system are obtained when the number and timing of animal visits are controlled by the investigator, which is easily achievable in a tie-stall barn situation (Branco et al., 2015; Hristov et al., 2015b), or measurements have to take place over a prolonged period (3-5 weeks, depending on the study objectives; Renand and Maupetit, 2016). Studies conducted in pasture conditions may need longer time to achieve the number of required visits than those conducted in confinement. Recommended GF calibration and background gas collection procedures have to be strictly

adhered to (Hristov et al., 2015a). Similar to the SF_6 technique, GF cannot measure methane excreted through the rectum.

Another direct technique with limited application is the ventilated hood chamber or box (Kebreab, 2015), which is a polycarbonate chamber enclosing the head of the animal, allowing continuous collection and analysis of eructated and exhaled gases. A neck sleeve allows the animal to lie down and eat while measurements take place. The chamber is under constant vacuum, and incoming and exhaust air is analyzed for methane concentration. Detailed description of such a chamber can be found in Place et al. (2011). Drawbacks of this technique are that (1) hood chambers require a significant investment, (2) the animals must be extensively trained to minimize stress during the experiment, (3) the animals' feed intake will likely decrease while fed in the chamber, and (4) the technique is not suitable for measuring methane emissions from a large group of animals.

Indirect approaches have been proposed and used to measure enteric methane emissions from livestock. One approach uses estimated carbon dioxide emissions and measured carbon dioxide/methane ratio in exhaled air to estimate methane emissions (Madsen et al., 2010). This method is based on the fact that most of the carbon dioxide is produced by intermediary metabolism of the animal and can be predicted. If total carbon dioxide production and the carbon dioxide/methane ratio are known, total methane production can be calculated. Hellwing et al. (2013) compared the carbon dioxide method to respiration chambers and found a significant underestimation of emissions by the carbon dioxide method. Changes in digestive and metabolic activities at the same level of feed intake, differences in feed efficiency, and variation in rumen fermentation can influence the amount of carbon dioxide produced by the animal and thus affect the predicted methane emissions (Huhtanen et al., 2015).

Another indirect method proposed by Garnsworthy et al. (2012) relies on estimating methane emissions during an eructation event and the frequency of eructation during a measurement period. Gas samples are collected from the air in the feed manager of an automated milking system when the animal is milked. The attractiveness of this approach (also referred to as the "sniffer" method) is that emissions can be measured in on-farm conditions and on a large number of animals. This method does not account for methane exhaled through the lungs. The authors have reported a good correlation between the "sniffer" and chamber measurements for the same animals (Bell et al., 2014; Garnsworthy et al., 2012). However, even small changes in head position can result in large differences in gas concentration (Huhtanen et al., 2015). In two experiments with lactating cows, Huhtanen et al. (2015) found larger variability with the "sniffer" method and no relationship to emissions measured using the GF system.

Another recent study also concluded that the capability of the "sniffer" method to adequately measure and rank methane emission rates among dairy cows is highly uncertain and requires further investigation into the sources of variation (Wu et al., 2017).

A technique similar to the "sniffer" method utilizes a laser methane detector to measure methane concentration in the air between the laser device and the animal (usually 1-3 m). The method allows methane measurements in on-farm conditions and from a large number of animals; however, comparative studies found a positive but weak relationship between the laser method and chamber measurements (Chagunda et al., 2013; Ricci et al., 2014). Environmental factors such as temperature, wind velocity (particularly important for grazing conditions), and humidity can affect the accuracy of the measurements).

Accurate techniques for measuring enteric methane emissions from livestock are available. Although some of these techniques can measure methane emissions from a significant number of animals (about 20 per piece of equipment) in their natural environment, they are inappropriate for screening of animals at the population level for selection of low-methane emitters.

Manure Management

Manure management systems may include open areas for drying, stacking, or composting manures as well as liquid/slurry storage systems consisting of separation basins, mechanical separators, tanks, pits, and lagoons. Depending on the type of system present at a facility, the measurement techniques for estimating emissions from these sources will vary. For enclosed barns that are mechanically ventilated, emission rates can be determined by mass balance methods. For open housing systems, measurement techniques can include mass balance, external tracer techniques, inverse dispersion modeling, and micrometeorology techniques. Measuring methane emissions from manure storage is typically accomplished using external tracer techniques, inverse dispersion modeling, micrometeorology techniques, or chambers.

Facility-level emissions will include emissions originating from both enteric emissions and manure management, while manure management emissions aim to target those emissions originating from manure in housing as well as manure handling and storage areas. Facility-level emissions can be determined with a variety of larger-scale measurement platforms, such as airplane sensors (see earlier section in this chapter on airplane measurements) or inverse dispersion modeling. Information at this scale can provide overall emission rates for a given facility but are not able to discern the

source of emissions from within a facility. For airplane sensors, because of the expense of flight campaigns and the dependency on favorable weather conditions, data will likely only cover small temporal scales and in many instances only provide information during midday hours when emissions are likely to be greatest from a facility. Therefore, important diurnal and seasonal changes affecting overall annual emissions may not be captured. While inverse dispersion techniques can capture the temporal variability in emissions, individual sources within the facility may not be discernable.

At the component level (e.g., housing, manure handling, and manure storage), a variety of techniques can be utilized to determine emissions. Mass balance techniques can be used to measure emissions from enclosed barns or other areas (manure storage) that are mechanically ventilated. This technique consists of measuring the gas concentration continuously over time at the barn inlet and outlet along with the ventilation flow rate (Amon et al., 2001; Kinsman et al., 1995). The measured emissions will include both enteric (for barns) and manure. This measurement technique works well as long as the monitoring equipment is kept well calibrated for measuring the ventilation rate. Measuring emissions from naturally ventilated livestock buildings presents a greater challenge because it is difficult to determine the ventilation rate. In these instances the ventilation rates can be estimated using a carbon dioxide balance or tracer gas technique. The carbon dioxide balance technique utilizes carbon dioxide formed by animal respiration as a natural tracer gas with the ventilation rate estimated by calculating the mass balance of carbon dioxide flow (Pedersen et al., 1998). Alternatively, a tracer gas (i.e., ^{85}Kr or others) can be distributed inside the building and used to estimate ventilation rate (Marik and Levin, 1996; Samer et al., 2011). Measurement of methane within the barn, along with the estimated ventilation rates, is used to calculate the overall emission rate (Fiedler and Muller, 2011; Snell et al., 2003). These techniques can provide good estimates of emissions from housing areas; however, they will not directly allow estimation of the contribution of enteric versus manure emissions. They can also be employed over longer time periods that capture the temporal variability of emissions, providing better long-term emission estimates.

Additional methods can be employed that do not rely on calculating or estimating ventilation rates and can be applicable to open source areas (dry lots, pasture, manure storage areas, etc.). These include external tracers (Dore et al., 2004; Harper et al., 2011), dispersion models (Flesch et al., 2005; Harper et al., 2011), flux gradient, integrated horizontal flux, micrometeorological mass balance, and eddy covariance (Harper et al., 2011). All of these open-air techniques have the advantage of being able to measure methane emissions from a source area without disturbing animals or altering ambient conditions. Because they measure the emissions from the entire source area (or large portions of it), spatial variability of emissions is also accounted for. Most of these tech-

niques are also easily employed over longer time periods, which provide coverage of temporal variability, enabling more accurate prediction of longer-term emissions.

Techniques available for targeted analysis of specific surfaces include the use of chambers (Amon et al., 2001; Ellis et al., 2001; Misselbrook et al., 2001). Although these techniques can provide emission estimates for a given source area, there are several potential drawbacks to consider. Because of the small size of most chambers, the ability to capture the spatial variability of emissions from the source area may be difficult. During measurement, the chamber itself can alter the environment (e.g., temperature and airflow) of the source area, which may affect emissions. Capturing the temporal variation in emissions can also be difficult because chambers may not be able to be deployed for long periods of time because the disturbance to the ambient atmospheric conditions is too great. However, there have been some automated and floating chambers designed to work over long periods to overcome the challenge of capturing temporal changes in emissions.

Because of the temporal and spatial variability of emissions from livestock housing and manure management, measurements and monitoring need to occur over longer periods of time that cover both the daily and seasonal variations in emissions in order to accurately reflect annual emissions.

Petroleum and Natural Gas Systems

Methane emissions from petroleum and natural gas supply chain sources reported in national inventories include sources from the wellhead to the point of use of the fuel, but they do not include emissions associated with end use (e.g., unburned methane from electricity power generation). The emission sources are varied, as are the activity data and emission measurement approaches. In addition, in the petroleum and gas category, activity and emission factor data collection activities are linked. For example, if measurements of emissions are used to develop average emission factors for an entire population of sources (e.g., all pneumatic controllers used at natural gas wells), then the activity data are simply a count of the number of sources (e.g., the total number of controllers). In contrast, if measurements identify that emissions vary across subpopulations (e.g., pneumatic controllers of different designs, intended to have different emission rates) then emission and activity data would either need to be collected on multiple subpopulations or sampling would need to be done across all subpopulation categories in such a manner that each subpopulation is proportionally represented in the sample. Both approaches can be difficult to implement. Subpopulations may not be sufficiently defined prior to data collection, and randomized

sampling across subpopulations may be impossible due to expense, study extent (e.g., geographic extent of study region), or restricted access.

For each emission category, there are large numbers of sources to account for and considerable spatial and temporal variability in methane emissions both within and across category and component types. In the United States, there are currently over 600 gas processing plants and over one million pneumatic devices in combined petroleum and natural gas systems. Within each of these categories, a variety of subcategories of sources may exist with variability in emissions among the subcategories. For example, gathering and processing facilities can process from <1 to about 1,000 metric tons (or 0.001 Tg) of gas per hour, and emission rates can vary as a result. However, even among plants of equal size, Marchese et al. (2015) and Mitchell et al. (2015) found that normalized emissions (emissions as a percentage of natural gas throughput) ranged from less than 0.1 percent to more than 10 percent. Within specific equipment categories, such as pneumatic devices, there are also multiple potential emission subcategories, based on the method of operation of the device (for pneumatics, low bleed, high bleed, intermittent), as well as the type of service in which they are used (for pneumatics, plunger control, separator level control, emergency shutdown, and many others). Allen et al. (2015a) found that emissions per controller varied by more than an order of magnitude between controllers in different types of service (e.g., separator level control versus controllers on process heaters). Thus, while activity data such as numbers of gas processing plants are generally available for estimating methane emissions from sources in the petroleum and gas supply chains, it is not clear that the level of detail in the activity data of the inventory is sufficient for accurately estimating annual methane emissions.

Measurement Studies to Update Emission Factors and Activity Data

Prior to 2013, many of the emission factors that were used in developing methane emission inventories for petroleum and natural gas systems relied on a comprehensive study by the Gas Research Institute and the U.S. Environmental Protection Agency (EPA), conducted in the 1990s (Harrison et al., 1996). Since 2013, however, a number of studies have reported new emission factor data for petroleum and natural gas. Many of these recent studies were coordinated by the Environmental Defense Fund (EDF) and companies owning and operating assets across the natural gas value chain[2] from production segment to distribution. In addition, the U.S. Department of Energy (DOE)

[2] The major sectors or operational components of the petroleum and natural gas industry include exploration and extraction, storing, marketing and transporting, and refining and processing.

has funded multiple methane measurement projects.[3] Measurements in these studies were conducted by independent, primarily university-based researchers, generally overseen by independent advisory committees and in some cases with industry co-sponsors. Sources on which data have been collected include well completions, pneumatic controllers, pneumatic pumps, leaks, liquid unloadings, flares, gathering operations, gas processing facilities, transmission facilities, and pipelines. The measurement techniques used in EDF-coordinated and DOE studies and other recent emission studies have employed most of the methods described in Table 3.1.

Because the EPA has incorporated some of this new information into Greenhouse Gas Inventory (GHGI) development and new regulations have been finalized that have reduced emissions from specific types of equipment and operations, large changes in the estimated inventories of methane from petroleum and natural gas systems have occurred. For example, in Marchese et al. (2015), Zimmerle et al. (2015), and Lamb et al. (2015), results were employed to update methane emissions from the gathering and boosting, transmission, and distribution segments, respectively (see Chapter 2). In some cases, the changes in emissions are the result of changes in regulations and operating practices. For example, in the 2011 GHGI (released in 2013), emissions from natural gas well completions, summed over the duration of the completions, were estimated to total 0.65 Tg from a total of 8,077 well completions, resulting in average methane emissions per well completion of 81 metric tons (or 0.000081 Tg). With the promulgation of New Source Performance Standards, requiring reduced emission completions for natural gas wells beginning in 2012, methane emissions were reduced by approximately 99 percent compared to an uncontrolled well completion for a limited number of wells on which completion emissions have been measured (Allen et al., 2013). In the 2017 GHGI, well completion emissions, including well workovers with hydraulic fracturing, were estimated to be about 0.03 Tg (an average of 2 metric tons per well).

Other emission inventory changes have been due largely to changes in activity counts. For example, in the 2011 GHGI for natural gas, an activity count for pneumatic controllers averaging one controller per well was used. A series of field studies, together with data on average controller counts per well collected through the Greenhouse Gas Reporting Program (GHGRP), have led to a revision of the activity data for pneumatic controllers. The 2015 GHGI reports an average of 1.9 controllers per well (EPA, 2017b).

[3] See https://energy.gov/sites/prod/files/2016/08/f33/Methane%20Emissions.pdf and https://www.energy.gov/under-secretary-science-and-energy/articles/doe-announces-13-million-quantify-and-mitigate-methane.

These updates, while important in improving the accuracy of emissions documented in the GHGI, can lead to fluctuations in the GHGI from year to year (Figure 2.9).

A common element in many of the recent methane emission studies on natural gas is the presence of high-emitting sources, that is, a small number of sites or equipment that contribute a disproportionately high fraction of the cumulative total emissions recorded (Box 2.2). Some measurements of high emissions may be due to the size of the facility. For example, a natural gas processing plant with a capacity of greater than 1 metric ton (or 0.000001 Tg) per hour might be expected to have greater emissions than a plant with a capacity of less than 1 metric ton per hour; however, even when emissions are normalized by gas throughput or gas produced, a small number of observations with high normalized emissions have been identified. As documented in Table 3.3, these high-emitting sources are found in many studies of various source categories, including many studies with site access and cooperation of industry participants.

A meta-analysis[4] by Brandt et al. (2016) of about 15,000 measurements from 18 studies (including many cited in Table 3.3) found that methane emissions from natural gas systems follow an extreme distribution, resulting in a small fraction of observed emissions accounting for a vast majority of the emissions from the population sampled. Schwietzke et al. (2017) attribute observed known high-level emissions to episodic events in manual liquid unloadings. Compliance inspections have observed potential design constraints and operational issues that may result in chronic high emissions.[5] Stochastic events arise from malfunctions that could result in high-emission events and are difficult to predict.

For petroleum and natural gas, factors that cause certain subpopulations to become high emitters are not well known. Research is needed to gain a mechanistic understanding of high-emitting sources and establish appropriate estimation methods. Conducting campaigns in coordination with owners and operators of the facilities within the regions would help ensure the availability of contemporaneous information concerning operations.

[4] "Meta-analysis" is a statistical analysis that combines the results of multiple scientific studies.

[5] See https://www.epa.gov/enforcement/noble-energy-inc-settlement#violations, https://www.epa.gov/sites/production/files/2015-04/documents/noble-cd.pdf, and https://www.courthousenews.com/wp-content/uploads/2017/10/pdc-cd.pdf.

TABLE 3.3 A Sample of Bottom-Up Measurement Studies in the Natural Gas Supply Chain

Geographic Region Sampled	Devices Sampled	Emission Factor	High-Emitting Sources	Reference
Natural Gas Production Sites				
U.S. national sample of natural gas sites	Well completions, unloadings, leaks, pneumatic pumps, and controllers	Emission factors for leaks and pneumatic controllers higher than in EPA GHGI; emission factors for well completions lower than in GHGI.	Observed for unloadings, pneumatic controllers.	Allen et al., 2013
U.S. national sample of primarily natural gas sites	Pneumatic controllers	Emissions per controller 17% higher than average in GHGI (5.5 scfh [0.2 scmh] whole gas, 4.9 scfh [0.1 scmh] methane).	19% of controllers accounted for 95% of national emissions from pneumatic controllers.	Allen et al., 2015a
Oklahoma petroleum and natural gas sites	Pneumatic controllers	Emissions averaged 1.05 scfh (0.03 scmh) whole gas for all devices.	3.5% of controllers accounted for 73% of controller emissions.	Gibbs, 2015
Utah petroleum and natural gas sites	Pneumatic controllers	Emissions averaged 0.36 scfh (0.01 scmh) whole gas for all devices.	Majority of emissions came from 14 of the 80 controllers; 11 of the 14 high-emitting controllers were malfunctioning.	Thoma et al., 2017
U.S. national sample of natural gas sites	Liquid unloadings	Average emissions equivalent to those reported in EPA GHGI.	2-3% of wells account for more than half of national unloading emissions.	Allen et al., 2015b

TABLE 3.3 Continued

Geographic Region Sampled	Devices Sampled	Emission Factor	High-Emitting Sources	Reference
Marcellus Shale natural gas site	Flare	Very high combustion efficiencies (>99.5%) for a single well completion flare; bottom-up inventories generally assume 98% efficiency.	A single flare measured had intermittent high emissions.	Allen et al., 2013
Marcellus Shale, Bakken Shale petroleum and natural gas sites	Flares	All flares were >99.80% efficient at the 25% quartile; bottom-up inventories generally assume 98% efficiency.	No high emitters detected	Caulton et al., 2014a
Bakken primarily petroleum sites	Flares	37 production flares in the Bakken had a median destruction efficiency of 97%.	Some flares with destruction efficiency <80%.	Gvakharia et al., 2017
Natural Gas Gathering and Processing Operations				
U.S. national sample of natural gas sites	Downwind sampling of sites	Emissions averaged 0.20% of throughput for gathering facilities and 0.075% of throughput for processing facilities.	Some gathering facilities had emissions that were in excess of 10% of gas throughput and 30% of gathering facilities contributed 80% of the total emissions; all processing facilities had emissions <1% of throughput.	Marchese et al., 2015; Mitchell et al., 2015

continued

TABLE 3.3 Continued

Geographic Region Sampled	Devices Sampled	Emission Factor	High-Emitting Sources	Reference
Natural Gas Transmission and Storage				
U.S. national sample	Downwind sampling of sites, with onsite measurements and emission estimates	Emission factors both higher and lower than inventory factors observed; largest emission factor from open-ended lines (measurement factor of 5 greater than GHGRP emission factor).	Highest-emitting 10% of sites (including two high-emitting sources) contributed 50% of aggregate methane emissions.	Subramanian et al., 2015; Zimmerle et al., 2015
Natural Gas Distribution, Metering, and Regulating (M&R)				
Thirteen urban distribution systems	Direct sampling of emissions	Emissions of 0.10% to 0.22% of the methane delivered, equivalent to 36% to 70% less than the 2011 EPA GHGI; emission factors reported for multiple types of pipes and for M&R facilities, multiple pressures.	Large reductions in emissions from high-emitting facilities, compared to measurements made in early 1990s (Harrison et al., 1996).	Lamb et al., 2015
Multiple cities	Downwind sampling	Emission rates were empirically correlated with maximum concentrations measured by an instrumented vehicle, using calibration experiments.	Urban areas with corrosion-prone distribution lines leaked ~25-fold more methane than cities with more modern pipeline materials.	von Fischer et al., 2017
Boston	Centralized monitors on tall buildings	2.7 ± 0.6% of natural gas use, also including urban end-use emissions.	Not applicable.	McKain et al., 2015

SOURCE: Adapted and expanded from Allen, 2016.

Landfills

In contrast to other anthropogenic sources of methane, simple (activity data multiplied by emission factor) calculations are generally inappropriate for estimating landfill methane emissions because of the complexity of soil-gas transport and oxidation processes in landfill cover soils (see also Chapter 2). The two major drivers for landfill methane emissions at specific sites are seasonal climate and site engineering/operational practices, including (1) the thickness and physical characteristics of cover materials and (2) the extent of engineered biogas extraction (Gebert et al., 2011; Goldsmith et al., 2012; Scheutz et al., 2009; Spokas et al., 2011, 2015). Major field campaigns and process-based model development have occurred in recent years, providing important new results quantifying methane emissions from landfills and providing improved inventory approaches. Also, landfills must presently comply with minimum cover requirements, standards for biogas management, required biogas recovery at larger sites, quarterly surface scans for elevated methane concentrations, and other operational guidelines under both Subtitle D of the Resource Conservation and Recovery Act and Clean Air Act mandates. These requirements vary somewhat among states to conform with regional differences in landfill practices as well as state requirements that may be stricter than federal minimum standards.

Landfill emissions are challenging to quantify because of high spatial and temporal variability (Scheutz et al., 2009; Spokas et al., 2011, and references cited therein), including drastically different emission signatures from adjacent cover soils (daily, intermediate, final) and temporal variability in soil oxidation. Both gaseous transport and oxidation rates are dependent on dynamic changes in soil temperature and moisture resulting from local weather fluctuations, as well as longer-term climate trends (Spokas et al., 2011). Laboratory study of cover soils conducted over a wide range of temperature and moisture conditions indicates that optimum oxidation rates occur at soil temperatures around 35°C and soil moisture potentials near the water-holding capacity (about 10 kPa; Spokas and Bogner, 2011).

In general, the highest average emission flux (normalized to grams of methane per square meter per day) has been associated with the working face/daily cover areas at sites in humid subtropical climates, while lower emissions are associated with thicker final cover soils (Babillote, 2011; Goldsmith et al., 2012). At many sites, however, it can be demonstrated that the intermediate cover areas emit the largest percentage of total emissions due to their large surface area and thinner cover soils (than final covers) (Spokas et al., 2015). Importantly, the presence or absence of engineered biogas recovery under a particular cover area (either vertical wells or horizontal collectors installed concurrently with filling) determines the "base of cover" soil gas methane

concentration and the driving force for diffusive methane emissions to the atmosphere (Spokas et al., 2011).

Multiple field campaigns during the last two decades have greatly improved understanding of landfill methane emission processes at U.S. sites. Moreover, during the last decade, a process-based model (CALMIM, California Landfill Methane Inventory Model) has been developed and field validated to provide a predictive framework for site-specific climate and cover-specific gaseous transport and oxidation processes over a typical annual cycle (Spokas et al., 2011, 2015). At present, this model has not been incorporated into the U.S. GHGI or GHGRP.

Field Measurements and Modeling

Field measurement techniques for landfills range from square meter to square kilometer scales, including chambers, tracer techniques, micrometeorological approaches, vertical radial plume mapping (VRPM), and aircraft mass balance approaches, as discussed below and previously summarized in Table 3.3.

In general, the parallel use of labor-intensive static chambers deployed at ground level in combination with other techniques discussed below is desirable because chambers (1) can be deployed at any hour of the day or night, (2) constitute a direct measurement technique that does not require atmospheric modeling to infer methane mass flux rates, and (3) can quantify the spatial and temporal variability of emissions across a given cover type. Moreover, static chambers can also quantify "negative" emissions (e.g., uptake of atmospheric methane), which can occur in landfill cover soils with high seasonal oxidation capacities (Bogner et al., 1997, 2011; Scheutz et al., 2009, and references cited therein). In addition, soil gas probes used in parallel with static chambers are useful to characterize in situ molecular and isotopic profiles for improved understanding of methane generation, transport, and oxidation dynamics. Innovative techniques used in landfill settings include double tracer techniques deployed at field scale (Scheutz et al., 2011), soil gas "push-pull" tests to quantify oxidation (Streese-Kleeberg et al., 2011), and refinements of micrometeorological approaches to better capture atmospheric transport dynamics at landfills (Taylor et al., 2016).

Landfill methane recovered directly from the buried (anaerobic) waste has a relatively constant isotopic signature for carbon ($\delta^{13}C$ of around –60‰); hence, techniques that quantify the change in $\delta^{13}C$ for oxidized landfill methane in chambers, probes, or downwind plumes can directly quantify the extent of oxidation at field scale. Research results indicate that seasonal oxidation is highly variable and underestimated by the current Intergovernmental Panel on Climate Change (IPCC, 2006) default of 10 percent,

with average values in the 30 percent range (Chanton and Liptay, 2000; Chanton et al., 2009, 2011; Liptay et al., 1998; see also Chapter 2). Isotopic fingerprinting using the $\delta^{13}C$ of methane and carbon dioxide has also been used to verify seasonal methane production in a landfill cover soil (Bogner et al., 2011). In general, the $\delta^{13}C$ of emitted landfill methane can range from −60‰ (negligible oxidation) to −30‰ due to oxidation (Bogner et al., 1997, 2011), generally negating its value for fingerprinting landfill methane in atmospheric studies. It should also be noted that all landfills typically have a combination of operational areas with thin daily cover soils, recently completed areas with thicker intermediate cover that will be subject to future vertical expansion, and areas at final grade with very thick or geomembrane composite permitted final covers. This complexity further exacerbates use of atmospheric carbon isotopes to fingerprint landfill methane.

Using modern sequencing techniques, new insights into methane-oxidizing landfill soil microbial communities are also emerging. For example, Henneberger et al. (2015) assessed spatial and temporal changes in methane-oxidizing communities in a landfill cover soil using field-based measurements of oxidation activity, stable-isotope probing of polar lipid-derived fatty acids, and microarray analysis of *pmoA* genes and transcripts. Because of variable environmental conditions (temperature, moisture, soil processes), active microbial communities were highly diverse with distinct spatial and seasonal clustering, including the concurrent presence of atmospheric methane oxidizers.

Recent multiple-landfill U.S. field campaigns have relied on diverse bottom-up field techniques to quantify site-level landfill methane emissions and oxidation, thus providing important insights into the strengths and weaknesses of various methods. For example, a comparative study of methane emissions from two adjacent Wisconsin landfills using five methods (Babillote, 2011) included (1) tracer correlation using N_2O, (2) an optical remote sensing method (VRPM), (3) static chambers with stable C isotopes to quantify soil oxidation, (4) an eddy covariance micrometeorological method, and (5) differential absorption Lidar (DiAL). Results indicated that the tracer method had minimum error and lowest variability; however, the VRPM, DiAL, and tracer results were all within the same order of magnitude. Moreover, using the DiAL method, working area emissions could be shown to be reduced approximately 50 percent at the end of the working day following the placement of daily cover. Complementary data on methane oxidation using a stable carbon isotopic method (Chanton and Liptay, 2000; Liptay et al., 1998) ranged from 7 to 25 percent for daily covers and from 15 to 45 percent for intermediate covers, with differences attributable both to variable cover thickness and decreased methane loading to the base of the cover due to the biogas extraction system. These results support the continued use of multiple techniques in

parallel to quantify the variability of emissions for individual cover materials at various temporal scales. Goldsmith et al. (2012) subsequently reported on use of a tunable diode laser spectrometer for path-integrated methane within a VRPM based on the EPA OTM-10 method at a large number of U.S. sites. Conclusions emphasized two important challenges with the routine use of VRPM for landfill applications: the topographic irregularities typical of landfill sites and the need for improved quantification of the area contributing to the calculated flux (Abichou et al., 2010; Goldsmith et al., 2012; Thoma et al., 2010).

Recently, joint efforts between the waste industry and the EPA have focused on developing a standardized field methodology for "whole-landfill" emissions with the goal of certification by the EPA as an other test method. This has included the development and application of a tracer correlation method using a C_2H_2 tracer with the Piccaro cavity ring-down spectrometer (Foster-Wittig et al., 2015). Quantitative acceptance criteria were developed to screen data resulting from insufficiently advected plume transport or poor tracer correlations. The high-emitting sites had total emissions greater than 6,000 g methane min^{-1}. More recently, measured emissions during a 3-year period at a newly opened landfill using the tracer correlation technique discussed above were compared by de la Cruz et al. (2016) to various methane generation and emission models. Their study concluded that IPCC (2006) and similar standard landfill methane generation-based models overestimated emissions by factors ranging from 4 to 31. It is not appropriate, however, to extrapolate these site-specific multipliers to other sites or to the national total due to site-specific differences in operational practices and climate. As previously discussed in Chapter 2, there are fundamental problems with the current inventory methodology, including a lack of systematic field validation for emissions as well as a lack of systematic correspondence with independent field measurements.

During the last decade, a new process-based model (CALMIM) has been developed and field validated for use in quantifying "whole-landfill" methane emissions over an annual cycle. The model provides improved site-specific estimates as the sum of cover-specific methane emissions with and without oxidation for 10-min time steps and 2.5-cm depth increments over a typical annual cycle (using embedded U.S. Department of Agriculture models for average 30-year weather data with 0.5° × 0.5° latitude/longitude reliability). Moreover, CALMIM has utility for other research and engineering applications when used with local annual weather data to examine annual emission trends or assess emissions from proposed alternative cover materials, or when paired with climate projections (e.g., CMIP5) to estimate future emissions (Bogner et al., 2011, 2014; Spokas and Bogner, 2011; Spokas et al., 2011, 2015). This JAVA tool directly models diffusive emissions inclusive of soil oxidation, without any linkage to a theoretical methane generation model

(e.g., IPCC, 2006). To facilitate model use for future inventories, inputs are limited to site latitude/longitude, waste footprint area, cover soil areas, thickness and physical properties of each layered cover soil, and percentage of cover area with underlying biogas recovery.

International field validation for CALMIM included a direct comparison of results to independent field measurements derived from a wide variety of techniques for 40 cover materials at 29 landfill sites on 6 continents (e.g. Bogner et al., 2011, 2014; Goldsmith et al., 2012; Spokas et al., 2011, 2015). Overall, model comparisons to field measurements resulted in a *d* index of 0.765 using site-specific data (Willmott index of agreement; Willmott, 1981), a Pearson *r* value > $|0.8|$ for modeled versus measured comparisons at 25 of 29 sites, and an average mean error across all covers of 12 g methane m^{-2} day^{-1} (see additional uncertainty discussion in Chapter 4). Regional trends can be distinguished; for example, in comparisons with field data at 10 California sites, sites with hot/dry summers consistently had large seasonal increases in emissions due to reduced oxidation (Spokas et al., 2015).

At specific sites, this model can provide a temporal framework for expected emissions with and without oxidation for comparison to field measurements. Figure 3.3 compares whole-landfill methane emissions for an Indiana landfill using an aircraft mass balance technique, tracer correlation, and modeled monthly emissions with and without oxidation (Cambaliza et al., 2017). Here the model provides a temporal framework for expected emissions using 30-year average weather data with and without oxidation for comparison to the field values. Importantly, cover-specific field measurements and modeling concluded that >90 percent of the total site emissions were derived from the daily working area, which constituted <10 percent of the total site area. This is directly attributable to an operational practice that is not universally practiced at U.S. landfills; namely, an underlying intermediate cover was stripped prior to vertical expansion for new cell development. Hence, new waste directly overlaid old methanogenic waste without an intervening cover, resulting in high emissions. At sites where this is standard practice, the total site emissions can be largely dependent on the daily filling area, and boundary conditions within the CALMIM model (e.g., methane at base of cover) can be readily adjusted to accommodate this practice. For many other sites, however, a high percentage of total site emissions can be attributed to intermediate cover areas, which typically cover large areas and have thinner cover soils than final covers (see Spokas et al., 2015, addressing California emissions). In general, estimation of landfill emissions using this model requires limited inputs: cover areas, their physical properties and thickness, and the extent of installed biogas recovery on a percent cover area basis.

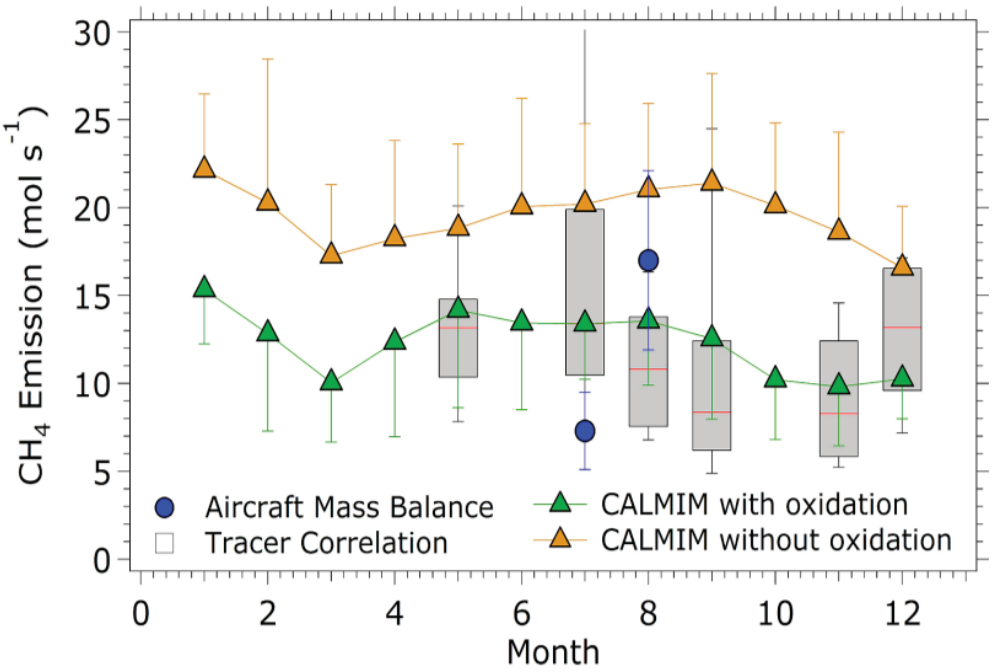


FIGURE 3.3 Comparison of CALMIM-modeled to measured emissions at an Indiana landfill in moles methane per second (1 mole = 16 g). Measured emissions included tracer correlation (TCA) and aircraft mass balance (AMB) methodologies. Percentile values for TCA box and whisker plot: box bottom, 25th; top, 75th; whisker bottom, 10th; top, 90th; red line, median. AMB emission estimates were taken on August 30, 2012, and July 3, 2014. CALMIM data include average modeled monthly emissions (using 30-year climate data and site-specific cover soils): (1) with oxidation + standard deviation; (2) without oxidation – standard deviation. SOURCE: Cambaliza et al., 2017.

CALMIM has also been applied in California to a new 2010 state-level inventory and compared with the existing 2010 state inventory using IPCC (2006) (which assumed 75 percent biogas collection efficiency and 10 percent oxidation; Spokas et al., 2015). The three most common California cover types used for this simulation were taken from an independent dataset developed by the California Department of Resources Recycling and Recovery (Walker et al., 2012). Site-specific emissions between the two inventories varied inconsistently in both directions due to the different drivers for emissions, namely, mass of waste using IPCC (2006) and, more realistically, the combination of soils and seasonal climate using CALMIM (see Figure 4.2).

Use of and further improvements to field-validated, process-based models (e.g., the California Landfill Methane Inventory Model) that rely on site-specific drivers for emissions (e.g., area, thickness, and texture of each cover soil; extent of installed biogas recovery; site climate) can provide more realistic estimates of methane emissions than current GHGI and GHGRP methods. In particular, robustly linking cover-specific oxidation to site-specific climate is warranted.

Coal Mines

Methane in coal can be generated thermogenically, as part of the coalification process,[6] or biogenically owing to activity of microbes. Thermogenic methane is produced from coal organic matter by chemical degradation and thermal cracking mainly above a temperature of 100°C. In contrast, biogenic coal-bed methane is generated by the breakdown of coal organic matter by methanogenic consortia of microorganisms at lower temperature, usually below 56°C. Because of these two different mechanisms of generation, typically coals of low coalification levels are targets for biogenic methane, whereas coals of high coalification level may contain thermogenic methane (e.g., Mastalerz, 2014). Coal extracted by underground techniques is expected to have more methane because of its better preservation at greater depth. In addition, deeper coals typically have a higher coalification level because of deeper burial and also because their emissions are supplemented by the methane from affected underlying or overlying sediments. In contrast, shallow coal uncovered in surface mines has less methane primarily because of its easy migration through the shallow cover to the surface over geological time. However, methane content in coal can vary significantly between coal basins, between coal beds within the basins, or even within individual coal beds (e.g., Strąpoć et al., 2008), depending on coal rank, coal type, stability of associated clastic formation, and complexity of local geological and hydrological conditions, making methane emission predictions from coal mines difficult.

Emission Estimates

Active Underground Mines

In underground coal mining, activity data such as numbers of mines and quantities of coal produced are well known and emission estimates rely on stack-based sampling of

[6] Transformation of plant biomass into peat and coal (Diessel, 1992).

underground mine ventilation systems and measurements of degasification volumes. These numbers are regularly reported to the EPA.

Ventilation systems in active underground mines are the largest source of coal-mining methane emissions. Gas emitted from walls and pillars enters the ventilation system of mines when it is not captured by boreholes. Methane emissions from ventilation systems are assessed based on the airflow and the methane concentration in the ventilation air. While ventilation flow measurements do not show large variations (being a function of the size and capacity of the specific ventilation fan), the methane content in the ventilation air can vary significantly in response to changes in coal-seam properties and to changes in daily coal production. The Mine Safety and Health Administration (MSHA) requires that trained MSHA inspectors perform mine safety inspections at least quarterly by testing methane emission rates at each coal mine. Air bottle samples are collected at the mine's main ventilation fans along with airflow rate measurement. If emission levels are greater than 3.86 metric tons (or 200,000 cubic feet) per day, more frequent inspections take place, every 5-15 days depending on the emission level. MSHA maintains a database of measured methane emissions from all mines with detectable levels of methane in the ventilation air (MSHA, 2015). Independent of MSHA measurements, individual coal mines perform frequent methane emission measurements to ensure safe working conditions. Emissions are measured, typically weekly, with handheld methane detectors and flowmeters at the base of the ventilation air shaft in the mine. Continuous monitoring devices are used primarily to warn miners if methane concentrations exceed 1.0-1.5 percent, and these concentrations are not recorded. Consequently, gassy underground U.S. mines have high-resolution methane emission data collected underground.

To prevent the occurrence of high methane levels in gassier mines, degasification of coal seams takes place prior to mining. This methane drainage reduces the gas content of the coal and decreases the risk of gas outbursts by decreasing the pressure in the rock formations (Karacan et al., 2011; Noack, 1998). Degasification is accomplished by in-mine horizontal boreholes or surface boreholes, and can be carried out before or after mining (Figure 3.4). In addition, post-mining wells recover methane from the overburden. While horizontal boreholes are often used to capture methane, surface boreholes are used to control seam gas and are typically vented into the atmosphere. The amount emitted is monitored daily or every few days at the wellhead with methane detectors and flowmeters. Some mines use continuous systems that monitor various parameters simultaneously.

In addition to emission assessment based on ventilation and degasification described above and used in the GHGI, various empirical models have been developed for

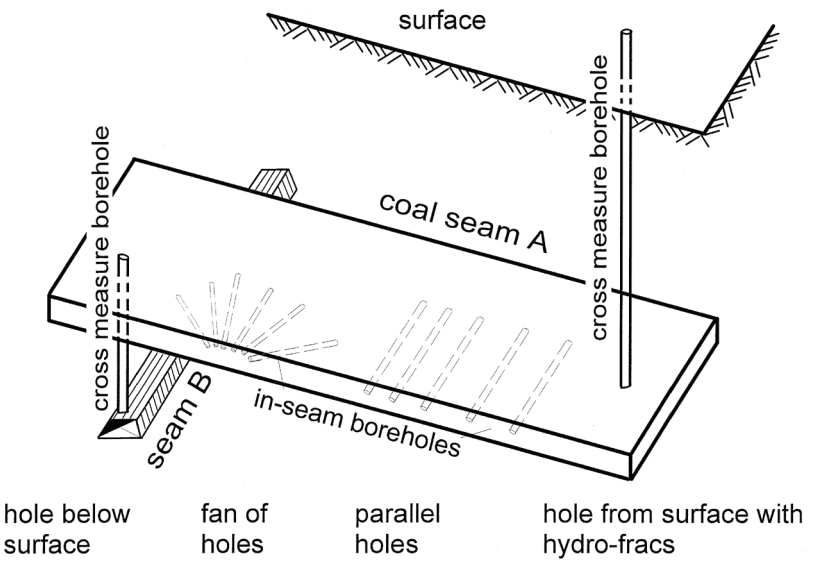


FIGURE 3.4 Methods of predrainage of coal seams. SOURCE: Noack, 1998.

underground mines by various research groups in the United States and elsewhere (Kirchgessner et al., 1993; Lunarzewski, 1998). Empirical methods typically require only a few input parameters (e.g., coal production, gas content, and methane emission rate), but with the large number of parameters that influence emissions, the accuracy of the results is not always satisfactory (Karacan et al., 2011). To generate more accurate emission predictions from longwall mines, a modular software suite, Methane Control and Prediction,[7] was developed using artificial neural networks in combination with statistical and mathematical techniques (Dougherty and Karacan, 2011). This software predicts emissions based on a number of parameters related to coal characteristics, mining conditions, and productivity, and can also conduct sensitivity analysis (Karacan et al., 2011).

Abandoned Underground Mines

Even though current methane emissions from abandoned underground mines account only for 9 percent of the total coal mine emissions, the increasing number of

[7] See https://www.cdc.gov/niosh/mining/works/coversheet1805.html.

underground mine closings in recent years (e.g., decline from 523 in 2014 to 465 active mines in 2015 [EIA, 2016]) warrants efforts to improve emission estimates from this category. Gassy underground mines continue emitting methane after they are closed. The emissions are typically reduced compared to their active phase, but can still be substantial if gas can find conduits to migrate to the surface. The level of emissions varies depending upon many factors including gas content of the coal, mine flooding, the presence of conduits, the quality of mine seals, and the time since the mine closure. As discussed in Chapter 2, the EPA produced a methodology for abandoned underground mines in the United States (EPA, 2004), and annually reports methane emissions. In general, emission estimates from abandoned underground mines are based on the emissions during the active phase of the mine, assuming that emissions experience a hyperbolic decline after abandonment. The main challenge with the estimation of methane emissions from the abandoned underground mines is generation of an accurate decline curve. Methane adsorption isotherms, coal permeability, and pressure at mine abandonment are required to establish a reliable decline curve. Mine-specific data are used to fit the decline curve equations (Karacan et al., 2011).

Estimates from abandoned underground mines carry uncertainties related to a decline-curve generation. With an increasing number of underground mine closings, this is an important category that requires improvement in methane emission predictions.

Surface Mines

Surface coal mines release methane as overburden is removed and the coal is exposed. Methane can be emitted both from coal and associated clastic sediments (overlying or underlying rocks) that are affected by mining activities. Compared to underground mines, the level of emissions from the surface mines is much lower, primarily owing to low gas content of shallow coals that are mined from the surface. Therefore, emission measurements are not required for surface mines, and mine-specific emission data are rarely available. Consequently, the emissions are estimated using production data and coal and gas data. The GHGI uses Tier 2 country-specific emission factors and the volumes of the produced coal (EPA, 2005). As discussed in Chapter 2, the emission factor currently used in the United States is based on 150 percent of the in situ gas content of the coal (EPA, 2017b).

Efforts to develop direct methane measurements or mine-specific assessments in surface coal mines of the United States and elsewhere have also been attempted. For example, open-path Fourier-transform infrared spectroscopy followed by

Gaussian-based plume dispersion modeling showed that methane emission rates can range over an order of magnitude for a single mine (EPA, 2005). Use of a chamber method combined with measurement of surface gas emission flux in Australian surface mines yielded promising results but proved to be impractical to use. That technique required good measurement coverage to obtain a representative methane value for the mine, which, because of safety issues and lack of access to some areas, was practically impossible (Saghafi et al., 2004). Saghafi (2012) proposed a new Tier 3 method to estimate emissions from Australian surface mines based on an emission model that considered coal seams and surrounding horizons as individual gas reservoir units. The main input data required are in situ gas content, gas composition, and thickness of the gas-bearing horizons. The outputs of the model are gas emission factor, expressed in cubic meters of gas released per ton of coal extracted and/or gas emission density expressed in cubic meters of gas released per square meter of ground surface. In this method, two or three core drillings per mine are typically required to characterize a gas-emitting zone and to provide the main input of the model. Because of the limitations of the standard gas content measuring method, different limits of gas content measurability can lead to significant differences in the estimation of methane emissions.

These direct or mine-specific measurement efforts demonstrate that, although it is very desirable to estimate methane emissions for each surface mine, it is a highly challenging task because of variations in gas content and also because of the difficulty of gaining enough access to the sites to guarantee statistically sound measurement coverage.

Estimates of surface mine emissions are based on coal production data, often imprecise gas content, and assumed gas emission factors. Therefore, the estimates carry larger uncertainties than those from underground mines. However, underground mining has a much higher contribution to total methane emissions and therefore is a priority for efforts to improve methane emission estimates from coal mining.

TOP-DOWN TECHNIQUES FOR MEASURING METHANE EMISSIONS

Global Methane Monitoring Observations

Top-down emission estimates for methane, for the United States or any other region, rely on atmospheric measurements of methane and a quantitative understanding of the sources and sinks of methane in the atmosphere. Because U.S. emissions account

for a small portion of the global methane budget, and because the long atmospheric lifetime of methane allows emissions to be distributed globally, it is not possible to quantify U.S. emissions from atmospheric concentrations of methane without considering the contributions of global sources and sinks to methane concentrations. Global methane monitoring networks provide this information.

Monitoring of atmospheric methane was built on carbon dioxide monitoring efforts. It was initiated by the Rowland-Blake Group at the University of California (UC), Irvine, in 1978 and is ongoing, making these observations the longest-running time series of atmospheric methane concentrations. Air samples at approximately 45 sites distributed throughout the Pacific Basin from Alaska to New Zealand are collected four times per year, with many of the sampling sites located on remote islands in the Pacific and along the West Coast of the United States. Analysis of air samples also includes about 100 halocarbons and hydrocarbons, including some that are potentially useful for understanding sources of methane.

The National Oceanic and Atmospheric Administration (NOAA) Cooperative Air Sampling Network methane measurements started in 1983 and continue through today at more than 60 sites where volunteers collect samples that are shipped to the NOAA *Earth System Research Laboratory* (ESRL) in Boulder, Colorado, for analysis (Dlugokencky et al., 1994). The sampling frequency is about once per week, although at NOAA observatories, continuous observations are possible because air is sampled and analyzed in situ. Air samples have been collected from a variety of platforms including cargo ships, small aircraft, and tall telecommunications towers. NOAA aircraft and tower measurements are mainly at sites in the United States.

The Advanced Global Atmospheric Gases Experiment[8] (AGAGE, sponsored by the National Aeronautics and Space Administration's [NASA's] Upper Atmosphere Research Program of Earth Science) started high-frequency methane monitoring observations in the mid-1980s at five globally distributed "baseline" sites (Cunnold et al., 2002) and continues today at over a dozen sites globally. The AGAGE network also measures more than 50 other atmospheric compounds, many of which are related to methane.

There is a wide range of signals to be detected in atmospheric methane using spatially distributed observations that are sustained over time. The latitudinal gradient of methane (the annual mean difference between the North and South Poles) is about 150 ppb, compared to the global average dry-air mole fraction (the ratio of moles of methane compared to number of moles of all components) concentration

[8] See https://agage.mit.edu.

of ~1,850 ppb. Much smaller longitudinal gradients occur between the Pacific and Atlantic: 10-20 ppb, based on estimates of U.S. emissions and transit times across the United States. Differences in the Pacific-Atlantic gradient are particularly important for determining U.S. emissions because the Pacific is generally upwind and the Atlantic downwind of the United States. Near strong local sources, gradients can be much larger, hundreds to thousands of parts per billion over relatively small distances. The seasonal cycle of methane is on the order of tens of parts per billion, while decadal trends have ranged from <1 to >10 ppb yr^{-1}.[9] The ability to accurately quantify trends and spatial gradients that allow continental or regional emissions to be inferred places strong demands on the precision and accuracy of network observations.

Retrievals of column-average methane dry-air mole fraction (XCH_4) from space-based remote sensing data such as the Scanning Imaging Absorption Spectrometer for Atmospheric Chartography (SCIAMACHY) and the Greenhouse Gases Observing Satellite (GOSAT) can provide useful information about the gradient across the United States, especially since these data could have much higher spatial and temporal resolution than is possible with in situ observations. However, precision and accuracy are worse than what can be achieved using the ground-based network, making the quantification of large-scale trends more difficult. Given the impact of stratospheric methane and topography on column-averaged methane abundances—which are measured by the satellite—full atmospheric inversions are required to infer total U.S. emissions. On the other hand, satellite retrievals are useful for detection of localized high emissions at small scales over which variations in topography, stratospheric methane, and tropopause height are not significant. Enhancements near strong localized sources can range from tens of parts per billion to greater than 500 ppb (Chen et al., 2016; Frankenberg et al., 2016; McKain et al., 2015; Thompson et al., 2016). For example, methane enhancements of 40 ppb were observed over the Four Corners region of the southwestern United States (Kort et al., 2014).

Uncertainties in top-down emission estimates are influenced both by uncertainties in atmospheric methane measurements and by uncertainties in the models used to estimate emissions based on atmospheric measurements (Box 3.1; for more detailed discussion of uncertainties, see Chapter 4). The uncertainty of network observations plays an important role in determining the sensitivity of the network to spatial and temporal variability of methane, and this translates into information about source distributions and their variability. The uncertainties of both the NOAA and AGAGE network observations are very small, amounting to only about 0.06 percent of global average methane mole fraction, meaning that the network observations are sensitive across

[9] Ed Dlugokencky, NOAA/ESRL (www.esrl.noaa.gov/gmd/ccgg/trends_ch4/).

BOX 3.1
DATA QUALITY CONTROL AND MEASUREMENT ERROR FOR THE NOAA NETWORK

One source of uncertainty in top-down emission estimates is uncertainties in atmospheric methane measurements. Practices used to control and characterize atmospheric methane measurement errors include sampling designed to minimize impacts of local sources, duplicate sampling, frequent calibration against standards, and documentation of datasets.

- **Minimizing impact of local sources:** Regional observatory sites are selected to minimize the influence of local emission sources; however, not all local source influences can be eliminated. At many sites, sampling protocols have been established to ensure that regionally representative air is sampled rather than air influenced by local sources. For example, at Barrow, Alaska, air sampled when winds are from the direction of the Arctic Ocean provides samples that are representative of regional air, rather than the nearby wetlands and the town of Barrow.
- **Duplicate samples:** Air samples are collected in pairs, and disagreement between pair members indicates a possible problem with the samples, resulting in flagging of those samples for determination of use.
- **Frequent calibration against standards:** Methane in air samples is measured using gas chromatography with flame ionization detection. The measurements are calibrated to the World Meteorological Organization standard scale (Dlugokencky et al., 2005), currently maintained by NOAA. Scale propagation errors are quantified by repeated measurement of standards. Because there is uncertainty on the methane mole fraction even in the standards themselves, it is desirable that measurement systems be calibrated to the same calibration scale. The AGAGE network uses a calibration scale developed by Tohoku University (Japan), and agreement between AGAGE and NOAA is remarkably good, within 1 ppb. This lends confidence to the long-term data records from these two measurement programs.
- **Documentation of datasets:** Measurement uncertainties are given for each observation and described in files available with data downloads (Dlugokencky et al., 2017). Repeatability of the measurement system and the stability of the calibration scale over time are considered. Repeatability is determined by using agreement between sample pairs excluding flagged pairs.

Overall, the total error in atmospheric methane measurements has ranged from 2.4 ppb (95 percent confidence) early in the observational record to 1.1 ppb as of 2016. For reference, the global average measured atmospheric concentration of methane as of May 2017 was 1,846 ppb.

a large range of spatial and temporal variability. Using the current understanding of methane sources and sinks of methane, each 1-ppb increase of methane distributed globally requires emissions of 2.8 Tg methane (Fung et al., 1991). The 2016 uncertainty in mean modeled global tropospheric methane abundance (1.1 ppb) is equivalent to 3.1 Tg methane emissions globally, meaning that changes of 0.6 percent in the global methane budget can be detected (assuming a global total budget of 550 Tg methane

yr^{-1}). On the other hand, space-based methane retrievals, which have a precision of 10-50 ppb, are difficult to use for accurately quantifying gradients between the Pacific and Atlantic and defining methane upwind and downwind of the United States. The high-precision methane observation networks currently in place provide a rigorous mechanism for tracking changes in global emissions.

International Methane Monitoring Efforts

In addition to methane network observations collected by NOAA, NASA (through AGAGE), and UC Irvine, monitoring of methane is conducted by many other nations and these measurements are important for understanding factors that influence the flux of atmospheric methane that enters the United States. For example, Environment and Climate Change Canada collects long-term observations at Alert, Nunavut, and other locations throughout Canada. A long-term record of methane for the well-mixed Southern Hemisphere has been collected at the Cape Grim Observatory in Tasmania by the Commonwealth Scientific and Industrial Research Organization, Australia.

The use of monitoring observations from multiple institutions can significantly improve data coverage; however, it is necessary to ensure that the data are of comparable quality and are calibrated to the same scale. To facilitate this, the World Meteorological Organization has set up a framework to ensure that data submitted to the World Data Centre for Greenhouse Gases (WDCGG) meet quality and calibration standards and that relevant metadata are distributed along with the data. The commitment to regularly submit data to the WDCGG varies, with some institutions providing frequent updates and others lagging by years. A map showing current sites for which greenhouse gas observations have been submitted is shown in Figure 3.5.

Monitoring observations have also been made from commercial aircraft by European, Japanese, and Australian investigators (Brenninkmeijer et al., 2007; Machida et al., 2008). These data provide information about the upper troposphere and lower stratosphere. Profiles are made during ascents and descents mostly in polluted urban environments, potentially making them useful for estimating urban emissions.

Monitoring of Related Atmospheric Trace Species

Global monitoring observations are also available for atmospheric trace species that are important for understanding the methane budget. For example, NOAA air samples are measured for $^{13}CH_4$ by the Institute of Arctic and Alpine Research (INSTAAR) at the University of Colorado. This methane isotope is useful for attributing emissions to biogenic

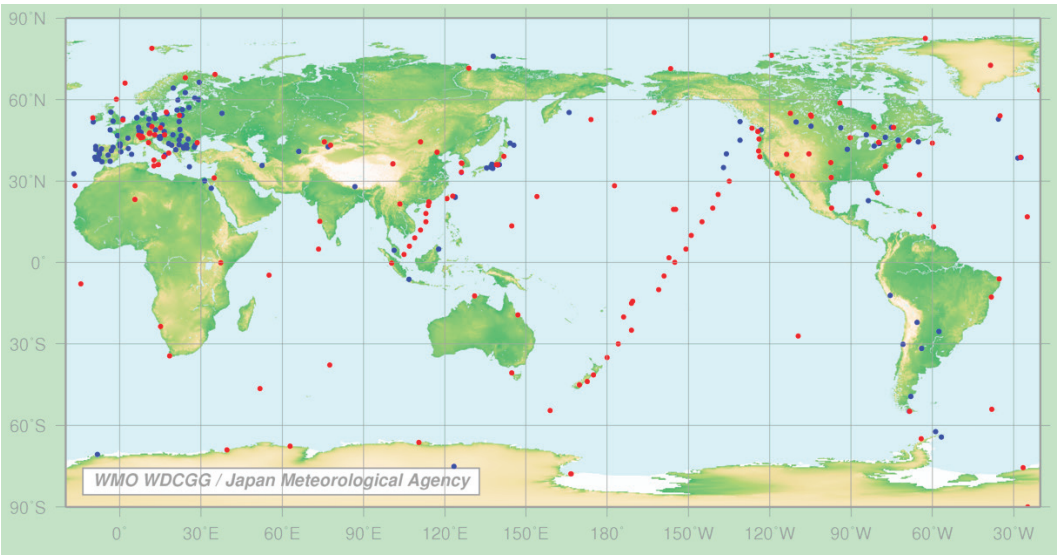


FIGURE 3.5 Locations of sites where methane observations have been submitted to the WDCGG (blue and red dots). Red dots indicate submissions between 2016 and 2017. SOURCE: World Data Centre for Greenhouse Gases Data, http://ds.data.jma.go.jp/gmd/wdcgg/.

or thermogenic sources (Schaefer et al., 2016; Schwietzke et al., 2016). Methyl chloroform can be used to infer the strength of the chemical sink of atmospheric methane because its emissions are thought to be well known, and its only chemical loss, as for methane, is by reaction with hydroxyl radicals (e.g., Rigby et al., 2017). Measurements of methyl chloroform are made by NOAA/ESRL, UC Irvine, and the AGAGE network.

Observations of some hydrocarbons such as ethane and propane may also help to quantify emissions from petroleum and natural gas production since they are co-emitted with methane from this source. The ratio of the emissions of these higher hydrocarbons relative to methane varies considerably and is not well characterized at present (Allen et al., 2017; Peischl et al., 2015, 2016). However, both ethane and propane are increasing rapidly in the atmosphere, possibly due to increased petroleum and gas production in the United States (Franco et al., 2016; Helmig et al., 2016), although methane emissions from petroleum and gas production are thought to be stable (Bruhwiler et al., 2017; Schwietzke et al., 2016). Monitoring observations of some non-methane hydrocarbons are currently being made in NOAA/ESRL air samples by both NOAA and INSTAAR, and by UC Irvine, and as in situ measurements at AGAGE stations.

Observations Using Remote Sensing Techniques

Observations of methane column abundance from satellite platforms may significantly increase the spatial and temporal coverage of observational constraints (Jacob et al., 2016) on forward and inverse models used to estimate emissions. Satellite measurements typically use methane absorption features in the shortwave or thermal infrared spectral range to derive methane abundances. Remote sensing in the shortwave infrared is based on absorption spectroscopy using the sun as a light source, which makes it very sensitive to methane in the entire atmospheric column, including near-surface variations (e.g., Buchwitz et al., 2000). However, using the sun as a light source excludes nighttime measurements. Retrievals in the thermal infrared use blackbody radiation from the surface and the atmosphere as the light source and are less sensitive to the surface, with peak sensitivity in the free troposphere (e.g., Wecht et al., 2012; Worden et al., 2013).

One of the primary advantages of remote sensing is that, in principle, it enables global, frequent coverage with a single instrument. However, satellite-based retrievals will never be able to be as accurate or precise as ground-based in situ instruments, as the measurements are always affected by other confounding factors such as aerosols, which can never be fully eliminated with passive remote sensing (see Chapter 4). If proven successful, future active remote sensing using Lidar (Light Detection and Ranging), such as the Methane Remote Sensing Lidar Mission Merlin (Pierangelo et al., 2016), might alleviate these caveats and enable year-round measurements from pole to pole. Active measurements are unlikely to achieve true global coverage, however.

Satellite observations of near-surface methane were spearheaded by the European and Japanese space communities. The first instrument to measure methane globally was SCIAMACHY, a near-infrared solar absorption spectrometer that has sensitivity to the near-surface atmosphere and a horizontal footprint size of 30×60 km (Frankenberg et al., 2005). Launched in 2002, data from SCIAMACHY were collected until 2012, when the instrument failed. Figure 3.6 shows an example of a long-term average of SCIAMACHY observations in the United States at $0.33° \times 0.33°$ spatial resolution.

The Thermal and Near Infrared Sensor for Carbon Observation (TANSO-FTS, Hamazaki et al., 2005) is a similar, but higher spatial and spectral resolution (80 km^2) instrument that was launched aboard GOSAT in 2009. The TROPOspheric Monitoring Instrument (TROPOMI)[10] was launched in 2017 and has a much better spatial coverage at slightly better spatial resolution (7×7 km). The first U.S. satellite with high surface sensitivity will be the Geostationary Carbon Cycle (GeoCARB) Observatory (e.g., O'Brien et al.,

[10] See http://www.tropomi.eu.

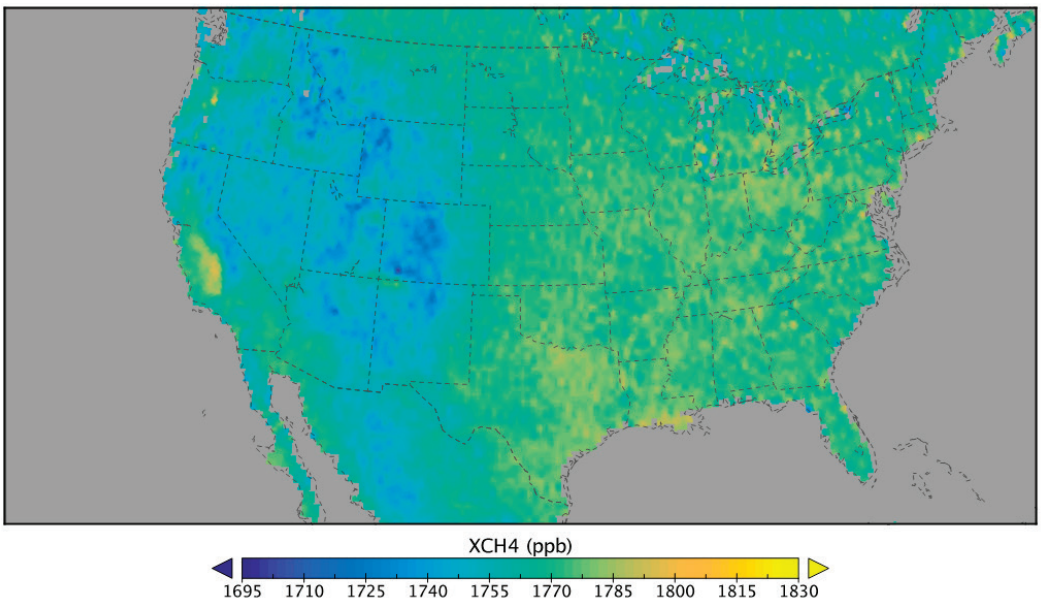


FIGURE 3.6 Space-based methane observations over the United States, averaged from SCIAMACHY satellite retrievals from 2003 through 2006 (similar to Frankenberg et al., 2011). Note that column-averaged concentrations are typically lower over elevated terrain, because the stratosphere (which has lower mean concentrations) has greater weight in the column.

2016), promising higher spatiotemporal resolution. These higher-resolution instruments may allow for mass balance approaches to be used to estimate emissions with higher spatial resolution than is currently possible. Potential future missions might also be able to map localized plumes from space (Thompson et al., 2016; Thorpe et al., 2016), a technique that is currently only achieved using airborne platforms (e.g., Bradley et al., 2011; Buchwitz et al., 2000; Frankenberg et al., 2016; Hulley et al., 2016; Thorpe et al., 2014; Tratt et al., 2014). This strategy of very fine spatial resolution from space (<100 m) is followed by some commercial satellites such as GHGSat.[11] Although the strategy is promising, it is unclear yet whether the commercial instruments are meeting the requirements and whether datasets will be publicly available.

[11] See http://www.ghgsat.com/.

Continental-Scale Monitoring Observations

Atmospheric monitoring of greenhouse gases for the United States, including methane, occurs as part of the Global Greenhouse Gas Reference Network (GGRN) operated by NOAA and partners at universities and federally funded research institutions (Figure 3.7). The NOAA Cooperative Air Sampling Network is a subset of the NOAA GGRN. In addition to the GGRN, since 2012, Earth Networks, Inc., has established more than 40 monitoring locations throughout the United States. The company has closely collaborated with numerous government and academic organizations

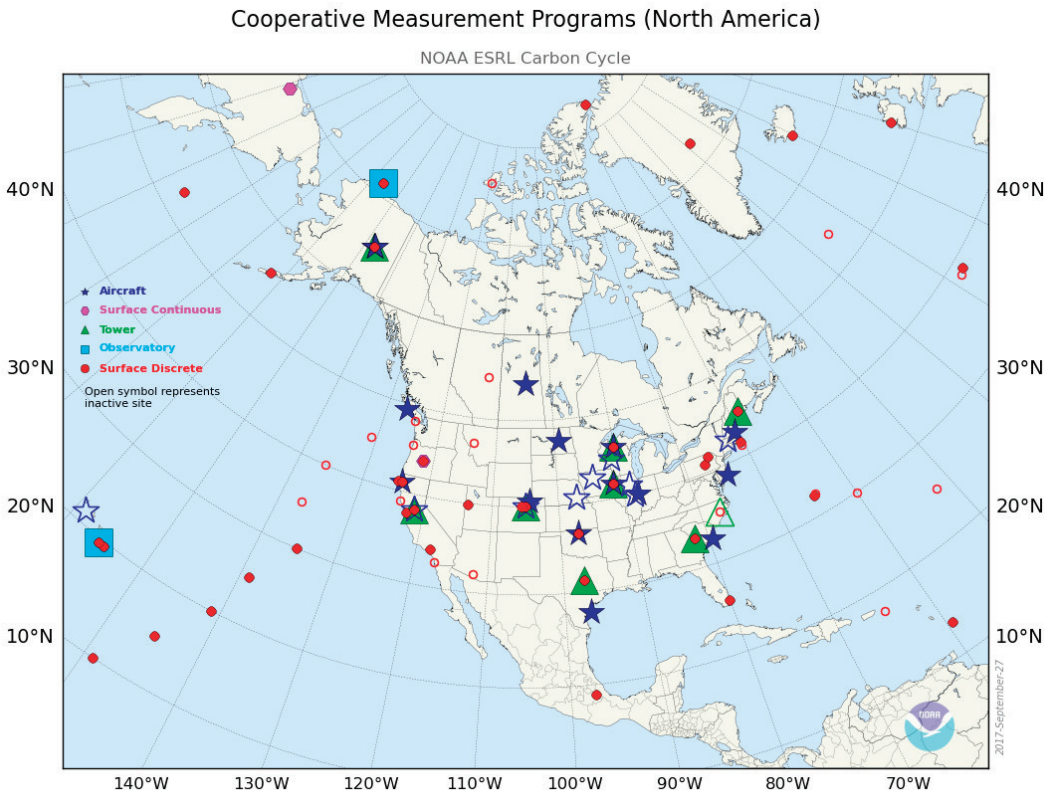


FIGURE 3.7 Map of current North American network sites. All of the aircraft, surface discrete, and observatory sites measure methane. The tower sites measure discrete methane except for two sites in California, which have in situ analyzers. The red and magenta dots show locations of surface samples. The light blue squares show observatories. Samples are also collected from light aircraft (dark blue stars) and tall communications towers (green triangles). SOURCE: NOAA/ESRL Global Monitoring Division.

on urban measurement projects primarily in the Los Angeles Basin and Northeast Corridor. Data from the efforts are being made broadly available and several papers leveraging associated measurements have been or are in the process of being published (e.g., Brown, 2016).

Tall towers (~300 m) are a useful way to understand regional greenhouse gas (GHG) variability because as the wind changes direction, it is possible to detect signals from surrounding nearby sources. However, most of the NOAA tower network is not equipped to measure methane continuously, although there are some Earth Networks data available for urban areas, as noted above. Analysis systems deployed at tall-tower monitoring sites are based on commercial nondispersive infrared absorption sensors. Measurements of methane are not possible using these analyzers. However, cavity ring-down spectrometers (Crosson, 2008) or off-axis integrated cavity output spectrometers (O'Keefe et al., 1999), which do measure methane, have been installed at two tower sites in California. An example is Walnut Grove, California, where a cavity ring-down spectrometer was installed in September 2007.

Air samples have also been collected since the late 1990s using light aircraft (Sweeney et al., 2015). Currently, profiles of GHGs including methane are collected every 2 or 3 weeks at 17 locations (Figure 3.7) from the planetary boundary layer (0.5 km above sea level) to the free troposphere (up to 8 km above sea level). This aircraft program has provided information about large-scale horizontal and vertical methane gradients across the United States and their seasonal cycles. A climatology constructed from aircraft profiles clearly shows the accumulation of methane from west to east across the continental United States (Sweeney et al., 2015).

Regional Monitoring Observations

Regional atmospheric methane observations can be made using networks of tower sites similar to those used in continental networks, but at a smaller scale. For example, the California Air Resources Board (CARB) has a network of eight sites that have been continuously collecting methane data since 2010. The goal is to provide top-down (atmospheric) constraints on California methane emissions for comparison with bottom-up inventories (Figure 3.8; Hsu et al., 2010; Jeong et al., 2013, 2017). Regional tower and tall-building-based observations have also been made at the scale of individual cities, including Indianapolis (Lamb et al., 2016) and Boston (McKain et al., 2015).

Short-term, regional observations have also been conducted by aircraft, often in regions dominated by particular types of methane emission sources. Table 3.4 summarizes recent aircraft measurements that have been made primarily in petroleum

FIGURE 3.8 Map of the CARB greenhouse gas monitoring network. SOURCE: California Air Resources Board.

TABLE 3.4 Sample of Regional Methane Emission Studies Conducted Using Aircraft Plus Complementary Data

Region Studied	Reference	Methods for Measurements
Fayetteville Shale	Schwietzke et al., 2017	Aircraft-based measurements upwind and downwind of production region, complemented by ground-based data.
Bakken Shale	Gvakharia et al., 2017	In situ samples near flares.
Bakken Shale	Kort et al., 2016	Aircraft-based measurements of methane, ethane, carbon dioxide, carbon monoxide, and other compounds downwind of production region (but not upwind).
Bakken Shale	Peischl et al., 2016	Airborne in situ measurements of methane, carbon dioxide, carbon monoxide, and ethane downwind of the production region (but not upwind); mass balance inversions.
San Juan Basin	Smith et al., 2017	Airborne in situ samples for mass balance inversions.
San Juan Basin	Frankenberg et al., 2016	Airborne imaging spectroscopy (remote sensing of methane plumes).
Barnett Shale	Karion et al., 2015; Smith et al., 2015	Aircraft-based measurements upwind and downwind of production regions, complemented by extensive component and facility-scale emission studies.
Haynesville, Fayetteville, and NE Marcellus Shales	Peischl et al., 2015	Aircraft-based measurements upwind and downwind of production regions.
Haynesville, Fayetteville, and NE Marcellus Shales	Peischl et al., 2015	Aircraft-based measurements upwind and downwind of production regions.

TABLE 3.4 Continued

Region Studied	Reference	Methods for Measurements
Marcellus Shale	Barkley et al., 2017	Aircraft-based measurements of methane, carbon dioxide, and carbon monoxide, upwind and downwind of production region, complemented by facility-scale emission estimates; data used for aircraft mass balance inversions and atmospheric transport model optimization.
Indianapolis	Cambaliza et al., 2015	Aircraft-based measurements with multiple transects upwind and progressively downwind of Indianapolis; methane and carbon dioxide measured using high-precision, high-time-resolution instruments, spectrometry at precise infrared wavelengths.
Denver-Julesburg	Petron et al., 2014	Aircraft-based measurements upwind and downwind of production regions; methane measured using high-precision, high-time-resolution instruments, spectrometry at precise infrared wavelengths.
Southwestern Marcellus	Caulton et al., 2014b	Aircraft-based measurements downwind of production region (but not upwind); methane measured using high-precision, high-time-resolution instruments. Some measurements of single production sites.
Uintah Basin	Karion et al., 2013	Aircraft-based measurements upwind and downwind of production regions; methane measured using high-precision, high-time-resolution instruments, spectrometry at precise infrared wavelengths; light alkanes analyzed from discrete air samples.
Los Angeles	Peischl et al., 2013	Aircraft-based measurements of methane, carbon dioxide, carbon monoxide, and C2–C5 alkanes using high-precision, high-time-resolution instruments.
Los Angeles	Wennberg et al., 2012	Aircraft-based measurements of methane, carbon monoxide, and ethane.

SOURCE: Adapted and expanded from Allen, 2016.

and natural gas production regions. In general, these studies involve making measurements upwind and downwind of the source region during periods when the atmosphere is assumed to be well mixed. The instrumentation used in aircraft measurements can be varied, but generally relies on instruments with high time resolution and precision. Aircraft measurements are used to estimate regional emissions by multiplying (1) the methane concentration difference between upwind and downwind measurements by (2) the ventilation rate for the region. These types of observations have revealed significant regional variability in the intensity of methane emissions (units of methane emissions per unit methane produced) from petroleum and gas supply chain sources.

Estimating Emissions from Top-Down Observations

The observed spatial distribution and temporal variability of atmospheric methane is a "top-down" constraint on its sources and sinks. A variety of models are used to deduce information about emission and sink processes from spatially distributed time-series measurements of methane. At global, continental, and regional scales, forward and inverse modeling methods are used. At regional scales, some analyses employ mass balance approaches.

Both forward and inverse modeling approaches are powerful analysis tools that can increase understanding of the global and regional budget of methane. Inverse techniques are diagnostic because they allow a look backward in time to understand trends in emissions. They may provide guidance on whether policy aimed at mitigating methane emissions is effective, and they may alert scientists of increased emissions from Arctic wetlands and permafrost. Diagnostic modeling also can lead to improvements in prognostic modeling. By using inverse modeling to evaluate bottom-up models of emissions, improvements can be made to the bottom-up models, and the result may be better confidence in coupled climate–carbon cycle predictions.

Forward Methods for Estimating Emissions from Top-Down Observations

The forward approach involves use of bottom-up estimates of emissions and sinks, along with an atmospheric transport model to simulate atmospheric methane that can be compared with observations. Bottom-up estimates come from inventories of the type described in Chapter 2. Process model data or up-scaled flux observations can be used to prescribe emissions from natural wetlands, as well as methane uptake in dry soils (when soil acts as a sink). Differences between forward simula-

tions and observations provide information about possible gaps in understanding of unaccounted-for methane sources, which require adjustments to modeled source/sink processes to reach better agreement with observations.

The canonical example of this type of approach applied to atmospheric methane is the study by Fung et al. (1991), who comprehensively tested multiple possible methane budgets against observations such as the meridional gradient and seasonal variability of methane. They found a "best" global budget that totaled 500 Tg yr^{-1} in emissions, with losses due to uptake in soils and chemical sinks totaling 460 Tg yr^{-1}. The imbalance between sources and sinks leads to increasing atmospheric methane, in agreement with the observed methane growth at that time. Fung et al. (1991) concluded that anthropogenic emissions were responsible for about 60 percent of the annual methane budget (recently supported by Saunois et al. [2016] using an ensemble of global inversions and bottom-up data). Interestingly, they also found that several budget scenarios could satisfy observational constraints, a finding that has important implications for the inverse approach.

Inverse Methods for Estimating Emissions from Top-Down Observations

While the forward approach uses models of atmospheric transport to convert emissions to atmospheric abundance, the inverse approach converts atmospheric abundance to emissions. Differences between atmospheric methane simulated using atmospheric transport models, first-guess emissions (i.e., "priors"), and observed atmospheric methane are used to solve for revised emissions. The numerical techniques employed range from simple mass balance approaches to data assimilation methods similar to those used in numerical weather forecasting. A very simple global inverse model approach using the global continuity equation for atmospheric methane was used by Dlugokencky et al. (2003) to propose that global methane was reaching a steady state during the late 1990s and early 2000s. Spatially resolved atmospheric transport models range from one-dimensional diffusion models (Bolin and Keeling, 1963), to zonal average models (e.g., Brown, 1993, 1995; Enting and Mansbridge, 1989; Tans et al., 1989), to detailed global atmospheric models with simple chemistry to calculate chemical loss (e.g., Bergamaschi et al., 2013; Bousquet et al., 2011; Bruhwiler et al., 2014).

Most inverse models are based on Bayesian inference, wherein new information coming from observations is systematically combined with bottom-up information (the *priors*) (Hein et al., 1997; Kandlikar, 1997). The resulting estimated emissions (*posterior estimates*) are in optimal agreement with both the priors and the observations, given

input uncertainties. In a Bayesian analysis procedure, the solution is strongly influenced by the relative weighting of information coming from the prior estimates and information coming from observations. This weighting is defined by estimated uncertainties of the prior emissions and observations. The observation uncertainty represents transport model uncertainty as well as measurement uncertainty; however, the latter is typically much smaller than transport model uncertainty for in situ observations. Defining the prior uncertainty estimates is challenging and may not be well constrained by independent information. For example, bottom-up estimates of emissions from inventories often lack associated uncertainty.

In addition, it is especially challenging to quantify model transport error, especially for measurement sites where the distribution of local sources may not be adequately known; therefore, it is difficult to determine whether model-data differences are due to a lack of knowledge of sources or transport errors. Díaz Isaac et al. (2014) found that, because of a lack of detailed knowledge of underlying source distributions, they were unable to definitively show that a high-spatial-resolution transport model was able to simulate observations better than a coarser-resolution global model.

For regional inverse modeling, McKain et al. (2015), among others, discussed the difficulty of disentangling transport errors from errors in specifying the locations of the emission sources. The atmospheric concentration data alone do not constrain both. Simulation methods for atmospheric transport are developmental, and current uncertainties limit the reliability of regional inversions.

Inverse models have proved to be an important tool, yet challenges to their usage remain, notably (1) the inability of the surface network to adequately reflect the full spatial variability of emissions, leading to multiple solutions that may significantly differ in spatial allocation of emissions and allocation of emissions among sources; and (2) the requirement that point measurements be accurately simulated with typically coarse-resolution transport models. Inverse modeling could provide information about variability and trends in atmospheric methane. It could also provide important insights into performance of bottom-up emission models, some of which may be coupled with climate models that are capable of predicting feedbacks between trace gas emissions and climate, leading to improved confidence in climate predictions. For example, by seeing how prior estimates of wetland methane emissions are changed by use of observations, biases in wetland emission process models may be identified and remedied.

Understanding global methane emissions is important for understanding U.S. emissions because knowledge of what is flowing into the United States is needed to

estimate what is being added to the atmosphere by the U.S sources. Houweling et al. (1999) found that compared to the a priori distributions of emissions, a posteriori emissions were reduced at high northern latitudes and increased at tropical and southern latitudes, a result obtained by many global inversions since (Bergamaschi et al., 2013; Bousquet et al., 2011; Bruhwiler et al., 2014; Houweling et al., 2014). Possible reasons for this include overestimated bottom-up emissions at high northern latitudes and underestimated bottom-up emissions at low and southern latitudes, as well as biases in model transport and chemical loss. In addition, it is difficult to rule out biases in atmospheric transport models. For example, a too-stable planetary boundary layer could systematically lead to underestimated emissions.

Adequate observational coverage in space and time is required to fully constrain inverse models at national or regional scales. There are only about 100 surface sites globally that measure atmospheric methane, and many of these sites are sampled only weekly, although a small number of sites collect continuous measurements. Many surface network sites have been selected to represent the background atmosphere remote from strong local sources. Some regions are therefore inadequately resolved by inverse models, for example, the tropics, where long-term monitoring is often logistically challenging and emissions are likely to be significant. Sparse data coverage has important implications for inversions; Hein and Heimann (1994) and Hein et al. (1997) used a full global atmospheric transport model to estimate global methane emissions and concluded that their estimated emissions reproduced large-scale features such as the interhemispheric methane gradient reasonably well, but not grid-scale emission variability.

Improving atmospheric transport models will also lead to more accurate estimates of emissions using inverse models. Patra et al. (2011) evaluated and compared a suite of atmospheric transport models for 1990-2007 using observations of methane, radon, SF_6, and methyl chloroform at background sites and satellite retrievals of methane in the upper troposphere and stratosphere. Analysis indicated a considerable range in interhemispheric transport exchange time among models (1.2-1.8 yr), and differences due to vertical mixing, convection, and stratosphere-troposphere exchange were found. By using multiple inverse models, Locatelli et al. (2013) found that inverse modeling estimates of global methane emissions due to atmospheric transport differences could be as large at 27 Tg methane yr^{-1}, comparable to an amount that could account for observed interannual variability. At continental scales, transport model differences led to even larger differences, with differences for North America of up to 36 Tg methane yr^{-1}.

Coupling increased observations of atmospheric methane with improved measurements of important diagnostic quantities for atmospheric modeling (such as planetary boundary-layer depth) will likely help improve the accuracy of emission estimates, increasing observational constraints and providing critical datasets that may be used to improve atmospheric transport models.

Use of Satellite Retrievals in Inverse Models

Observations of column-average methane from satellite platforms may significantly increase the spatial and temporal coverage of observational constraints. Satellite data can be used in atmospheric inversions in the same way as ground-based observations. In fact, both data streams can be used in a single inversion, helping to ensure consistency and to point out potential biases in satellite data, which typically have lower accuracy due to their indirect measurement technique. Current satellite instruments have been shown to have persistent biases in space and time (e.g., Bergamaschi et al., 2013; Houweling et al., 2014) that must be accounted for if satellite data are to be assimilated into atmospheric inverse models. Remotely sensed observations of column methane using ground-based upward-looking Fourier spectrometry (e.g., the Total Carbon Column Observing Network) have been used to detect biases in the satellite data and to develop bias correction schemes (Houweling et al., 2014; Wunch et al., 2011). In terms of monitoring, successive instruments will be needed to monitor over multiple decades, and care will have to be taken to ensure that instruments are comparable.

Multiple studies have successfully used satellite data in atmospheric inversions (e.g., Bergamaschi et al., 2007; Cressot et al., 2014; Fraser et al., 2013; Fung et al., 1991; Houweling et al., 2014; Meirink et al., 2008; Turner et al., 2015) and underline the potential to reduce methane emission uncertainties on regional through global scales. Bergamaschi et al. (2009) noted good agreement between inversions using only surface network observations and inversions using surface observations and the revised retrievals at large scales. They also proposed that use of the satellite retrievals and estimation of emissions at grid scale resulted in information about how emissions vary at subcontinental scales, a result that was later questioned by Bousquet et al. (2011) based on comparisons of SCIAMACHY retrievals with model simulations of column-average methane using multiple inversion emission estimates. The use of their water-vapor-constrained bias correction led Houweling et al. (2014) to the conclusion that variability in tropical emissions is larger if SCIAMACHY retrievals are used in addition to surface observations and that the variability is more robust if bias correction parameters are not estimated along with emissions in the inversion.

Regional Estimates of Methane Emissions Using Top-Down Techniques

Some attempts to increase transport model resolution have been made using global models with increased horizontal resolution over regions of interest, a computationally cheaper alternative to global high resolution. Bergamaschi et al. (2005, 2010) applied a global model with two-way nested grids to estimate emissions from individual European countries using a nested grid of 1° × 1° resolution over Europe and a resolution of 6° × 4° over the global domain. Both studies found significantly higher emissions for parts of Europe compared to the values reported by the United Nations Framework Convention on Climate Change (UNFCCC). In particular, Bergamaschi et al. (2010) found emissions that were considerably higher than those of EDGARv4.0 (21 percent) and the UNFCCC (40 percent). Turner et al. (2015) used a global model with a nested high-resolution grid for North America and found much higher U.S. emissions than EDGAR and EPA estimates (40-43 versus 25-27 Tg yr^{-1}), results consistent with other global time-dependent inversions (Bruhwiler et al., 2017; Saunois et al., 2016).

It is difficult to accurately simulate point measurements with a coarse-resolution model because of variability due to strong local sources, surface topography, and high-frequency atmospheric variability. For this reason, some recent studies have used regional models that simulate atmospheric transport at resolutions of 10 km or less. The most common strategy involves use of a Lagrangian particle dispersion model, such as the HYSPLIT (Hybrid Single Particle Integrated Trajectory Model; Draxler and Hess, 1997) or STILT (Stochastic Time-Inverted Lagrangian Transport; Lin et al., 2003) models, to simulate the backward trajectories of particles from measurement locations, keeping track of cumulative contact with the surface layer where emissions can influence the trace species concentrations in air parcels. A surface sensitivity or response function matrix is constructed, and inverse techniques are used to estimate sources, just as for the global case. Driving meteorology from high-resolution global analyses or regional models such as the WRF (Weather Research and Forecasting; Skamarock and Klemp, 2008) model is used to calculate particle trajectories.

The advantage of using a regional atmospheric model is that transport can be simulated at higher resolution and is likely to be more accurate than with a coarser global model. The disadvantage is that boundary conditions at the edge of the domain must be specified, and there is not good observational coverage to do this accurately. The solution is very dependent on the estimated boundary condition and Gourdji et al. (2012) found that use of different estimates of the boundary conditions could lead to differences in estimated fluxes of CO_2 that were as large as the net annual flux over the region of interest, North America.

A Lagrangian approach with the Weather Research and Forecasting–Stochastic Time-Inverted Lagrangian Transport (WRF-STILT) model configuration was used by Kort et al. (2008) to analyze methane data collected by the CO_2 Boundary Layer Regional Airborne–North America (COBRA-NA) airborne campaign. They concluded that the bottom-up emissions of EDGARv32FT2000 for North America were in good agreement with their top-down results. A later study using the same WRF-STILT model configuration concluded that for 2007 and 2008, anthropogenic emissions were significantly underestimated for North America (Miller et al., 2013). Emissions from ruminants and manure were found to be as much as a factor of 2 higher than estimated by the EPA and EDGARv4. In addition, Miller et al. (2013) found that emissions from fossil fuel production could be almost five times larger than estimated by EDGAR.

Bergamaschi et al. (2018) used both global inversions with high-resolution nested grids over Europe and Lagrangian inverse models to estimate European methane emissions. They found that the inverse estimates were substantially higher than those from bottom-up inventories and suggested that natural emissions from wetlands could be higher than bottom-up estimates. No systematic differences between global nested-grid and Lagrangian inversions were highlighted; however, the Lagrangian inversions used background methane from the global inversions, thereby eliminating a major source of difference between the two approaches. The study by Bergamaschi et al. (2018) also demonstrated the value of having a relatively dense network of quasi-continuous measurements; they were able to use a network of 18 sites, as well as additional sites with less-frequent discrete sampling.

Inverse modeling has also been used to estimate emissions at urban and petroleum and natural gas basin scales. For example, Lamb et al. (2016) used a WRF-STILT modeling system and measurements from the INFLUX campaign to estimate methane emissions for Indianapolis. They found significant differences between their inverse estimates and both bottom-up and mass balance estimates using measurements taken from aircraft. They found that 48 percent of methane emissions were from biogenic sources, with the remaining portion from fossil fuels, including citywide diffuse leakage. Jeong et al. (2017) employed a Bayesian inversion model to attribute methane and volatile organic compound emissions measured in the San Francisco Bay area. The authors conclude that landfills dominate the total emissions, and methane emissions from natural gas systems are approximately 0.3-0.5 percent of total natural gas consumed. Barkley et al. (2017) used the WRF regional model in Eulerian mode (i.e., without a Lagrangian calculation of sensitivity to surface sources) to estimate emissions from a portion of the Marcellus basin. They found agreement between their estimates and mass balance estimates based on aircraft observations, as well as leakage rates

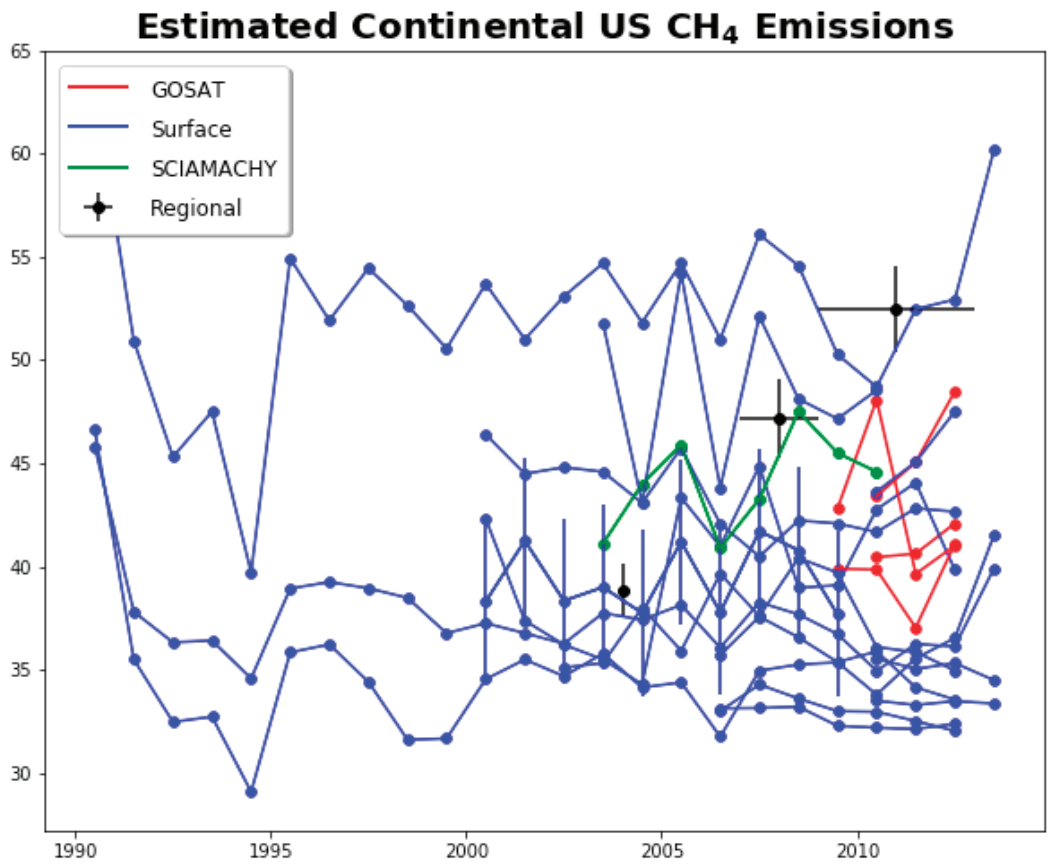


FIGURE 3.9 Annual U.S. methane emissions from time-dependent global inversions (blue) collected by the Global Carbon Project. Green and red lines indicate inversions using space-based retrievals of column-average methane (red, GOSAT; green, SCIAMACHY). The black points are results from regional inversions that have limited temporal extent: (left to right) Wecht et al. (2014a), the WRF-Stilt inversion of Miller et al. (2013), and Turner et al. (2015).

relative to total production for unconventional production and gathering facilities that were low compared to other basins (0.36 ± 0.09 percent).

Top-Down Estimates of U.S. Methane Emissions

Estimated emissions for the contiguous United States show a large spread, about 30-50 Tg methane yr^{-1} for 2000-2012 (Figure 3.9). These results are described by Saunois et al.

(2016) and represent an ensemble of global inverse model results contributed to the Global Carbon Project by the international global modeling community.[12] The inversions use different combinations of observations (in situ and retrievals of column-average methane from SCIAMACHY and GOSAT), different atmospheric transport models, and different inversion setup choices (prior emissions and uncertainties, inverse technique). These differences account for the range in emission estimates. Inversions that sequentially estimate emissions over time (time-dependent inversions) are shown as lines, while inversions representing time averages are shown as points. Total methane emissions are shown because estimates of total emissions are more robust while source attribution is less certain due to sparse observations and inaccurate prior estimates.

Inversions using space-based retrievals of column average do not appear to significantly differ from those using only in situ observations, at least for the continental United States. The inversions by Wecht et al. (2014a) and Turner et al. (2015) give time-averaged estimates of U.S emissions, and both studies used a global modeling framework while solving for U.S emissions at high spatial resolution (100 km and 50 km). These studies were constrained only by column-average methane from SCIAMACHY and GOSAT. The inversion by Miller et al. (2013) is the only inversion that uses a regional modeling approach and their results lie well within the range of the other inversions.

Top-down estimates have also been produced for specific regions of the United States. The studies by Miller et al. (2013), Wecht et al. (2014a), and Katzenstein et al. (2003) found that emissions for the south central United States were higher than bottom-up estimates. Regional top-down estimates showed that emissions from fossil fuel production in the Four Corners region of the southwest are likely to be much higher than the EDGARv4.2 inventory (Kort et al., 2014; Turner et al., 2015). More recently, Smith et al. (2017) found that emissions in the Four Corners region have likely not changed since estimates were made for 2003-2009 using space-based column-average data, and that these estimates were consistent with the EPA 2012 inventory.

The top-down approach has also been used to estimate emissions from the state of California. Wecht et al. (2014b) used a global modeling framework and observations from the CalNex aircraft campaign and found that California methane emissions were about 30 percent higher than both the EDGAR and CARB (California Air Resources Board) inventories. Likewise, the study by Zhao et al. (2009) found that emissions in California were underestimated by 37 percent compared to prior estimates, the largest underestimate likely due to livestock.

[12] See http://www.globalcarbonproject.org/methanebudget/index.htm.

Mass Balance Approaches for Estimating Emissions from Regional Aircraft Measurements

In contrast to forward and reverse inversion methods, the models used to estimate emissions for regional aircraft observations are much simpler. Aircraft transects are flown upwind and downwind of the study region. The total flux of air pollutants into and out of the region can be calculated by multiplying average concentrations of the air pollutant along the transect by wind speed perpendicular to the transect, the length of the transect, and the mixing height. Regional emissions are then estimated by subtracting the flux out of the region from the flux into the region.

There are several assumptions associated with this approach to estimating emissions. Since flights are typically done over multiple hours and upwind and downwind data collection can be done hours apart, the emission estimates assume that wind speeds, wind directions, and mixing heights remain constant over the sampling period. Since most aircraft flights sample at a single elevation or do only limited vertical spirals, the method also assumes that air pollutants (including methane emissions) are uniformly distributed throughout the mixed layer. These and other assumptions, such as limited sinks in the region, typically lead to uncertainty estimates for individual aircraft flights in the 20-40 percent range (see, e.g., Karion et al., 2015). Schwietzke et al. (2017) improved the mass balance methods by explicitly accounting for nonuniform upwind methane mole fractions in the planetary boundary layer in the study area. In addition, uncertainties were reduced by doubling the number of transects and employing a wind profiler.

Multiscale Observing Systems

For the reasons mentioned previously, accurate ground-based and spatially contiguous satellite observations should be seen as complementary to other approaches, with the combined systems overcoming weaknesses in the individual elements. The trade-offs between frequent global coverage and lower accuracy and precision need to be taken into account when evaluating advantages and disadvantages of the accurate long-term ground-based network versus satellite data records. Accurate hemispheric averages and decadal variations can only be fully captured by long-term in situ sampling networks, which must be the backbone of any global observing strategy. On the other hand, space-based observation offers the unique capability to spatially map local gradients of atmospheric methane across the globe, revealing source processes and, potentially, emission rates.

With improving spatial resolution and temporal coverage, satellite data may also help identify key regions where the largest discrepancies between observed and expected (based on inventories) methane abundances exist. The Four Corners region in the United States is a primary example of how a regional hotspot was detected from space; the ensuing follow-up field investigations used both in situ samples and airborne remote sensing (e.g., Frankenberg et al., 2016; Kort et al., 2014; Smith et al., 2017). Using satellite data to identify key regions might lead to dedicated ground-based and/or airborne campaigns to quantify regional fluxes for individual source categories, ideally complemented with direct flux measurements on the ground. This can in turn improve inventory development on larger scales by identifying the drivers of underlying discrepancies per source category. This multiscale strategy could involve scales ranging from direct flux measurements at the facility level to the global view from space.

High-quality, long-term, multiscale surface and space-based data records are necessary for quantifying and tracking changes in methane emissions on regional scales.

COMPARISON OF BOTTOM-UP AND TOP-DOWN APPROACHES

Top-down and bottom-up approaches yield complementary information about methane emissions. Bottom-up methods provide information about the magnitudes and patterns of emissions from specific sources, and as a result they provide the type of information that is necessary to mitigate emissions. As shown in Chapter 2, however, bottom-up inventories of emissions may not account for all sources, and, as outlined in this chapter, the methods may have uncertain or inaccurate activity data and emission factors. Top-down estimates of emissions include emissions from all sources (even unknown ones) because they are based on atmospheric observations, but they may have difficulty in attributing emissions to specific sources and be subject to errors in atmospheric transport as discussed previously. Top-down approaches may also need to use prior emission estimates to constrain solutions due to sparse data coverage, and these may also have biases and errors that lead to biased top-down emission estimates. Both top-down and bottom-up measurements used to estimate emissions can also be spatially and temporally sparse, leading to biases. For example, when aircraft measurements are used to obtain data, the flights are typically limited to just a few days, and the measurements are generally done in midday when the atmosphere is well mixed. These measurements will therefore lead to information about emission sources that is limited to midday hours, and these emissions may be different than at other times of day, which limits direct comparisons with methane inventories such

TABLE 3.5 Comparison of Top-Down and Bottom-Up Approaches to Estimating Methane Emissions That Introduce Challenges in Estimating Emissions Using Both Approaches

Approach	Top-Down Data	Bottom-Up Data and Inventories
Spatial scale	Facility to global	Individual site level to global
Temporal scale	Instantaneous to annual or multiyear averages	Generally reported as annual averages for inventory purposes from limited time duration data collected at various temporal scales
Source attribution	Involves use of models and assumptions as well as molecular and isotopic tracers	Calculated from source-specific activity data
Potential for missing sources	Measurements reflect all sources that contribute to observed atmospheric concentrations	May not account for all sources in a given region

as the GHGI (Chapter 2). Table 3.5 summarizes issues related to missing or undocumented sources, source attribution, and spatial and temporal scales for top-down and bottom-up approaches.

The complementary information provided by top-down and bottom-up methods offers the opportunity to combine their strengths in coordinated measurement campaigns. Only a limited number of highly coordinated campaigns have been performed that utilize both types of methodological approaches, however, and the most comprehensive of these studies have been performed in regions dominated by petroleum and natural gas supply chain emissions.

In 2013, the Environmental Defense Fund organized a coordinated top-down and bottom-up measurement campaign in the Barnett Shale petroleum and gas production region in north central Texas. Multiple teams of investigators performed aircraft measurements of methane and ethane, leading to top-down emission measurements on multiple days. Several teams of investigators did ground surveys downwind of individual sites, collecting site-specific emission estimates for hundreds of petroleum and natural gas sites, including production sites as well as other, downstream sources. All of this bottom-up and top-down information was synthesized into a portrait of

methane emissions in the region (Zavala-Araiza et al., 2015) wherein estimates from both approaches converged, but this convergence was possible because of (1) a spatially resolved inventory wherein the national activity data for bottom-up estimates were supplemented by local counts of facilities and (2) enhanced sampling strategy and application of a statistical model to account for and characterize high-emitting facilities.

In the Fayetteville Shale natural gas production region in Arkansas, a top-down and bottom-up comparison was performed in 2015 with DOE and industry sponsorship (Bell et al., 2017; Schwietzke et al., 2017; Vaughn et al., 2017; Zimmerle et al., 2016, 2017). The study featured contemporaneous application of top-down and bottom-up techniques with site access and operational data from the major natural gas producers in the region to develop a spatiotemporally resolved bottom-up inventory. This effort found significant day-to-day variability in bottom-up emission estimates, depending on the nature of the planned natural gas production operations occurring on particular days. Because operations at individual sites varied from day to day, there was significant spatial variability in emissions from day to day. Top-down measurements confirmed the daily variability in emissions, and overall, the study confirmed that knowledge of both local facilities and daily operational schedules are important in comparing top-down and bottom-up emission estimates.

Coordinated, contemporaneous top-down and bottom-up measurement campaigns, conducted in a variety of source regions for anthropogenic methane emissions, are crucial for identifying knowledge gaps and prioritizing emission inventory improvements. Careful evaluation of such data for use in national methane inventories is necessary to ensure representativeness of annual average assessments.

CHAPTER FOUR

Addressing Uncertainties in Anthropogenic Methane Emissions

Improvements in the accuracy and precision of methane emission estimates will require both top-down and bottom-up measurements, as described in Chapter 3. The improvements should be directed at the portions of the inventory with the greatest uncertainties, and this chapter describes current understanding of uncertainties in both bottom-up and top-down approaches to estimating emissions. Overall, the major drivers for uncertainty in atmospheric methane emission estimation methods are

- lack of accurate activity data throughout all the major source categories;
- deficiencies in sampling procedures, resulting in unrepresentativeness of the samples and therefore resulting in unrepresentative emission factors;
- poor understanding of temporal and spatial variability of emissions, including climate-driven feedbacks;
- presence of sources that are not accounted for;
- presence of episodic high-emitting sources;
- inadequate spatial coverage of observational networks;
- difficulty using top-down approaches in attributing emissions to particular sources;
- inherent uncertainties associated with methods utilizing atmospheric transport models; and
- incorrect assumptions used in calculations and models of methane emissions and atmospheric concentrations.

Additionally, uncertainty arises due to deficiencies in instruments and techniques used to measure methane emissions, which were discussed in Chapter 3.

In this chapter, uncertainties associated with bottom-up estimates are described for each major emission source category. For top-down approaches, uncertainties associated with both the spatial coverage of monitoring networks and the models used to estimate and attribute emissions are described. Uncertainties in methods used to compare top-down and bottom-up emission estimates are also discussed. Finally, this chapter addresses key features for the design of future methane measurement studies to improve the accuracy and precision of emission estimates.

SOURCES OF UNCERTAINTIES IN THE BOTTOM-UP APPROACH

Reported Emissions and Uncertainties

Although some sources of uncertainties are common across major methane emission categories, individual sources have specific types of uncertainties and approaches to address them. The sources of uncertainty, magnitudes of emissions and uncertainties, and recommended approaches for addressing uncertainties are summarized by source category in Table 4.1 and Figure 4.1.

Table 4.1 and Figure 4.1 report uncertainty ranges from the U.S. Environmental Protection Agency's (EPA's) 2015 Greenhouse Gas Inventory (GHGI), as well as some other published estimates. There is relatively little documentation of the uncertainty estimates in the GHGI, and the research literature for individual source categories typically indicates larger uncertainties than those reported in the GHGI. The sections that follow describe current understanding of uncertainties in individual source categories, as documented in publicly available sources. In addition, the Committee evaluated the reliability of the uncertainty estimates reported in the GHGI based on the individual source categories discussed here and their deficiencies in methane estimates. Figure 4.1 provides a qualitative assessment of the confidence level of the GHGI uncertainty estimates (high, medium, and low confidence levels).

Enteric Fermentation and Manure Management

The uncertainties associated with methane emissions from enteric fermentation and manure management are generally due to the accuracy of the activity data and the equations used to estimate emissions. For enteric fermentation, as noted in Table 4.1, the uncertainties are due to (1) activity data for cattle numbers, feed intake, and feed composition; and (2) emission factors adjusted by state or region that may be inaccurate on a local scale. Uncertainties associated with the activity data in the GHGI were estimated as ±10 percent, but those related to calculation of emission factors were estimated to be twice that level in the GHGI (EPA, 2017b). Overall estimates for uncertainties in enteric methane emissions in the GHGI were −11 to 18 percent (EPA, 2017b). In comparison, the gridded inventory of Hristov et al. (2017) estimated uncertainties in cattle enteric emissions of 15.6 and 16.9 percent (lower and upper 95 percent confidence bounds, respectively).

Evaluation of models for estimating enteric methane show that the best models for North American cattle had uncertainties of about ±15 percent (Appuhamy et al., 2016),

and the IPCC Tier 2 methodology had over 20 percent uncertainty for the United States (IPCC, 2006). These uncertainties are comparable to the level of uncertainty described in Chapter 3 for individual enteric emission measurements. Based on these uncertainty estimates from independent sources as well as the current state of knowledge of the factors controlling emissions from enteric fermentation, the Committee classifies the estimates of enteric fermentation uncertainties under a medium confidence level (Figure 4.1).

For manure management, uncertainties exist in the activity data and emission factors. The Intergovernmental Panel on Climate Change (IPCC, 2006) methodology estimates that the uncertainty in manure emissions is ±20 percent; however, this may be underestimated because it has been demonstrated with on-farm data that differences between observations and inventory estimates may be as much as 50 percent for some manure systems (Baldé et al., 2016; Leytem et al., 2017). The lower and upper 95 percent confidence bounds for manure emissions in the gridded inventory of Hristov et al. (2017) were even greater at 65.0 and 63.3 percent, respectively. A meta-analysis of on-farm studies by Owen and Silver (2015) reported that anaerobic dairy lagoon methane emissions were on average 368 kg head^{-1} yr^{-1} (or 3.68e^{-7} Tg head^{-1} yr^{-1}), but the standard deviation was 579, and the range of emissions was from 4 to 2,814 kg head^{-1} yr^{-1} (or 2.814e^{-6} Tg head^{-1} yr^{-1}), indicating a potentially large range in methane emissions based on the characteristics of any given site, which are likely not being accounted for in current inventory methodology. A lack of on-farm data for a variety of manure management systems under differing climatic conditions as well as a lack of knowledge of the variability of manure characteristics among farms are some of the underlying causes of these high uncertainties (Chapter 2). Because of the lack of activity data related to the distribution of manure (volatile solids) in different manure management systems, along with a lack of on-farm data verifying emissions for the different management systems, the Committee classifies the estimates of manure management uncertainties under a low confidence level (Figure 4.1). The uncertainty reported in the current EPA GHGI is ~20 percent, while the Committee expects the uncertainty to be higher than this, given the current state of the science.

Petroleum and Natural Gas Systems

Uncertainty in the methane estimates, reported in the EPA GHGI at a 95 percent confidence interval, were −19 to +30 percent for natural gas systems and −24 to +149 percent for petroleum systems (EPA, 2017b). Whereas some activity data, such as number of gas production wells, miles of pipelines, number of gas processing plants, and throughput of these systems, are well documented through various govern-

TABLE 4.1 Source of Uncertainties, Comparison of Uncertainty Estimates, and Approaches for Reducing Those Uncertainties in the Major Source Categories in the United States

Source	Published Estimates of Uncertainties, Tg CH_4 yr^{-1} and %	Key Uncertainties	Approaches for Reducing Uncertainties
Enteric fermentation	6.66 (5.93-7.86)[a] (−11% to +18%)[a] (−15.6% to +16.9%)[b] (±15%)[c] (±20%)[d]	• Activity data: uncertainty about cattle number, feed intake, and feed composition. • Emission factors adjusted by state/region may be inaccurate on a local scale.	• Improved inventory of cattle numbers by category. • Better documentation of feed intake and composition, particularly for cattle on pasture, as well as regional versus local variability.
Manure management	2.65 (2.17-3.18)[a] (−18% to +20%)[a] (−65% to +63.3%)[b] (±20%)[d]	• Activity data: data on distribution of manure (volatile solids [VS]) in different management systems. • Emission factors and estimation equations.	• Better understanding of the distribution of manure (VS) in the different manure management systems. • Increased availability of on-farm data to validate present GHGI equations for different manure (VS) management systems.
Petroleum and natural gas systems	Petroleum systems: 1.60 (1.21-3.97)[a] (−24% to +149%)[a] Natural gas systems: 6.50 (5.26-8.45)[a] (−19% to +30%)[a] (−24% to +29%)[e]	• Temporal variability in emissions (> ±50% on daily basis). • Sparse activity data yet abundance of emission sources. • Wide ranges in emission factors for individual sources. • Presence of unaccounted-for emission sources.	• Better characterization of high-emitting events through field measurement studies. • Supplementing the Greenhouse Gas Reporting Program (GHGRP) data with public records to develop more robust activity data for all petroleum and natural gas systems, including sources that are unaccounted for in inventories and those that are not required to report their emissions.

	Production 0.957 ± 0.200 (±21%)[f] Gathering and boosting 1.697 +0.189 or −0.185 (±11%)[g] Processing 0.506 +0.055 or −0.052 (+11 to −10%)[g] Transmission and storage 1.503 (1.220 to 1.950) (−22% to +30%)[h] Distribution 0.393-0.854[i]		• Updated characterization of emissions from key sources that still rely on emission factors from the 1996 Gas Research Institute (GRI)/EPA study.
Landfills	4.63 (4.21-5.04) (−9% to +9%)[a] *No alternative national assessments of uncertainties are available*	• Uncertain national activity data (annual landfilled waste). • Current methodology (IPCC, 2006) assumes that annual landfilled waste is the major driver for *emissions*, rather than site-specific climate and operational factors (area/thickness/texture of cover soils; extent of gas recovery). • Dynamic climate effects on soil gas methane transport and oxidation rates result in high spatial/temporal variability of emissions.	• Improved collection and statistical analysis of national and state data for waste generation, recycling/diversion, treatment, and disposal (landfilling, etc.) consistent with international norms (i.e., Eurostat). • Use and improvement of an existing process-based field-validated model (e.g., CALMIM) linked to site-specific soils and climate. • Very minor adjustments to data collected under GHGRP (e.g., cover soils) could facilitate initial national trial for process-based emission model.

continued

TABLE 4.1 Continued

Source	Published Estimates of Uncertainties, Tg CH_4 yr^{-1} and %	Key Uncertainties	Approaches for Reducing Uncertainties
Coal mining	Active coal mining: 2.44 (2.13-2.83) (−12.5% to +16.2%)[a] Abandoned mines: 0.26 (0.21-0.31) (−15% to +24%)[a] *No alternative national assessments of uncertainties are available*	• Underground mine ventilation measurements are not paralleled by emission measurements at the surface. • Relatively high uncertainties for abandoned underground mines and surface mines where emissions are calculated based on gas content and emission factors. • Gas contents used in calculations often not representative of specific mines. • Emission factors are state/region based and may not be accurate on a mine scale.	• For underground mines, including measurements from all entries and monitoring emissions at the surface. • Updated and more reliable gas content data need to replace those currently in use to improve surface mine estimates. • Abandoned mines need improved monitoring program that includes pressure buildup measurements and methane concentration at the surface.
Unaccounted sources[j]	Varies	• Known sources that are not reported. • Previously unrecognized sources.	• Increased measurements of sources ignored or assumed negligible based on screening studies and integrated top-down and bottom-up assessments.

[a] EPA, 2017b.
[b] Hristov et al., 2017.
[c] Appuhamy et al., 2016.
[d] IPCC, 2006.
[e] Littlefield et al., 2017.
[f] Allen et al., 2013. Emission sources measured: well completions, liquids unloadings, well workovers, equipment fugitive emissions, pneumatic controllers, and chemical pumps.

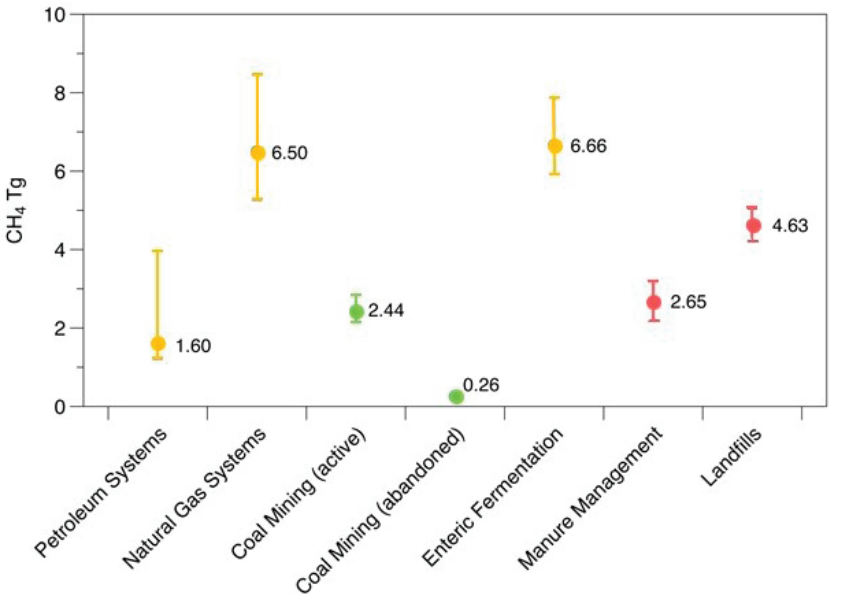
[g] Marchese et al., 2015.

[h] Zimmerle et al., 2015.

[i] Lamb et al., 2015.

[j] For example, residential and commercial operations, natural gas power plants and refineries.

NOTES: It is difficult to make direct comparisons between various uncertainty estimates because of different methodological approaches and data sources. This table includes national-scale estimates of methane emissions from major sources; regional estimates are discussed in the text that follows this table. EPA estimates are for the year 2015; reference years for the other cited assessments vary.



Confidence Level	Description	Source
High	Uncertainty interval calculation uses available data and accounts for current known uncertainties. Uncertainty range would be reduced with increased measurement data. Uncertainty estimate can be improved by updates reflecting additional data and evolving scientific consensus of evaluation methodology.	Coal mining (active) Coal mining (abandoned)
Medium	Uncertainty interval calculation partially reflects known uncertainties, and is partially based on available measurement data. Further research identifying and quantifying uncertainties would improve uncertainty quantification.	Petroleum systems Natural gas systems Enteric fermentation
Low	Uncertainty-interval calculation does not reflect current known uncertainties, and there are insufficient measurement data from which to base calculations. Fundamental research identifying and quantifying uncertainties is needed.	Manure management Landfills

FIGURE 4.1 Comparison of mean national methane emission estimates and their uncertainty ranges for major source categories, as reported by the U.S. Environmental Protection Agency in the Greenhouse Gas Inventory for year 2015 (EPA, 2017b). The uncertainty ranges indicated by vertical lines represent variations of 95 percent confidence intervals as determined by the EPA. There are wide differences in both the estimated emissions and the uncertainty ranges (EPA, 2017b). A Committee-assigned confidence level (CL) for each uncertainty value is also provided, with the descriptions and assigned source categories for the CLs given.

mental agencies, other activity data from the petroleum and gas industry, especially component- and subcomponent-level activity data (e.g., storage tank throughput, number of various types of pneumatic controllers, and reciprocating engines), have much higher uncertainty. Petroleum and gas infrastructure consists of millions of distinct emission sources, making measurement of emissions from every source and component practically unfeasible. Because of this, the extent of variability that may exist in these industries is not well understood and not captured in current emission estimates. Four primary sources of uncertainty, as documented in Table 4.1, are (1) temporal variability in emissions (> ±50 percent on a daily basis), (2) wide ranges in measured emissions for individual sources, (3) sparse activity data yet abundance of emission sources, and (4) presence of unrecognized or unaccounted-for emission sources.

Temporal variability in emissions and wide ranges in measured emission rates for individual sources both contribute to the observation of high-emitting sources in petroleum and gas systems (see Box 2.2). Some measurements of high emissions may be due to the size of the facility. However, as described in Chapter 3, even when emissions are normalized by gas throughput or gas produced, a small number of observations with high normalized emissions have been identified. Identifying and quantifying high-emitting sources remains a major challenge to improving bottom-up emission inventories for petroleum and natural gas systems; however, it is not fully understood why high-emitting sources exist. Episodic emissions can be measured or estimated by engineering methods. Malfunctioning high-emitting sources, however, are difficult to predict in terms of temporal and spatial occurrence and may lead to large uncertainties in mean emission estimates.

In addition to uncertainties in emission estimates due to high-emitting sources, there is uncertainty related to the activity data estimates used in the GHGI for key emission components (e.g., count of the different types of pneumatic controllers or condensate tanks). These uncertainties in activity data are difficult to quantify but can be significant. For example, for one of the largest sources of methane emissions in the natural gas supply chain—pneumatic controllers—the estimated number of controllers per well increased by 90 percent from the 2011 GHGI to the 2015 GHGI when new information from the EPA Greenhouse Gas Reporting Program was used to update activity data (see Chapter 3). As also described in Chapter 3, uncertainties arise from the granular estimates of emission factors and activity data for several emission categories (e.g., number of high-bleed, low-bleed, and intermittent pneumatic controllers; and number of centrifugal compressors with wet seals and dry seals).

Uncertainties in methane emissions from petroleum and natural gas systems also arise from emissions that are unaccounted for in current inventories (see Chapter 2).

In the past several years, there has been a significant effort to understand and quantify the uncertainties of methane emissions from petroleum and natural gas systems, and much has been learned about the top emission sources. The EPA is currently considering updates to petroleum and natural gas uncertainty estimates to incorporate these new data and revised methodologies into their inventory.[1] Further work to estimate activity factors, to improve sampling strategies to better understand the mechanisms leading to high-emitting sources, and to incorporate currently unaccounted emission sources would improve the uncertainty estimates. The Committee's assessment of the uncertainty estimation for this source category is at medium confidence level (Figure 4.1).

Landfills

Uncertainties within current landfill methane inventories are largely due to GHGI and GHGRP models, which do not rigorously account for site-specific climate and operational factors as discussed in Chapters 2 and 3. Realistically, uncertainties are much greater than current EPA estimates and require independent determination using site-specific data and process-based modeling with integrated uncertainty calculations. As discussed previously in Chapters 2 and 3, there are fundamental issues with the current IPCC (2006) methodology with regard to estimating site-specific landfill methane emissions for regional-scale inventories. Although it is important to track societal trends by quantifying annual U.S. waste generation, waste recycling/diversion strategies, and the residual mass of landfilled waste, there is no robust relationship between landfilled waste mass and annual emissions, as assumed by current inventory methods. Conversely, it can be readily demonstrated that waste mass is linearly related to the mass of recoverable methane using engineered biogas recovery systems. Chapter 3 previously addressed this relationship using 2010 data for 129 California sites (Spokas et al., 2015). The implication is that methane generation from landfilled waste can proceed at a relatively steady rate over decadal time frames, as opposed to the current IPCC (2006) first-order kinetic equation, wherein methane generation from a given mass of waste peaks in the year of disposal and declines exponentially thereafter. At present, there is approximately a half century of national U.S. experience with the controlled burial of organic waste in engineered landfills and concurrent biogas recovery.

[1] See https://www.epa.gov/sites/production/files/2017-06/documents/updates_under_consideration_for_2018_ghgi_natural_gas_and_petroleum_systems_uncertainty_estimates_508.pdf.

Emissions, on the other hand, can be related to two major factors emphasized in recent literature: (1) site-specific operational practices (i.e., area/thickness/texture of cover soils, extent of biogas recovery, whether intermediate cover soils are stripped prior to "vertical expansions"; see Chapter 3) and (2) site-specific climate, which affects temporal methane transport and oxidation rates in cover soils. In general, landfill emissions have large spatial and temporal variabilities, which contribute to inherently high uncertainties.

To better quantify those uncertainties, a field-validated process-based model (e.g., the California Landfill Methane Inventory Model [CALMIM] 5.4), also discussed in Chapter 3, could be applied to develop a complementary national inventory in parallel with the GHGRP during the next annual reporting cycle. A modest amount of additional data would be required for this task, namely, the area, thickness, and texture of facility-specific cover soils, as well as the extent of underlying biogas recovery. Spokas et al. (2015) previously compared 2010 California emissions (372 sites) using CALMIM to estimated 2010 site-specific methane emissions using IPCC (2006), as reported by the California Air Resources Board. Figure 4.2 gives an indication of the relative magnitude of those site-specific differences for individual California landfill sites. The total 2010 state emissions were serendipitously similar (0.30 and 0.34 Tg methane yr^{-1} for IPCC and CALMIM, respectively). However, the highest-emitting sites differed substantially, as also shown in Figure 4.2. The highest emitters using IPCC (2006) were the sites with the largest mass of waste, whereas, using CALMIM, the highest-emitting sites had large areas of intermediate cover (thinner than final cover) and low seasonal methane oxidation rates. The highest-emitting sites shown in the figure using CALMIM corresponded primarily to Central Valley and desert sites with deficient soil moisture and daily temperatures exceeding optimal oxidation conditions. Overall, the intermediate cover areas were responsible for 96 percent of the total state emissions. Currently, both the GHGI and the GHGRP "assign" percent methane recovery and oxidation values without complementary site-specific climate modeling; hence, those values may differ substantially from field reality, introducing large uncertainties. If CALMIM is applied to a national database such as the GHGRP, it could provide high-resolution output for cover-specific emissions at each site (10-min time steps and 2.5-cm depth increments) and cover-specific annual emissions, as well as cover-specific standard deviations for monthly and annual timescales.

In summary, the current methodology is outdated and does not explicitly consider the major drivers for emissions: (1) site-specific operational practices as discussed above (i.e., cover soils, extent of biogas recovery) and (2) site-specific climate (variable methane transport and oxidation rates in cover soils due to temporally variable soil moisture and temperature). It is important to note that IPCC (2006), as well as exten-

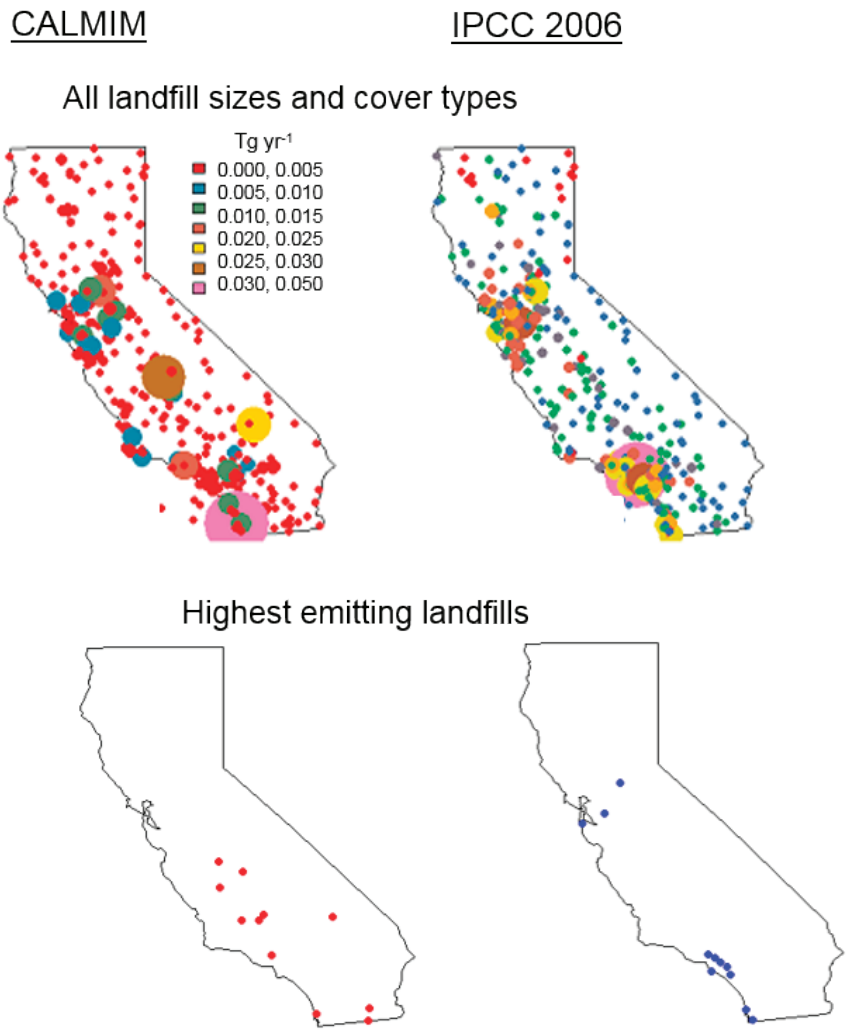


FIGURE 4.2 Model comparison of site-specific California landfill methane emissions, (top) Comparison of California landfill methane emissions using CALMIM 5.4 (left) and IPCC (2006) (right); (bottom) highest-emitting sites from both methods CALMIM 5.4 (left) and IPCC (2006) (right). For IPCC (2006), the highest-emitting sites contain the largest mass of buried waste. For CALMIM, the highest-emitting sites are characterized by large areas of thinner intermediate cover soil and lower seasonal oxidation. See also discussion in Chapter 3. SOURCE: Modified from Spokas et al., 2015.

sions of that methodology for the GHGI and GHGRP, was never field-validated specifically for emissions and retains a major dependency for emissions on the mass of buried waste at each landfill site. Because of these deficiencies, the Committee classifies the estimates of landfill emission uncertainties under a low confidence level (Figure 4.1).

Coal Mining

In active underground mines, methane emission measurements from degasification systems are relatively easy to monitor because degasification systems are localized, and the measurements are usually performed at the surface. Therefore, the uncertainty of emission estimates for degasification systems is low.

Emission estimates from the ventilation systems carry larger uncertainty. These measurements are taken in mines to ensure safety by controlling the percentage of methane in the ventilation air. The measurements are usually performed at predetermined locations that are indicated in the mine's ventilation plan submitted for approval and at the locations mandated by the U.S. Mine Safety and Health Administration. The monitoring devices can be handheld or machine-mounted sensors. As long as the equipment is functioning well and the measurements are taken frequently, methane emission estimates are reliable. However, the position of the sensor with respect to the cross section of the entry and how the measurements are taken can be critical. This is due to methane layering in low-velocity areas and variable airflow rates in high-velocity entries. For ventilation systems, methane emissions are calculated based on the flow rate and the methane content in the ventilation air. Both measurements rely on underground observations in entries connected to the ventilation shafts. Since the emission estimate relies on individual measurements in the entries rather than the total output on the surface, accurate reporting can be obtained by visiting and measuring all entries. Usually, there are no measurements conducted at the surface to confirm the values obtained underground, yet such measurements are needed to verify the current techniques. Further, methane emissions from mines change based on atmospheric pressure variations, and so continuous measurements are warranted. Therefore, a set of measurements that miss a major atmospheric change in pressure and temperature (e.g., large rainfall) may grossly underestimate or overestimate the actual emissions. Even for current measurements in underground mines, differences in annual emissions of 10 percent have been reported (Mutmansky and Wang, 2000).

For surface mines, although the production data are relatively accurate, uncertainties are present in the gas content data and the emission factor. Because gas content

can vary widely between and within the coal (e.g., Strąpoć et al., 2008), especially for shallow basins that have surface mines, basin-specific gas content data used in the calculations give only a very general estimate. Moreover, shallow coals, which are not a target for coal-bed methane (CBM) because of their low gas content, usually have limited gas content data; thus the basin gas content average may be far from accurate. Most gas content data come from coal occurring deeper than 76 m, which is typically gassier than shallow coals. If these gas content values are used, the values would overestimate the gas content and consequently the emissions. Emission factors may vary as well, depending on specifics of the mining method and coal and overburden handling in the mine, but their impact is likely lower than that of variation in gas content. As mentioned in Chapter 2, the current emission factor to calculate emissions from coal is a factor of 1.5 (or 150 percent of the in situ gas content; EPA, 2017b), an assumption based on the studies by Environment Canada (Jaques, 1992) and the EPA (Kirchgessner et al., 1992). A follow-up study of Canadian emissions (King, 1994) applied emission factors categorized by mine type, coal basin, and coal rank using mine-specific data and also suggested increasing gas content data by 50 percent to account for the emissions from unmined strata. Adding data about coal rank and mine-specific factors would decrease the uncertainty.

Post-mining emission factors currently assume 32.5 percent of in situ gas content (same for surface and underground mines; EPA, 2005), following a study on British coals (Creedy, 1993). For comparison, a 20 percent factor is used in Australian methodology, after data by Williams et al. (1993). For U.S. coals, Kirchgessner et al. (2001) estimated emission factors of 72-78 percent for surface mines (55-59 percent for underground mines). EPA uncertainty analysis for active coal mining (EPA, 2017b) indicates that, for example, in 2015, methane emissions from coal mines were estimated to be between 2.13 and 2.82 Tg methane at 95 percent confidence level, which suggests that approximately 16.2 percent above and 12.5 percent below the reported estimates could be expected.

The uncertainties for abandoned underground mines are related to uncertainties in generating a decline curve which, in turn, depends on (1) coal methane adsorption isotherms, (2) coal permeability (which determined methane flow capacity), and (3) pressure at abandonment. Methane adsorption isotherms can vary within the same coal seams and the same mines (Mastalerz et al., 2004). Isotherms are often not available for a specific coal or mine, necessitating the use of an isotherm of some other coal mine that may not be representative. Coal permeability is another parameter that is not often available for the specific coal and mine. Improved monitoring for abandoned mines could include pressure buildup and methane concentration measurements at the surface. EPA uncertainty analysis indicates that for 2015, emissions from

abandoned underground mines, a range of 0.21 and 0.32 Tg methane at 95 percent confidence level translates to a range of 18 percent below and 24 percent above the 0.26 Tg methane emission estimate for 2015 (EPA, 2017b).

There are several ways to reduce uncertainties in coal mining (Table 4.1). However, because the number of both surface and underground mines is well documented and there is good understanding of coal production, the Committee classifies the estimates of both active and abandoned mining uncertainties under a high confidence level (Figure 4.1).

Unaccounted-for Sources of Emissions

In addition to the uncertainties of the sources that are listed in the inventories, bottom-up emission inventories also have uncertainties due to emission source categories that are missing from the compiled estimates (see Chapter 2).

Both known unaccounted-for sources and previously unrecognized emission sources can be quantified and revealed (for previously unknown sources) by integrating top-down and bottom-up assessments. For example, Kort et al. (2014) discovered the largest point source of methane in the Four Corners region by carefully aggregating a decade of data from the Scanning Imaging Absorption Spectrometer for Atmospheric Cartography (SCIAMACHY) satellite with ground-based observations. Later analyses suggested that the dominant source was microbial coal-bed methane from active mining (e.g., Arata et al., 2016). In another example, by combining bottom-up and top-down approaches to partition emissions in an urban setting of Indianapolis, Lamb et al. (2016) suggested that the presence of diffuse, widespread emissions was the reason for lower bottom-up methane estimates.

Identifying and quantifying unaccounted-for emissions through multiscale measurement campaigns is critical to addressing uncertainties in emission inventories and to improving understanding of methane emissions in general.

Overall Source Category Conclusions

Based on the source category–specific discussion about uncertainties, the Committee concludes that

Each source category has a wide range of uncertainties for methane emission estimates: sparse activity data and limited emission measurements are the primary reason for uncertainties in most source categories. Reducing these

uncertainties requires collecting and reporting activity and emission data in a consistent and comprehensive manner and will be challenging because of cost, time, and technical limitations.

Priority anthropogenic sources for future research on methodological and data improvements are petroleum and natural gas systems, enteric fermentation, manure management, and landfills because of these sources' high uncertainties and/or overall high contribution to total anthropogenic U.S. methane emissions (Figure 4.1).

SOURCES OF UNCERTAINTIES IN THE TOP-DOWN APPROACH

The sources of uncertainties in top-down approaches to estimating emissions can be due to sparse networks and infrequent sampling, models used to estimate emissions from atmospheric measurements (inverse models), and methods used to attribute top-down emissions to specific source categories. These uncertainties and approaches for addressing uncertainties are summarized in Table 4.2.

Sparse Atmospheric Monitoring Observations

As described in Chapter 3, methods for measuring atmospheric methane using high-quality, globally distributed networks have uncertainties of 1.1 ppb (95 percent confidence, as of 2016), or only 0.06 percent assuming a global average atmospheric methane concentration of 1,850 ppb. However, the coverage of these measurement networks is sparse, and sampling is weekly or even less frequently at many sites. Even though current aircraft and surface sites that sample the continental United States are more densely located relative to many other parts of the world, the U.S. network is still very sparse. At continental scales, the presence of strong local sources and atmospheric variability requires dense and frequent sampling to produce accurate and precise emission estimates. Figure 4.3 shows the large variability in atmospheric methane from a continuous analyzer at Walnut Grove, California, that likely reflects large signals from nearby sources and variability in transport of the source signals. In addition, stable nighttime or wintertime meteorological conditions play a role in producing some of the large peaks because emissions can be trapped near the surface under stable conditions, leading to large anomalies. For this reason, current inverse modeling systems often use data that have been filtered to retain deep, well-mixed boundary-layer conditions that can occur during the afternoon hours. This is necessary because even high-spatial-resolution regional atmospheric transport models have difficulty

TABLE 4.2 Sources of Uncertainties in Top-Down Emission Estimates

Source of Uncertainties	Recommended Approaches to Reduce Uncertainties
Sparse networks	
a. Spatially and temporally fixed ground networks and aircraft measurements of continental atmospheric methane are sparse. b. Temporal measurements of regional emission fluxes are sparse.	a. Increase network observation frequency and density. b. Design data collection strategies to account for temporal and spatial variability.
Inversion models	
a. Inversion modeling is based on different combinations of observational datasets. b. Atmospheric transport models may be inaccurate and have biases.	a. Data should be freely shared so that researchers can evaluate the effects of using or not using various datasets. Sharing data also increases the size of our collective observing system. b. There is a need for improved transport models that can accurately simulate transport especially for continental regions. Higher spatial and temporal resolution will be necessary as will new techniques for model evaluation.
Attribution methods	
a. Many sources do not have unique molecular and isotopic fingerprints. Some sources require multiple species that may not be sufficiently inert or useful for robust atmospheric identification.	a. Additional isotopic and chemical approaches are needed to constrain emission sources.

simulating the shallow nocturnal boundary layer, and filtering the data for this biases sampling toward particular times of the day.

Uncertainties in current top-down methane emission estimates at global and continental scales are increased by sparse surface observation networks that do not capture the full spatial variability in emissions.

Characterization of methane over continental regions is difficult due to the presence of local sources of emissions and atmospheric variability, which make more frequent and denser network observations necessary.

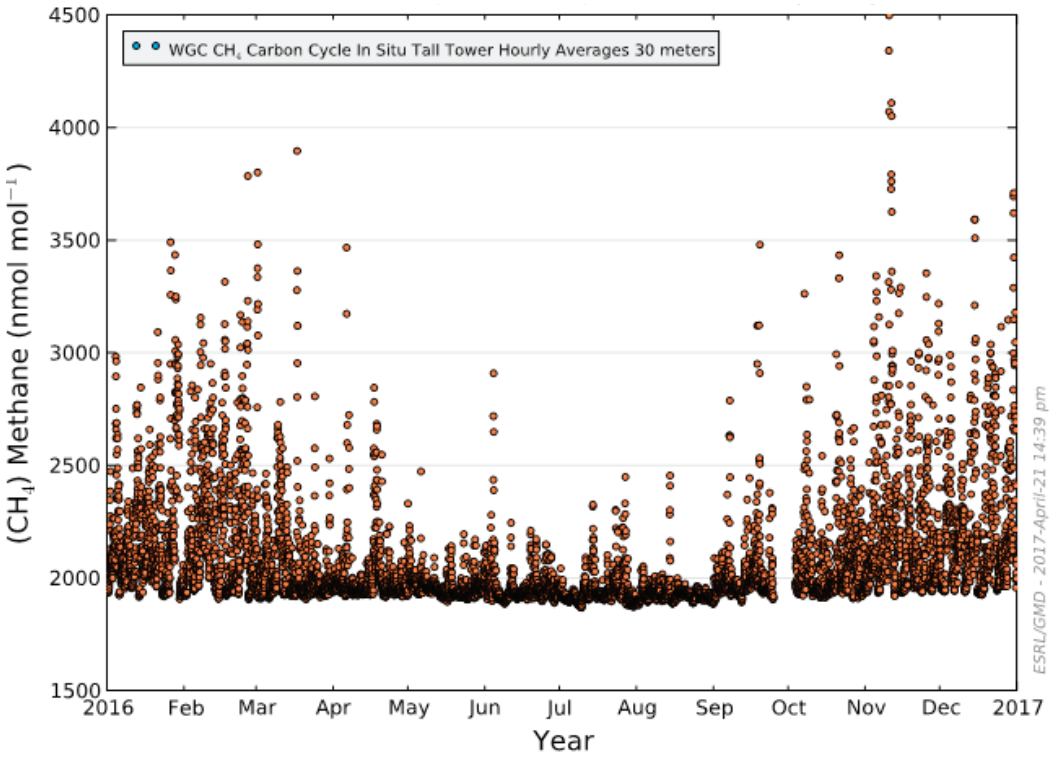


FIGURE 4.3 Hourly averaged observed methane at Walnut Grove, California. SOURCE: NOAA, https://www.esrl.noaa.gov/gmd/ccgg/insitu/.

Continental methane mole fraction measurements have been used with mass balance approaches to estimate emissions for continental-scale regions. Upwind and downwind observations are required for this approach as is accurate knowledge of winds and atmospheric stability, which are often not well quantified. Aircraft monitoring observations collected along the Pacific and Atlantic coastal boundaries of the United States are a logical choice for quantifying background methane emissions (Crevoisier et al., 2010). However, infrequent sampling and large atmospheric variability likely limit the accuracy of boundary conditions derived from interpolated aircraft profiles (Bruhwiler et al., 2017).

Satellites can provide a complementary view of regional methane abundances from their vantage point in space. However, remotely sensed data are not as accurate as in

situ measurements, which can be calibrated against standards (see Chapter 3). In fact, current satellite instruments such as SCIAMACHY have been shown to have persistent biases in space and time (e.g., Bergamaschi et al., 2013; Houweling et al., 2014) that need to be accounted for if satellite data are to be assimilated into atmospheric inverse models. These biases are much reduced for the higher-spectral-resolution instruments (e.g., the Greenhouse Gases Observing Satellite; Butz et al., 2011; Schepers et al., 2012). Biases can be reduced with improved retrieval algorithms and instrument specifications and in comparison to ground-based remote sensing, for example, from the Total Carbon Column Observing Network (Wunch et al., 2010), many biases might remain that will be on the order of a few parts per billion for the column-averaged methane concentration. Atmospheric inversions employing satellite retrieval data must account for these systematic errors, which are often the same order of magnitude as the gradients used for inversion analysis.

For studies at smaller (e.g., regional) spatial scales, these larger-scale biases might not matter as long as observed gradients in methane can be much larger than these potential errors. A combination of ground-based background stations to provide accurate methane measurement in pristine air and satellite data to quantify strong local and regional gradients of methane has the potential to improve spatial and temporal coverage of measurements.

Top-down measurements using aircraft have also been used to estimate emissions at the spatial scale of a fossil fuel basin, but these measurements, while having a fine spatial resolution, are limited in temporal coverage. Steady winds and consistency in other meteorological conditions are needed, meaning that there are practically few flights where these conditions are met. Furthermore, these aircraft measurements are limited to midday periods when the planetary boundary layer is fully grown and well mixed. Hence, these measurements provide only a snapshot of emissions for that period, in contrast to tower or other measurements that provide a continuous time series. Measurement uncertainties can be reduced by employing a wind profiler and conducting multiple downwind transects. Since not all emissions are constant throughout the day (Allen, 2016; Allen et al., 2017; Schwietzke et al., 2017), care must be taken in comparing aircraft flights to bottom-up emission estimates. Daily and diurnal variability in emissions can be substantial (greater than 50 percent of the mean emissions) in some petroleum and gas production regions (Allen et al., 2017; Schwietzke et al., 2017). A significant investment in top-down measurement flights would likely be required to gather enough estimates to adequately characterize emissions, their intermittency, and their trends and, consequently, to reduce existing uncertainties.

Methane Flux Inversions

Emission estimates from methane flux inversions vary widely among different modeling systems, and this implies uncertainties in top-down methods. Global total emissions are well constrained by observations, and inversions using these observations should theoretically be in close agreement. As part of the Global Carbon Project (GCP) Methane Activity, Saunois et al. (2016) assembled 30 atmospheric inversions from nine different modeling systems. The GCP ensemble found that annual total global emissions for 2003-2012 were 558 Tg methane yr^{-1} with a range of 540 to 568 Tg methane yr^{-1} (5 percent of the mean value). Differences among the inversions for the north-south distribution of emissions were found to be larger, although the inversions agree that methane emissions are largest in the tropics and populated northern midlatitudes. In the tropics, the range of the inversions can approach 50 percent of the mean zonal emissions. Even larger differences in estimated emissions occur at continental scales.

There are several reasons for the disagreement between the inversions. Observations are sparse in space and time, even for "well-observed" regions such as the United States; therefore, inverse techniques must rely on "first-guess" or "prior" emission estimates to stabilize the solution, and uncertainties in prior emissions are usually difficult to quantify. In particular, natural emissions such as those from wetlands are highly uncertain, and estimates of emissions from process wetland models can vary widely (Melton et al., 2013; Poulter et al., 2017). Biases in these models used for prior emissions can result in biased posterior flux estimates. These uncertainties have been summarized in the previous section of this chapter. Increasing the coverage of observations is needed to improve the ability of inverse modeling systems to accurately estimate emissions. For example, quasi-continuous observations are collected at 18 sites in Europe as part of the Integrated Non-CO_2 Greenhouse gas Observing System project. These measurements are calibrated and carefully controlled for quality. Bergamaschi et al. (2018) demonstrated the value of these observations for estimating European methane emissions. Currently, the U.S. sites that measure methane continuously are located mainly in California and the Northeast. Consideration should be given to increasing the spatial coverage of continuous monitoring sites.

Increasing the spatial coverage of quasi-continuous observations over the United States will decrease uncertainties in top-down estimates of U.S. methane emissions. Different choices of prior emission estimates and their associated uncertainties is a driver for disagreement among inversions. Development and use of prior estimates that are as accurate as possible is a priority for improving top-down emission estimates using inverse models.

Some inversions use only observations from the National Oceanic and Atmospheric Administration surface network to avoid differences in analysis systems. Other modeling systems may use observations from different institutions that may not be comparable. Some modeling systems use only sites where data records of a certain length exist because in early years there were fewer sites, and changes in a sparse network over time can lead to abrupt and unrealistic changes in estimated emissions (e.g., Bruhwiler et al., 2011; Rödenbeck et al., 2003). The use of space-based data and their error covariance is another significant difference between inverse modeling systems since retrievals of average column abundance can have systematic biases that vary spatially and over time (Monteil et al., 2013). Finally, observations not available to all researchers have been used by some top-down studies, resulting in estimated emissions that can be significantly different. If observations are not made available, then these results cannot be reproduced, violating the scientific principle that studies should be reproducible.

An important source of disagreement among atmospheric inversions is the choice of observations and their weighting relative to prior information. Given that in situ observations are sparse and large regions are unconstrained, it is essential that existing observations are carefully calibrated and shared freely among the global research community.

A major source of difference among inversions is atmospheric transport, and Locatelli et al. (2015) showed that differences in modeled transport can change the source apportionment among regions. In particular, using relatively coarse-resolution global models to represent in situ point measurements is challenging. It may be possible to produce a fairly accurate simulation of methane at remote sites, but continental sites near strong local sources introduce additional complexity. Simulation of atmospheric transport at continental sites is further complicated by topography and processes that are difficult to resolve in coarse-resolution transport models, such as convection and the diurnal collapse and growth of the planetary boundary layer. An additional difficulty is determination of the transport model error for use in inversions since it is difficult to separate errors arising from lack of knowledge of the underlying emission distribution from model transport errors. Although it might be expected that higher model spatial and temporal resolution would lead to more accurate simulations at measurement sites, it has been difficult to prove (Díaz Isaac et al., 2014). More accurate transport models will likely require more computationally intensive models that have high spatial and temporal resolution.

At all scales, uncertainties in top-down methane emission estimates arise due to uncertainties in atmospheric transport models.

Current global and regional atmospheric transport models being used for atmospheric inversions are likely unable to accurately represent small-scale processes. As a result, it is difficult for these models to accurately simulate observed methane at continental sites. Developing higher spatial- and temporal-resolution atmospheric transport models and approaches for evaluating these models would likely improve transportation simulations.

Current inverse models suffer from several limitations that prevent them from being fully exploited to track methane emissions. To track changes in emissions and to quantify budgets on regional scales, a societal commitment to high-quality, long-lasting data records with adequate spatial coverage needs to exist. The in situ network should be supplemented by space-based observational strategies in order to increase spatial and temporal coverage. Data records need to be shared among international institutions so that results can be replicated by multiple groups. Furthermore, collaborations between the atmospheric modeling and weather prediction communities could lead to significant improvements in atmospheric transport models. Novel approaches to making measurements of important diagnostic quantities (such as planetary boundary layer depth) will also further the development of atmospheric transport models. It is hoped that the end result will be better understanding of how anthropogenic and natural emissions of methane evolve over time to influence the chemistry and radiative balance of the atmosphere.

EMISSION INVENTORY IMPROVEMENT STUDIES: DESIGN AND DATA ANALYSES

Improvements in the accuracy and precision of methane emission estimates will be maximized through the use of both top-down and bottom-up measurements. While working toward this goal, consistency in measurement and modeling approaches and development of study protocols need to be transparent to the researchers involved in methane emission measurements. As noted in prior chapters, one barrier to incorporating results from measurement studies into the GHGI is the mismatch of the spatial and temporal timescales of interest. The GHGI is tasked to provide national, annual average emission estimates, whereas bottom-up and top-down studies are conducted typically at much smaller spatial scales and are often paired to compare estimates over contemporaneous and short time periods. In addition to pairing multiple multiday top-down and bottom-up methods contemporaneously (Chapter 3), improvements to measurement studies, as discussed in more detail below, would enable the potential adoption of results from these studies to the GHGI.

Sampling Strategy and Statistical Analysis

An early study design question to be answered is sample size. Determining the sample size is difficult if the distribution is unknown. Before collecting data, sample size calculations are often done so that the predicted uncertainty (such as the width of the confidence interval [CI]) is below a desired level set by the researcher. However, such calculations require presumptions about the underlying distribution of the data, and achieved CIs may be wider than anticipated by sample size calculations. Brandt et al. (2016) illustrate that the achieved CI for data that exhibit heavy-tailed (see below) behavior is wider than the CI that results from a hypothesized lognormal distribution.

When enteric methane emissions are measured in livestock, sample size will depend on the method used. As described in Chapter 3, the use of respiration chambers is limiting the number of animals that can practically be included in a study. The use of the other two established methods for measuring enteric emissions, the SF_6 tracer method and the GreenFeed® system, allow a larger number of animals to be studied. In the latter cases, the sample size will be determined based on the experimental design (i.e., randomized block or crossover), the expected response to treatment, and the variability in the parameters measured. Usually, a sample size of 12-20 cattle/treatment is sufficient for randomized block design studies to statistically detect a difference in emissions of >10-20 percent. A minimum of eight cattle may be required to detect such a difference in a crossover design study. The length of measurement is also important; a minimum of 3 days is required for respiration chambers and a minimum of 5 days for the SF_6 method. The length of measurement for GreenFeed® will depend on the environment in which it is used. When animal access to GreenFeed is controlled by the investigator, eight measurements over a 24-hour cycle are sufficient; however, when the animals have free access to GreenFeed, a longer period is required to collect gas samples from all animals in the study and at times representative of a feeding cycle (see Renand and Maupetit, 2016).

When manure emissions are measured, it is usually done on a farm-by-farm basis. Unfortunately, no farm can truly be replicated because there are always differences in diet as well as manure handling and storage practices. Replication of measurements on several farms will provide data as to the potential range of emissions on farms. However, it may be more beneficial to report emissions per unit of volatile solids in storage over any given time period. This way a comparison can be made across farms that have variation in management practices. In addition, other variables that affect methane emissions need to be collected, including temperature, pH, and wind speed, in order to develop prediction equations that are meaningful across a range of management and climatic conditions.

Landfill emissions require consideration of the multiple cover soils at each site (e.g., thickness and properties), whether engineered biogas recovery exists under each cover, and seasonal climate effects on soil gas methane transport and microbial oxidation. Thus, combinations of techniques that can capture the spatial and temporal variability of emissions are frequently required, often along with a randomized statistical design for small-scale measurements for each cover type. In addition, linkage with climate models and temporal collection of site-specific weather data, as well as soil gas temperature and moisture data, are desirable to understand transient changes in soil gas transport and oxidation rates.

High-emitting sources are a small number of sources that contribute a high fraction of the cumulative total emissions, resulting in a data distribution that exhibits a fat, or heavy, tail. High-emitting sources have received a great deal of attention in petroleum and natural gas systems, and landfills can have "hotspots"; however, the question of whether other source categories have estimation issues due to high-emitting sources is relatively unstudied. The weight of a heavy distribution's tail can be quantified by a parameter that can be estimated from data. Brandt et al. (2016) estimated extremely heavy tails in the distribution of emissions from petroleum and natural gas sources. Although there were large uncertainties associated with these estimates because of small sample sizes, tails were estimated to be heavier than those of other known heavy-tailed phenomena, such as crop losses and income distribution.

The presence of high-emitting sources contributes to increased uncertainty in mean methane emission estimates. Quantifying uncertainty in the case of heavy-tailed distributions is more challenging and should be addressed transparently and with statistical rigor. When data are heavy tailed, familiar distribution-based methods, which produce a symmetric confidence interval for the mean estimate, are clearly inappropriate. An attractive alternative is parametric bootstrapping, in which a distribution is assumed for the data, and the parameters for that distribution are estimated. Repeated samples are drawn from this fitted distribution, and mean estimates from these samples are used to produce the CI. However, even when the assumed distribution has a relatively heavy tail (such as the lognormal), these distributions can underestimate the magnitude of the largest observations when fitted to the data, resulting in an underestimated bootstrap uncertainty. Brandt et al. (2016) show that parametric bootstrapping methods can underestimate the uncertainty associated with the mean estimate for heavy-tailed distributions of methane emissions. Another alternative is nonparametric bootstrapping methods, which make no distributional assumption about the data. Rather than fitting a distribution, the original dataset is resampled, and mean estimates from these resamples are used to produce a CI. Even nonparametric bootstrapping methods are complicated by distributions with extremely heavy tails

because standard resampling methods may not be appropriate if the underlying distribution cannot be assumed to have a finite variance, and adjustments to the procedure have been suggested (Bickel et al., 1997; Politis et al., 1999).

To address the increased uncertainty arising from the presence of high-emitting sources, certain experiments have attempted to oversample the "tail" (Lan et al., 2015; Lyon et al., 2015; Yacovitch et al., 2015). By designing a study that oversamples the tail, it could be possible to reduce uncertainty in the mean emission estimate, and such a study likely may cost much less than a study with similar uncertainty resulting from a very large random sample. The result of such an experiment should be viewed as a stratified sample, and both study design and statistical analysis of the resulting data should reflect the stratification. Importantly, in addition to emission measurements being recorded for the general (nonexceeding) observations and the detected high-emitting sources, estimates of each stratum's proportion of the population are required. Further complicating the analysis, the detection procedure is likely not perfect; that is, not all high-emitting sources may be detected during the initial screening. If so, the probability of detection should be estimated and incorporated into the analysis.

Mechanistic understanding of the causes and frequency of large emissions would also reduce uncertainty resulting from the presence of these high-emitting sources. Conceptually, one could perform multiday screening measurements at various times of the day to detect the presence of a high-emitting source (here defined as an observation whose emission rate exceeds some prespecified threshold), and if detected, the observation's emission rate could then be quantified. Raster flights and mobile measurements paired with direct facility-level measurements across the area of interest could support this initial screening. Regardless, such screening needs to be "ground-truthed" with operator data on activities and classification of high-emitting sources as routine, episodic, or malfunctioning.

When emission data indicate a small number of high-emitting sources, uncertainty about the mean emission rate could be reduced by employing sampling strategies designed to better quantify the contribution from these high-emitting sources. Careful consideration of any assumptions underlying the statistical analysis is warranted and, when in doubt, selection of statistical methods with fewer distributional assumptions is optimal.

Much of the research thus far has been based on noncontemporaneous, offsite measurements without site data or access and has not attempted to attribute the classification of the high-emitting source (routine, episodic, or malfunctioning; Box 2.2). Without further classification of the observed high-emitting sources, oversampling the tail may assume that episodic events are prevalent for the entire year or that

chronic events have a higher statistical occurrence than in reality, which has direct implications for inventory estimates. Zimmerle et al. (2016) compared top-down and bottom-up measurements without reliance on statistical estimators by employing high-resolution spatiotemporal activity data from operators and measurements at operator sites.

Recent top-down and bottom-up studies have highlighted the importance of site access and collaboration with operators to improve emission estimates and provide a mechanistic understanding of emissions (e.g., Bell et al., 2017; Robertson et al., 2017; Schwietzke et al., 2017; Yacovitch et al., 2017). Inherent biases in measurement sample sites in bottom-up studies can be minimized through various strategies such as random selection of sites by the research team, paired measurements, review of operational records prior to site visit, and/or comparison of measurements at similar sites. Prescreen measurements employing raster flights and/or mobile methods around the study area of interest can aid the eventual sample selection process and provide an indication of the emission profiles of accessible sites relative to other sites. The opportunity to conduct paired emission measurements (i.e., measurements employing different methods contemporaneously) may reduce sampling bias between measured sites versus nonpartner sites. For example, conducting a tracer-flux measurement at a facility with site access and conducting aircraft measurements in the area can ascertain whether the sites are representative of operations in the area. In addition, having an independent site sampling coordinator to review operational and maintenance records, historical emission inventories, and distribution of emissions (including accounting for high-emitting chronic sites and episodic events) may help reduce the site selection bias. Further, having the independent site coordinator observe measurements and operational records during the field campaign helps to document potential bias of the sites being sampled. Additionally, conducting multiday measurements at sites with access may assist the researcher to ascertain variation in emissions from prior work.

Requirements for transparency regarding site access and communication of operational and maintenance details is vital for modeling the characteristics and frequency of all sources from a facility or a region.

Expanding the Observational Network

Many top-down approaches are inhibited by the limited number of spatial locations where methane concentration measurements are taken. It is logical and important to consider which additional locations would provide the most relevant information.

Observation system simulation experiments (OSSEs) can be conducted to determine how to best allocate resources when expanding the observation network. OSSEs involve using simulated data to explore the effect of their use in data assimilation, for example, atmospheric flux inversions. Because simulated data are used, hypothetical observation strategies can be explored. An example is the study by Basu et al. (2016) that found that with about 5,000 radiocarbon ($^{14}CO_2$) observations in the United States, uncertainties of top-down estimates of regional monthly fossil fuel emissions of carbon dioxide could be reduced to within 5 percent. Similar OSSEs could be developed to evaluate the potential benefit of measuring methane from commercial aircraft, or the distribution of monitoring sites needed to adequately define the temporal and spatial variability in methane inflow to the United States for regional top-down systems, or how frequent and dense observations must be to monitor emissions from a petroleum/gas field. An important caveat concerning the interpretation of OSSEs is that model errors must be carefully considered to prevent overly optimistic interpretation of the benefits of observing strategies. These errors are usually difficult to quantify, but possible approaches include using multiple independent atmospheric models and using model ensembles.

Top-down studies would benefit from careful consideration of how the placement of additional observation sites will influence the information they provide. Observation system simulation experiments can inform observation strategies and determine how best to allocate resources when expanding the observation network.

Source Attribution

Top-down measurements often result in total emission estimates; attributing these emissions to specific sources using the top-down approach can be done using forward and inverse models, as described in the preceding section. Molecular and isotopic tracers can also provide useful constraints on sources. Atmospheric molecular and isotopic trace species (e.g., ethane, methyl chloroform, and the methane isotope $\delta^{13}CH_4$) collectively provide more information about the sources of emissions contributing to top-down measurements. However, using tracers to constrain top-down estimates of methane emissions introduces other uncertainties. For example, it is uncommon to find unique isotopic or molecular markers for major sources. Moreover, for soil sources (i.e., landfill methane) both the carbon and hydrogen isotopes are variably fractionated by seasonal oxidation in cover soils and thus not useful for top-down fingerprinting of landfill sources. In general, the ratios of various carbon and deuterium isotopes of methane vary across sources. The trace components of landfill

gas also vary temporally with changing societal practices, regulatory approaches, and rates of biochemical degradation processes within both the waste mass and the overlying cover soils.

The methane isotopic signature technique has been used to identify source contributions to atmospheric methane. Schwietzke et al. (2016), using $\delta^{13}CH_4$ data, concluded that fossil fuel methane emissions are not increasing over time (although they reported 60-110 percent greater emissions than current estimates, such as the GHGI and European Commission [Emissions Database for Global Atmospheric Research]), implying that emissions of methane from microbial sources account for the recent global growth of atmospheric methane. Although Schwietzke et al. (2016) used a large database of source signatures, more data are still needed owing to the overlap of signatures from different sources. For example, relatively few source signature data exist for tropical wetland emissions, although available data are increasing (e.g., Brownlow et al., 2017).

For microbial processes, stable isotopic values depend on the substrate as well as the balance between methanogenesis and methane oxidation by methanotrophs, all of which can vary regionally as well as temporally (e.g., Strąpoć et al., 2011). As discussed above, for landfill emissions, for example, soil oxidation results in large shifts for $\delta^{13}CH_4$ from around −60‰ to oxidized values of −30 to −35‰, as well as any value in between (e.g., Bogner et al., 1996; Chapter 3). Therefore, even though the $^{13}CH_4$ analysis provides independent information, there are limitations. Additional isotope measurements such as $^{14}CH_4$, D/H, CDH_3, or clumped isotopes (heavy isotopes that are bonded to other heavy isotopes; Eiler, 2007; Stolper et al., 2014; Wang et al., 2015) would help to better discriminate individual source contributions but might not yet be feasible at the same scale as $^{13}CH_4$ observations.

Ethane has been used as a marker for petroleum and natural gas emissions, typically assuming that all petroleum and gas sources in a region will have a characteristic ethane-to-methane ratio (Franco et al., 2015, 2016; Hausmann et al., 2016; Helmig et al., 2016; Smith et al., 2015). However, a challenge with this approach is that the methane-to-ethane emission ratio from specific petroleum and gas sources can change from region to region and even from day to day or hour to hour within a region, depending on the types of activities under way (e.g., Allen et al., 2017; Kort et al., 2016). As shown by Peischl et al. (2015), this ratio can range from 1.7 to 15 based on measurements from nine different U.S. petroleum and gas production regions. Ethane can also be emitted from sources other than petroleum and gas operations. To make ethane a strong constraint on the methane budget, more information about ethane/methane ratios and their temporal trends from different producing areas is needed. Especially in

areas with significant subsurface geological structures (faults, folds) and historic seismicity (e.g., Los Angeles), as well as historic methane seepages, there may be overlapping and currently unknown seepages that may contribute to observed atmospheric signatures.

Although the information provided by isotopes and molecular tracers can be limited by uncertainty related to trace species due to the lack of unique tracers for individual sources, these measurements can still provide significant information on source attribution. An approach that has been used for decades in attributing sources of particulate matter and volatile organic compounds is to attribute not a unique tracer to individual sources but a fingerprint of multiple tracers. This technique, referred to as the chemical mass balance (CMB) method or geochemical fingerprinting (Friedlander, 1973; Watson, 2004; Watson et al., 2001), takes advantage of multiple concentration ratios to attribute sources. For example, while the isotopic ratios for carbon and deuterium may be similar for emissions from livestock operations and landfills, manure emissions will contain trace species not present in landfill operations, and vice versa. Landfills may emit methane with elevated ^{14}C due to buried older waste affected by atmospheric nuclear testing many decades ago. However, detailed source fingerprinting for minor and trace gases is landfill specific without widespread "universally" useful species; also, many trace hydrocarbon species are either anaerobically degraded in landfilled waste or aerobically degraded in cover soils. Allen (2016) describes how the CMB method can be used to identify emission source strengths that best match all observations of molecular and isotopic tracers.

Expanded use of complementary isotopic and molecular data (e.g., multiple C and H isotopic fingerprints, ethane, and other species) is needed to better constrain specific emission sources in top-down studies. This could include expanding compositional analysis of emitted gases.

Timing of Observations

Another issue in designing a sampling scheme is the timing of the observations. Depending on the specific bottom-up or top-down methodology employed, there can be a mismatch between measurements of short duration that are subsequently extrapolated to longer time frames (daily, monthly, seasonal, or annual). Temporal variability is related to human factors (e.g., site engineering and operations) as well as natural factors (e.g., diurnal and seasonal variability; Zimmerle et al., 2016). Often what is desired for inventory purposes is an annual estimate with defined error bars as

opposed to a simple extrapolation using a variety of existing data. There may also be a lack of winter data for sites with strong seasonality.

Episodic events require both an estimate of methane emissions during the event and an understanding of the frequency of such events. Incorrect handling of episodic emissions could result in upward or downward bias of inventory estimates. If observations tend to coincide with episodic events (e.g., both occur during the workday), then extrapolating emission rate over an entire day could result in overestimation. Conversely, if episodic events are discounted as outliers, the inventory could be underestimated. Both natural and anthropogenic episodic events occur in all sources that can influence estimated emissions for inventory reporting. Natural influences include longer-term climate and shorter-time weather events which affect gaseous transport and methanotrophic methane oxidation around pipelines, in manure management systems and manured soils, and in landfill cover materials (Bogner et al., 2011; Dungan et al., 2017; Leytem et al., 2017; Spokas and Bogner, 2011; Spokas et al., 2011, 2015). Anthropogenic influences include pipeline leakages due to hardware issues, maintenance of manure management facilities, and the installation and operation of landfill biogas recovery systems. The latter are frequently adjusted over short time frames to optimize methane recovery and reduce air intrusion. Often a stratified random sampling scheme that includes known sources of variability can provide critical input data. However, such sampling schemes may be expensive or infeasible, or they may require very large sample sizes in order to capture the temporal variability for purposes of annual inventory reporting.

In top-down assessments, accounting for temporal variability is also important. Aircraft-based mass balance approaches for estimating methane emissions are likely to exhibit temporal sampling issues because the timing of the aircraft measurements is not randomized. To study, for example, emissions from petroleum- and natural-gas-producing regions and livestock emissions, measurements are made for specific short time periods and only when conditions are conducive to the methodology (typically midday). Because of expense, aircraft measurements are made for only a small number of days, resulting in a very small sample size. Thus, aircraft observations can be very useful in validating contemporaneous bottom-up estimates for specific times. However, extrapolating estimates from the short periods when measurements are taken to obtain an estimate for a longer period (e.g., annual, which would be most relevant for GHGI development) would require an assumption that emissions were constant over time and that the sampled days are representative.

Spatial variability also needs to be accounted for. For natural gas, there have been many bottom-up emission studies that have focused on a particular region or produc-

tion area (see Chapter 3). It is tempting to consider combining the data from these various studies to inform national inventories. However, it would be erroneous to naively combine emission factor estimates from different regions to obtain a national estimate for natural gas. Brandt et al. (2016) investigated device-level estimates from multiple studies and concluded that distributions of commonly catalogued components differed significantly from study to study. Similarly, Allen et al. (2013, 2015a,b) found that emission rates for certain types of operations and equipment in natural gas systems varied significantly from region to region. It would also be erroneous to presume that different studies could be viewed as a stratified sample. A stratified sample requires that the population of interest be completely partitioned, the mean from each stratum estimated, and the proportion of each stratum to the population either known or estimated. Hence, the data from these regional studies can only be viewed as a sample of convenience. Although information provided by regional studies is relevant for considering updates to emission factors, incorporating this information directly is not straightforward and likely would require input from the scientific community.

Improved data collection strategies, monitoring observations (e.g., paired contemporaneous measurements), and process-based modeling (for soil sources encompassing large areas, i.e., landfills) are needed to better account for temporal and spatial variability in emissions. Bottom-up studies would be more rigorous with the assembly of comprehensive up-to-date spatially and temporally resolved emission estimates from all source categories, including emissions currently "unaccounted for" in the GHGI. This typically will require validated process-based models appropriate for facility-scale application.

CHAPTER FIVE

Presenting Methane Emission Data and Results

In the United States, methane emission data are generated by various entities including the U.S. Environmental Protection Agency (EPA), state and local governments, industry, and researchers from academia, national laboratories, and nongovernmental organizations (NGOs). The stakeholder community using these emission data is even broader and includes policymakers at various levels of government, industry, scientific communities, and the general public. The needs of these stakeholders are diverse, as are their academic backgrounds and their understanding of the generation and reporting of methane emission information. Careful consideration of the audience for any published methane emission data is a key step in generating products that will be scientifically valid and properly used. For the scientific community, presentation of results in peer-reviewed literature would be expected to facilitate dissemination of key technical findings to fellow researchers. Similarly, various governmental agencies, research institutes, industries, and NGOs also publish methane results and reports, but they may not have undergone the peer-review process. As a broader audience attempts to understand and apply the research findings, there is increasing potential for misinterpreting and incorrectly using the results.

Those generating methane information are trying to answer a specific question or otherwise fulfill a requirement or meet a need. Such needs include submission of the Greenhouse Gas Inventory (GHGI) to the United Nations Framework Convention on Climate Change or understanding the difference between bottom-up and top-down emission estimates for a specific region in the United States. Although research goals and end uses of the data may be different, there are some common approaches that could facilitate the presentation of study results for multiple uses. This chapter focuses on the presentation of methane emission data to facilitate comparisons among studies and to ensure that results are useful for policymaking.

DESIGNING THE STUDY

Our knowledge of methane emissions is evolving, and there is both a large community generating new methane emission information and an even larger community interested in using the new methane information. Furthermore, the methods utilized

for quantifying methane emissions and the accuracy of those measurement methods are not always clearly communicated to policymakers. Producing quality research findings and generating useful reports start with a good study design. Encouraging active participation of stakeholders in the early design phase of any research program would enhance the usability of the final results by the larger community. Such early participation would allow sufficient time for stakeholders to provide important operational and policy-relevant input, allowing for useful and practical answers to policy-relevant scientific questions. The current peer-review process for scholarly journal articles also helps ensure that the methane information made publicly available is not only of appropriate quality, but that the usability and applicability of that information is available for end users of that information. Applying a similar peer-review process for any published studies or reports on methane could enhance the quality of the overall body of literature on this matter.

Chapters 2 and 3 highlighted the advantages and disadvantages of bottom-up and top-down studies, and the applicability and usefulness of results stemming from such studies could be considered in the design phase. For example, although offsite or ambient measurements of methane can provide methane estimates, there are limitations in using such techniques to attribute emissions to specific sources, which would be needed if the goal of the study were to develop sector-specific programs and policies. Inherent biases in measurement sample sites in bottom-up studies can be minimized through various strategies such as random selection of sites by the research team, review of operational records prior to site visit, and/or comparison of measurements at similar sites.

Additionally, the establishment of research networks can help standardize project design to make the end data more valuable to a wider range of users. For example, in the agriculture sector, the Greenhouse gas Reduction through Agricultural Carbon Enhancement network, was initiated by the U.S. Department of Agriculture (USDA) Agricultural Research Service (ARS). The goal was to quantify greenhouse gas (GHG) emissions from cropped and grazed soils under current management practices using standardized protocols that all sites would follow, as well as to identify and further develop improved management practices that would enhance carbon sequestration in soils, decrease GHG emissions, promote sustainability, and provide a sound scientific basis for carbon credits and GHG trading programs. Data collected by participating researchers are regularly uploaded into a main template that is then made publicly available, allowing further use of the data for activities such as model development and validation and providing greater value than the data collected by individual

researchers.[1] Another example is the Conservation Effects Assessment Project, another USDA ARS project, focused on water quality, which provides data across 14 watersheds at 12 locations with all data made publicly available through the Sustaining the Earth's Watersheds, Agricultural Research Data System database. In the petroleum and natural gas industry, a network[2] was formed in 2012 among the Environmental Defense Fund and more than 100 universities, research institutions, and companies, who collaborated to investigate methane losses across the natural gas supply chain using a variety of different measurement techniques. In addition, the U.S. Department of Energy funded multiple methane measurement and monitoring projects across the natural gas systems. Similar to the networks noted above, one goal of this study was to make the latest methane information publicly available to a larger community. For landfill methane emissions, a current California study supported by the California Air Resources Board and the California Department of Resources Recovery and Recycling is systematically addressing statewide approaches for improved quantification of site-specific and regional emissions. This study is being conducted by the California Polytechnic State University and the University of California Irvine. Historically, methane emission research has been supported by the waste industry (i.e., the Environmental Research and Education Foundation, Waste Management, Inc., and Cooperative Research and Development Agreements with the EPA) as well as by public agencies such as the Los Angeles County Sanitation Districts and the Delaware Solid Waste Authority.

Research networks that help standardize project design through (1) consistent data collection methods and presentation within sectors and (2) the development and application of common protocols, if applicable, would facilitate better comparison of data between studies and generate more usable data for policymakers (e.g., consistent use of reporting units and measurements of key variables influencing emissions).

REPORTING THE DATA TRANSPARENTLY

Although final decisions regarding study design or the scope and content of a report are ultimately made by the relevant study lead (whether a principal investigator or a government agency), it is incumbent upon those who generate methane emission information to ensure transparent reporting of the study design, assumptions, methodology, and results so that readers understand the data and their possible uses and

[1] See https://www.ars.usda.gov/anrds/gracenet/gracenet-home/ and https://data.nal.usda.gov/dataset/gracenet-greenhouse-gas-reduction-through-agricultural-carbon-enhancement-network.

[2] See https://www.edf.org/sites/default/files/methane_studies_fact_sheet.pdf.

limitations. Transparent data reporting facilitates comparisons among studies, thereby promoting generation of information that is policy relevant. Similar conclusions have been reached by Heath et al. (2014) and Weber et al. (2013), who recommended standardization of definitions and assumptions when communicating methane emission data to policymakers and the general public.

Describing the Coverage (Scope and Spatial and Temporal Boundaries) of the Study

A clear description of the boundaries of a study (including not only the sources covered, but also the specific geographic and temporal scales) is essential to enable potential users of the data to interpret the results. The following questions, if considered when drafting reports, could help users know if and to what extent the results of a particular study can be used in their own work.

- Which processes or technologies are covered in the study and how are these defined? For example, if an estimate of methane emissions at a facility is reported, how is the facility defined? Which processes are included and excluded?
- What are the spatial and temporal boundaries of the study? The GHGI produces a national, annual emission estimate for each category in the United States. Other studies may present data for a specific unit or coal mine over the course of a week or two. Clearly articulating the geographic/spatial and temporal boundaries of the study helps users know the relevance of any resulting methane emission estimate, activity data, or emission factor for their own work or use. For example, a landfill study limited to the warm, dry summer months, a flyover of a natural gas production field during liquid unloading activities, or an estimate of methane emissions from a liquid manure storage operation during summer or winter may not be representative of national conditions over the course of the year for use in the GHGI. Researchers are encouraged to clearly document the spatial and temporal boundaries of a study, and users are likewise encouraged to be aware of this scope prior to using any data in their own work.

Knowing the technical coverage (types of processes covered) informs understanding of the completeness and applicability of the results of a study. Clarity on the spatial and temporal resolution is important because emissions are not uniformly distributed across the United States or over time, and without clear understanding of the boundaries used for a study, there is a risk of misinterpretation of the results.

When presenting results on methane emissions, clarity on the scope and spatial

and temporal boundaries is essential to enable potential users of the data to interpret the results.

The results from specific studies that are quoted and communicated to a broader audience could be misinterpreted as being widely applicable at multiple scales. As such, caution is warranted when study results from a specific bottom-up field study (or specific coordinated top-down and bottom-up studies) are extrapolated to arrive at estimates at larger regional- and national-level scales. This is especially important when measurements are done only at a small number of facilities, because they may not be representative of national conditions. On the other hand, when presenting the results of top-down studies of short duration, it is important to compare the results with the inventory of emission sources within the specific spatial area operating during the specific time period and with careful consideration of operating conditions of these emission sources. In the absence of these vital supporting data, top-down studies may be misleading and perhaps overestimate or underestimate emissions.

Clearly Articulating the Units of Measurement

Methane emissions are typically reported in the units of absolute mass per unit time. For example, the GHGI reports methane emissions in kilotons per year, but other units may be more relevant for other studies. The Committee observed the challenges of consistent reporting of metrics while striving to consistently document available data in this report. Different sectors were found to follow different conventions for units reported that seem to be influenced by the magnitude of emissions and timescales that are commonly reported (e.g., kilograms of methane per cow per year, grams of landfill methane per square meter per day, cubic meters per year from coal mines, and cubic feet per day from natural gas systems, to name a few). See Appendix F for a list of units that are used in this report and standard equivalents used to convert among units. As long as the units are commonly understood and transparently documented, conversion among units should be possible. If data are reported on a carbon dioxide equivalent (CO_2eq) basis, it is important to document the global warming potential value that was applied to methane.

In addition to an absolute magnitude of emissions, other intensity metrics such as leakage rate, flux rates, emissions per unit of product, and emissions based on life-cycle analysis have also been used to compare methane emissions across studies. Expressing methane emissions in terms of a methane intensity metric provides a convenient comparison of various operating areas, companies, producers, or regions. Intensity metrics may also facilitate comparison with the GHGI for some categories

(e.g., enteric fermentation, as described below), but they could introduce confusion for others (e.g., petroleum and natural gas systems, where the GHGI does not always have a clear delineation of whether methane is released from a petroleum- or gas-producing well).

In the agriculture sector, for example, there may be other more valuable representations of the emission data that would benefit policymakers, industry, and consumers. For livestock, in addition to reporting total kilotons of methane produced per unit time, emissions could be further expressed as methane produced per head of livestock per unit time, per unit of feed dry matter intake (i.e., emission yield), and per unit of product such as energy-corrected milk or kilogram of daily gain or carcass weight (i.e., emission intensity). When data are presented in this manner, it becomes easier to see if overall efficiency of the industry is improving over time, that is, less methane emitted per unit of milk produced. As agricultural production, energy production, and waste generation are expected to increase along with a growing population, there will likely be inherent increases in total methane produced from these sectors; however, efficiencies can be improved that would be reflected only in the intensity of GHG production when expressed on a production basis.

Providing methane data on an absolute mass/time basis as well as other intensity metrics (e.g., leakage rate, flux rates, emissions per unit of product, and emissions based on life-cycle analyses) is useful for comparing results across studies.

MAKING INPUT DATA PUBLICLY AVAILABLE

There is often a wealth of underlying activity data and emission factor, parameter, and model information used to generate emission estimates, whether for the GHGI, the Greenhouse Gas Reporting Program (GHGRP), or other local, state, regional, or national methane studies. However, these data are not always publicly available. For example, researchers studying emissions from petroleum and natural gas regions often create their own regional gridded inventories (e.g., Barnett, Fayetteville) and have to rely on state petroleum and natural gas commissions or private databases (see Chapter 2). The public release of basic activity and emission factor data in a machine-readable format, as well as more detailed information on any models used, including the underlying methods, assumptions, and equations used, could facilitate transparency. This would also help improve national methane emission estimates while supporting improved gridded inventories.

Advances have been made in recent years to make data more publicly available. For example, the activity data and emission factors used in the GHGI for petroleum and

natural gas systems is now publicly available in electronic format.[3] These efforts could be expanded to other sectors of the GHGI and to other groups publishing methane information. Nonconfidential data reported under the GHGRP also are made publicly available;[4] however, the dataset is updated frequently as a result of EPA verification activities and resubmissions made by individual reporters to correct errors. Although there are release numbers associated with the EPA's online data publication site,[5] there is no archive to allow retrieval of previously available datasets that may have been used in published studies, and it is therefore difficult to assess studies based on these estimates.

Future studies and emission estimate comparisons would benefit from increased data transparency by making underlying data used in reports publicly available in machine-readable formats, subject to confidentiality concerns, and improved documentation and archiving of Greenhouse Gas Reporting Program data. The development of a library of data that is properly documented, archived, and publicly accessible would enhance data integrity and facilitate its use.

GUIDANCE ON INCORPORATING INFORMATION FROM NEW STUDIES INTO THE GHGI

There is a value in convening multidisciplinary discussions with representatives of the research community, academia, industry, and policymakers that share an interest in methane emission measurement and reporting. Such representatives could be practitioners in the field, research scientists and academics, and those working on larger national and international policy issues and scientific questions. In recent years, the EPA has periodically convened stakeholder workshops to discuss possible forthcoming changes to the methane GHGI for petroleum and natural gas systems[6] and the waste sector[7] providing an opportunity for any interested stakeholders to offer feedback. These workshops are open to any interested individual and often focus on changes for the next GHGI submission. In addition to conducting these more informal workshops, establishing and maintaining a smaller, more formal advisory group composed

[3] See https://www.epa.gov/ghgemissions/natural-gas-and-petroleum-systems-ghg-inventory-additional-information-1990-2015-ghg.

[4] See https://www.epa.gov/ghgreporting/ghg-reporting-program-data-sets.

[5] See https://ghgdata.epa.gov/ghgp/main.do#.

[6] See https://www.epa.gov/ghgemissions/stakeholder-process-natural-gas-and-petroleum-systems-1990-2016-inventory.

[7] See https://www.epa.gov/ghgemissions/stakeholder-webinar-waste-sector-data-and-methodology-us-greenhouse-gas-inventory.

of experts from relevant research, scientific, and policy communities could help guide how evolving science could be incorporated into improving methane inventories in the short, medium, and long term. Such a group could consider questions such as

- Is there sufficient information available to justify updating existing emission factors or activity data?
- What other types of research efforts may be necessary before including data in the GHGI?
- Do the data reported at a facility level, or information generated by the top-down networks, suggest that updating current methods is warranted? Will such top-down information and facility-level data reduce uncertainty?

Any changes to the GHGI resulting from these activities should be transparently described and clearly communicated to the public.

An advisory group could help guide how new science should be incorporated into improving the methane portion of the Greenhouse Gas Inventory. Such an advisory group could be facilitated by the U.S. Environmental Protection Agency and the National Oceanic and Atmospheric Administration and comprised of experts from academia, industry, policymaking, other federal agencies, and non-governmental organizations. Its goal would be to facilitate timely improvements in activity data and enhance characterization of emission sources and quantities.

CHAPTER SIX

Meeting the Challenges of Characterizing Methane Emissions

This report outlines actions to improve estimates of the amounts of anthropogenic methane emitted in the United States and to improve the utility and usability of methane emission inventories to governments, industries, academia, nongovernmental organizations, and the general public. Atmospheric observations are fed into atmospheric inverse models to compute emission fluxes, called the "top-down" approach to emission estimation. The more familiar "bottom-up" approach is based on scaling up of data for emissions by individual components or facilities. Top-down and bottom-up approaches can be tested against each other to improve the application of both approaches.

The traceable attribution of emissions to specific sectors, processes, and components is a key output of bottom-up inventories, which are thus uniquely suited for applications in the sphere of mitigation and societal interests. Currently, however, the U.S. Greenhouse Gas Inventory (GHGI) of methane emissions cannot be independently tested against top-down measurements, because both spatial and temporal attributes are missing, and thus expected atmospheric concentrations cannot be inferred. There are many benefits of building a strong link between atmospheric measurements of methane concentrations and methane emission inventories, including the discovery of missing sources or processes, improved confidence in the basic data that enter into decisions by companies and governments, and better capability to detect trends over time.

The effective interlinking of top-down and bottom-up approaches involves strengthening both approaches, as recommended in Box 6.1. These steps will enable improved accuracy, better attribution of emissions to specific sectors/processes, and detection of trends in sectoral emissions.

The four recommendations that follow are interlinked, and if they are to meet the goals outlined in this report, they should be viewed as interdependent and addressed systematically[1] (Figure 6.1). The monitoring and verification of methane emissions is

[1] The Committee identifies agencies to implement the recommendations where possible but recognizes that the list it provides may not be exhaustive, and that the agencies should have the flexibility to parse out the tasks as they think will best serve the interests and missions of their agencies and the country.

BOX 6.1
RECOMMENDATIONS

1. Continue and enhance current atmospheric methane observations and advance models and assimilation techniques used by top-down approaches.
2. Establish and maintain a fine-scale, spatially and temporally explicit (e.g., gridded) inventory of U.S. anthropogenic methane emissions that is testable using atmospheric observations and update it on a regular basis.
3. Promote a sustainable process for incorporating the latest science into the GHGI, and regularly review U.S. methane inventory methodologies.
4. Establish and maintain a nationwide research effort to improve accuracy, reliability, and applicability of anthropogenic methane emission estimates.

a science that is, at least in part, still in early stages of development. The United States should take bold action now to match monitoring and measurement efforts to the importance of the task.

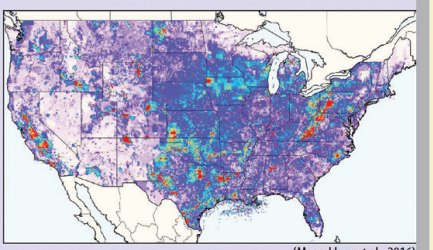
Recommendation 1: The National Oceanic and Atmospheric Administration and the National Aeronautics and Space Administration should continue and enhance current atmospheric methane observations and advance models and assimilation techniques used by top-down approaches.

FIGURE 6.1 Schematic summarizing the four major recommendations for improving characterization of anthropogenic methane emissions in the United States. To improve methane emission estimates in the United States, an expanded national research effort with improved linkages among measurement and monitoring approaches is recommended (beige box; Recommendation 4). Top-down estimates and monitoring of global atmospheric methane concentrations provide constraints on total emissions (blue box; Recommendation 1) while bottom-up estimates evaluate contributions from individual sources and source types (e.g., agricultural practices, petroleum and natural gas activities, landfilling of waste, and coal mining) and serve as the basis for the current U.S. Greenhouse Gas Inventory (GHGI) methane emission estimates (green box; Recommendation 3). Sustained and improved methodologies for both top-down and bottom-up approaches are needed. Better incorporation of existing and emerging research findings into the development of the GHGI should be used to complement new efforts to develop an annual gridded national-scale inventory (purple box; Recommendation 2). At a fine-scale spatial and temporal resolution, this gridded-inventory approach would refine understanding of national emissions, allow for verification of the GHGI, and contribute to the development of more accurate methane emission estimates in the United States.

Establish and maintain a nationwide research effort to improve accuracy, reliability, and applicability of anthropogenic methane emissions estimates.

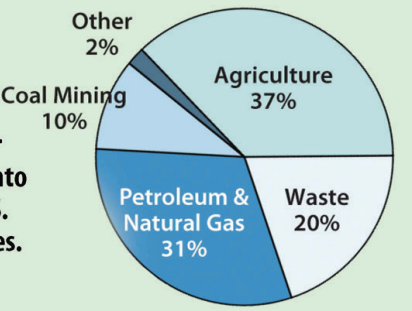
Continue and enhance current atmospheric methane observations and advance models and assimilation techniques used by top-down approaches.

Establish and maintain a fine-scale, spatially and temporally explicit (e.g., gridded) inventory of U.S. anthropogenic methane emissions that is testable using atmospheric observations and update it on a regular basis.



(Maasakkers et al., 2016)

Promote a sustainable process for incorporating the latest science into the GHGI and regularly review U.S. methane inventory methodologies.



Atmospheric observations of methane are the foundation for understanding anthropogenic and natural changes in methane concentrations. Long-term observations, together with atmospheric models, are critical for estimating methane emissions and detecting large-scale trends. A monitoring program needs sufficient spatial and temporal coverage to be able to determine anthropogenic and natural emissions and track changes over time. Some examples of dedicated efforts are the European monitoring initiatives, such as the Integrated Carbon Observation System and Copernicus, providing dense continuous methane monitoring sites. The Committee recommends continuing the existing U.S. and global background observational networks and expanding measurements across multiple spatial scales, including in the vertical dimension. Multiscale observational strategies (e.g., aircraft, surface, tower, and satellite remote sensing) supply complementary information and can provide flux estimates from the facility scale through the local and regional scale, enabling direct comparison with gridded inventories (Recommendation 2).

Because atmospheric measurements reflect both natural and anthropogenic methane sources, accurate knowledge of the spatiotemporal distribution of natural methane emissions is also required but currently lacking, especially in regions with spatial overlap between different source categories. This limitation inhibits our abilities to accurately attribute observed methane emissions to source categories and thus processes.

Measuring a suite of tracer species that provide additional information on the attribution of emissions should also be expanded. Related species used to obtain insight into underlying source processes can include carbon monoxide, ethane, $^{13}CH_4$, CH_3D, $^{14}CH_4$, and multiply-substituted (clumped) methane isotopes. Geochemical fingerprinting of various methane sources could assist with this effort by identifying multiple gases and conditions capable of unambiguously tracking specific types of sources. Scientific studies are also needed to identify necessary measurements to close observational gaps that result in current ambiguities of our methane budget (sources and sinks; Chapters 3 and 4).

In addition to investing in comprehensive monitoring of atmospheric methane and associated species, improvements in our ability to accurately simulate these data in models should be undertaken. Current models cannot adequately represent small-scale processes that affect measured concentrations, such as planetary boundary layer mixing and diurnal growth, convection, and complex effects of local topography. Advances in atmospheric modeling are needed, as well as innovative model evaluation tools.

Recommendation 2: The U.S. Environmental Protection Agency, in collaboration with the scientific research community, the U.S. Department of Energy, the National Oceanic and Atmospheric Administration, the U.S. Department of Agriculture, and the National Aeronautics and Space Administration should establish and maintain a fine-scale, spatially and temporally explicit (e.g., gridded) inventory of U.S. anthropogenic methane emissions that is testable using atmospheric observations and update it on a regular basis.

The development of a spatially and temporally resolved anthropogenic inventory is required for independent verification using atmospheric observations. A gridded inventory, including values for the major sources within the grid, is a prerequisite for detailed comparisons between bottom-up and top-down approaches, enabling feedback into improved inventories at the national scale. The recent efforts to report the GHGI in a spatially and temporally resolved form (Chapter 2) should be continued and expanded.

The GHGI has increasingly been used for purposes for which it was not initially designed, including comparisons with top-down estimates of methane emissions in specific regions at specific times. The gridded inventory should be consistent with the national GHGI inventory for integrated total emissions per source and have sufficient documentation to allow the scientific and policy communities interested in regional methane emissions to reproduce and adapt the inventory. For example, providing the gridded datasets used to create the inventory would facilitate direct comparison of top-down analyses with not just the bottom-up product (flux), but also the bottom-up methodology. The spatial and temporal resolution should be at as fine a scale as possible (e.g., $0.1° \times 0.1°$ or finer spatial resolution and monthly or finer temporal resolution), based on the data used to generate the inventory. Because expected uses of the inventory, such as comparison with top-down snapshots of daytime emissions, require a finer temporal resolution than the inventory would normally support, the inventory should also provide guidance on fine-scale temporal allocation of emissions.

Recommendation 3: The U.S. Environmental Protection Agency, U.S. Department of Energy, National Oceanic and Atmospheric Administration, and U.S. Department of Agriculture should promote a sustainable process for incorporating the latest science into the U.S. Greenhouse Gas Inventory and regularly review U.S. methane inventory methodologies.

The GHGI, in particular should be maintained at the federal level and data made publicly available on an annual basis. It is important to recognize, however, that the science is evolving. Some inventory methodologies become outdated; therefore, methodologies should be evolutionary to be consistent with the best scientific under-

standing and current engineering practice. Although emission estimates extending back to 1990 are needed for GHGI reporting to the United Nations Framework Convention on Climate Change, the need to back-cast to 1990 should not be a constraint in implementing new methods that improve emission estimates for current and future applications (Chapter 2).

Inventory improvements should be done in coordination with both the research community and stakeholders. However, the Committee recognizes that the inventory process evolves slowly. There is a need for an advisory group to guide how new science should be incorporated into improving the national GHGI (Chapter 5). Such a group could be facilitated by the U.S. Environmental Protection Agency and National Oceanic and Atmospheric Administration and composed of experts from academia, industry, policymaking, other federal agencies, and nongovernmental organizations. Their goal would be to facilitate timely improvements in activity data and enhance characterization of emission sources and quantities. Any resulting changes in the methodologies, process models, or underlying inputs should be transparently described and clearly communicated to the public.

Recommendation 4: The United States should establish and maintain a nationwide research effort to improve accuracy, reliability, and applicability of anthropogenic methane emission estimates at scales ranging from individual facilities to gridded regional/national estimates.

The Committee calls for a sustained coordinated national research effort to improve top-down and bottom-up estimation and monitoring methods and technologies. These efforts should include results from atmospheric observations, sustained spatial and temporal characterization of methane emissions for key sectors in the United States, improvements in models and assimilation techniques used by top-down approaches, and improvements in estimation techniques and process models. Results from such efforts could better support attribution of emissions to specific sectors or processes as well as trend detection. The improved monitoring network and recommended gridded national inventory (Recommendations 1 and 2) are necessary to conduct comparisons at the finest temporal and spatial scales that the data, models, and site access allow. The comparisons will enable stakeholders and the public to identify deficiencies in the gridded inventory as well as the atmospheric observations, catalyzing Recommendation 3 for continual improvement in all aspects of methane inventory development. The improvements should be informed by a national research effort (Recommendation 4) for which the guiding goal should be (1) better quantification and attribution of methane emission rates and trends over time and (2) identification of knowledge gaps and guidance for resolving those gaps (Chapters 3 and 4).

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Glossary

Activity data: Data on the magnitude of a human activity resulting in emissions or removals taking place during a given time period (e.g., head of cattle per year or number of gas processing facilities) (IPCC, 2006).

Atmospheric inverse models: As opposed to a forward model, which uses a prescribed forcing such as surface emissions, to calculate atmospheric concentration, an inverse model uses information about atmospheric concentration to estimate the forcing. In practice, this involves using a first guess of surface emissions (prior emissions) to simulate the atmospheric responses and then systematically comparing simulated and observed concentrations to produce revised estimates of surface forcing that result in optimal agreement with observations. Numerical estimation techniques used in atmospheric inversions to obtain surface emissions are similar to those used in numerical weather prediction and include variational and ensemble approaches. Resulting estimated (posterior) emissions are a weighted combination of information coming from observations and prior flux estimates. The weight of prior versus observational constraints in the estimated emissions is determined by the input uncertainties of observational and prior emissions where the uncertainty of observational information reflects measurement uncertainty as well as the ability to accurately simulate atmospheric concentration at measurement sites.

Atmospheric transport models: A mathematical model that solves the mass continuity equation for atmospheric trace species, resulting in simulated atmospheric concentrations. The mass continuity equation accounts for sources and sinks of trace species such as surface emissions and chemical loss processes taking place throughout the atmospheric column. It also accounts for transport by atmospheric motions. Transport due to small-scale processes that cannot be resolved because of limited model spatiotemporal resolution such as turbulent diffusion and convection are parameterized. Models can range in complexity from global average models to highly resolved global three-dimensional models. Although some models generate their own atmospheric motions, many models used for trace gas studies use atmospheric state variables such as winds and temperatures from atmospheric analyses or reanalyses from parent general circulation or weather models.

"Beyond the meter": Natural gas infrastructure (i.e., pipes, fittings, valves, and other components) after distribution service lines and customer meters, but before use (e.g., combustion) of the natural gas.

Blowdowns: Natural gas released due to maintenance and/or depressurization operations including compressor depressurization, pipeline depressurization, and emergency shutdown system testing (EPA, 2016b).

Bottom-up method: Based on measurements from a single facility or source; these source or facility-level measurements can then be extrapolated to larger scales (regional, national, global) in a bottom-up estimate.

Carbon budget: Quantification of the amount of carbon (often in the form of either methane or carbon dioxide) contained in different environments—including the atmosphere, ocean, and terrestrial biosphere—and the movement of this carbon among these sources and sinks.

Emission factor: A coefficient that quantifies the emissions or removals of a greenhouse gas per unit of activity. Emission factors are often based on a sample of measurement data, averaged to develop a representative rate of emission for a given activity level, under a given set of operating conditions (IPCC, 2006).

Eructation: Release of methane gas from the digestive tract (mainly the rumen) by ruminant animals (i.e., burping or belching).

Expiration: The phase in breathing when air leaves the lungs.

Flatulence: Release of methane gas produced in the intestines of ruminant animals through the rectum.

Fugitive emissions: Intentional or unintentional release of greenhouse gases that may occur during the extraction, processing, and delivery of fossil fuels to the point of final use (IPCC, 2006).

Greenhouse gas inventories: an estimation of the amount of greenhouse gas emissions discharged into the atmosphere over a specific spatial and temporal scale.

Greenhouse gas sinks: any process, activity, or mechanism that removes a GHG from the atmosphere. There are also biological sinks: methane is oxidized in soils and sediments by indigenous microorganisms under both aerobic and anaerobic conditions (IPCC, 2014).

Greenhouse Gas Reporting Program: As the GHGRP is codified in 40 CFR Part 98. The GHGRP requires reporting of greenhouse gas (GHG) data and other relevant informa-

tion from large GHG emission sources, fuel and industrial gas suppliers, and CO_2 injection sites in the United States—generally, facilities emitting ≥25,000 metric tonnes carbon dioxide equivalent (CO_2eq) per year.

Greenhouse gas sources: Any identified process or activity (natural or human-caused) that produces or releases a GHG to the atmosphere. Sources are typically characterized by sector, category, or components.

Gridded inventory: Presentation of anthropogenic greenhouse gas emission data at smaller spatial (e.g., 0.1°× 0.1°) and temporal (e.g., monthly) scales than are available at the national level. Development of a gridded inventory may include the use of the U.S. Environmental Protection Agency Greenhouse Gas Inventory data or other datasets and disaggregation of this inventory using state-, county-, local-, and point-source-level databases to allocate emissions to individual source types (e.g., Maasakkers et al., 2016).

High-emitting sources: Also known as fat tails or super-emitters, high-emitting sources are a small number of sources that contribute to a disproportionately high fraction of the cumulative total emissions recorded. They are typically found in the natural gas production and distribution sectors. These sources may be a result of episodic events, malfunctions, or their size and operating/design limitations.

Landfill gas/landfill biogas: A mixture of gases consisting primarily of methane and carbon dioxide that is produced by methanogenesis in landfills. Landfill gas (as recovered by engineered systems) can also contain oxygen and nitrogen resulting from air intrusion and a large number of trace components due to volatilization and internal landfill reactions.

Liquid unloadings: Gas well liquid unloading is a procedure, implemented periodically, where liquids that have accumulated in a gas well are removed to surface equipment. The liquid accumulation can include oil, condensate, and water, and may be due to a variety of causes, including decreases in gas velocity in the well, decreases in reservoir pressure, or changing gas-to-liquid ratios. As liquids accumulate, well production can decline and an operator may choose to unload the liquids from the well to restore gas production.[1]

Longwall mining: a type of underground mining where coal is extracted mechanically in long (up to 3,650 m) rectangular blocks, after which the mined area collapses, to be differentiated from older, room-and-pillar mining where "pillars" are left in place with only incidental collapses after mining is completed (Kentucky Foundation, 2007).

[1] See http://dept.ceer.utexas.edu/methane2/study/.

Methane oxidation: The process by which methane is aerobically (presence of oxygen) converted to carbon dioxide and water vapor by indigenous methanotrophic microorganisms in soils and sediments. Methane can also be anaerobically (absence of oxygen) oxidized in soils and sediments via multiple pathways.

Methanogenesis: The process by which methanogenic microorganisms biologically produce methane in the absence of air (anaerobic conditions). This process occurs in water-saturated soils and sediments in marine and terrestrial environments (e.g., wetlands). Normally, aerobic soils will also produce methane during periods of saturation. Methane produced during methanogenesis is considered to be anthropogenic when linked to human activities (landfills, wastewater, rice production, manure management systems, and rearing livestock for milk or meat).

Overburden: In mining it defines the material located above the economically valuable coal seam. Overburden can consist of hard rock, soft sediment, and soil.

Pneumatic controllers: Devices used in petroleum and natural gas systems to regulate liquid levels, valves, and gas pressure. When open, controllers powered by natural gas pressure release methane (EPA, 2016c).

Posterior emissions: Estimated emissions produced by atmospheric inversions. These are emissions that have been revised from prior emissions to agree optimally with observations.

Prior emissions: Emissions used as a first guess in atmospheric inversions. Emission inventories and results from process models of emissions are common choices for prior emissions.

Rumen: The largest segment of the complex stomach of ruminant animals, in which methanogenic archaea generate methane (predominantly) from hydrogen and carbon dioxide.

Top-down method: Approaches based on atmospheric measurements that are directed toward estimating emissions from regions that could include multiple facilities (Heath et al., 2015).

APPENDIX A

Acronyms and Abbreviations

AGAGE	Advanced Global Atmospheric Gases Experiment
AMB	aircraft mass balance
ARS	Agricultural Research Service
CAIT	Climate Analysis Indicators Tool
CALMIM	CAlifornia Landfill Methane Inventory Model
CARB	California Air Resources Board
CI	confidence interval
CL	confidence level
CMB	chemical mass balance
COBRA-NA	CO_2 Boundary Layer Regional Airborne–North America
CSIRO	Commonwealth Scientific and Industrial Research Organization, Australia
DE	digestible energy
DiAL	differential absorption Lidar
DMI	dry matter intake
DOE	U.S. Department of Energy
EDGAR	Emissions Database for Global Atmospheric Research
EF	emission factor
EIA	Energy Information Administration
EPA	U.S. Environmental Protection Agency
EREF	Environmental Research and Education Foundation
ESRL	*Earth System Research Laboratory*
FOD	first-order decay model
FTIR	Fourier-transform infrared
G&B	gathering and boosting
GAINS	Greenhouse gas and Air pollutant Interactions and Synergies
GCP	Global Carbon Project
GEI	gross energy intake

APPENDIX A

GeoCARB	Geostationary Carbon Cycle Observatory
GF	GreenFeed®
GGRN	Global Greenhouse Gas Reference Network
GHG	greenhouse gas
GHGI	U.S. Greenhouse Gas Inventory
GHGRP	Greenhouse Gas Reporting Program
GOSAT	Greenhouse Gases Observing Satellite
GRACEnet	Greenhouse gas Reduction through Agricultural Carbon Enhancement network
GRI	Gas Research Institute
GWP	global warming potential
HB	high bleed
IB	intermittent bleed
IEA	International Energy Agency
InGOS	Integrated Non-CO_2 Greenhouse gas Observing System
INSTAAR	Institute of Arctic and Alpine Research
IPCC	Intergovernmental Panel on Climate Change
LB	low bleed
LCA	life-cycle analysis
LMOP	Landfill Methane Outreach Program
LULUCF	land use, land use change, and forestry
MCF	methane conversion factor
MSHA	U.S. Mine Safety and Health Administration
NASA	National Aeronautics and Space Administration
NASS	National Agricultural Statistics Service
NGOs	nongovernmental organizations
NGPL	natural gas plant liquid
NGPP	natural gas power plant
NOAA	National Oceanic and Atmospheric Administration
NSF	National Science Foundation
OECD	Organisation for Economic Co-operation and Development
OSSE	observation system simulation experiments
OTM	other test method

PTW	pump-to-wheels
SCIAMACHY	Scanning Imaging Absorption Spectrometer for Atmospheric Chartography
SIT	State Inventory Tool
STEWARDS	Sustaining the Earth's Watersheds, Agricultural Research Data System
TANSO-FTS	Thermal and Near Infrared Sensor for Carbon Observation
TCA	tracer correlation approach
TCCON	Total Carbon Column Observing Network
TROPOMI	TROPOspheric Monitoring Instrument
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
USDA	U.S. Department of Agriculture
VOCs	volatile organic compounds
VRPM	vertical radial plume mapping
VS	volatile solids
WDCGG	World Data Centre for Greenhouse Gases
WIP	waste in place
WRF-STILT	Weather Research and Forecasting—Stochastic Time-Inverted Lagrangian Transport
WRI	World Resources Institute

APPENDIX B

Definition of U.S. Greenhouse Gas Inventory Categories

Brief descriptions of the U.S. Greenhouse Gas Inventory (GHGI) categories are provided below. For further discussion of these terms as used in the GHGI, refer to the respective section in the latest national inventory report (EPA, 2017b).

Abandoned coal mines: Methane emissions released from coal mines after their closure.

Coal mining (active): Methane emissions resulting from activities at underground coal mines and surface mines, as well as post-mining activities. The largest fraction of methane emissions comes from underground coal mines through ventilation and degasification systems.

Enteric fermentation: A natural by-product of microbial fermentation of carbohydrates and amino acids in the rumen and the hindgut of farm animals (e.g., cattle, buffalo, sheep, goats, swine, horses, and mules and asses). These emissions are considered biogenic methane.

Landfills: Methane emissions from the anaerobic decomposition of biodegradable waste fractions (e.g., food waste, garden waste, and paper) in municipal solid waste and industrial landfills. The mass of methane that is subsequently emitted to the atmosphere is a function of site-specific (1) operational practices (engineered biogas recovery and thickness and composition of cover materials) and (2) seasonal climate, which drives cover-specific methane transport and (aerobic) oxidation rates. These emissions are considered biogenic methane.

Manure management: Includes methane emissions from the anaerobic decomposition of manure. The release of methane is largely a function of the type of treatment and storage of manure, with solid systems (e.g., stacked or composted manure or manure directly deposited on pasture, range, and paddock) resulting in less methane than liquid systems (e.g., in lagoons, ponds, tanks, or pits), as well as the chemical characteristics of the manure (e.g., amount of volatile solids and pH), and environmental conditions (e.g., temperature and wind speed). These emissions are considered biogenic methane.

Natural gas systems: Includes fugitive and vented emissions from production (including gathering and boosting stations), processing, transmission, storage, and distribution facilities.

Petroleum systems: Covers emissions from both onshore and offshore operations, including the production of crude petroleum, transportation, and refining operations. Emissions may be a result of fugitive leaks, vents, operational upsets, and/or uncombusted methane.

Rice cultivation: Methane generated from methanogenesis occurring in flooded rice fields. The water management regime as well as soil properties (soil carbon) are primary factors determining the amount of methane generated.

Wastewater treatment and composting: Methane can be formed during wastewater transport, treatment, and post-treatment stages at domestic and industrial operations. Composting of organic waste, such as food waste, garden and park waste, and wastewater treatment sludge can also lead to methane emissions. The amount of methane released is a function of the amount of degradable organic material in the waste. These emissions are considered biogenic methane.

APPENDIX C

Other Anthropogenic Sources of Methane

Smaller anthropogenic sources of methane from the industrial, agricultural, and waste sectors are not covered in this study. The two largest sources excluded are rice cultivation and wastewater treatment. Methane emissions from land use, land use change, and forestry activities are also not covered.

RICE CULTIVATION

Methane from wetland (paddy) rice cultivation accounts for about 2 percent of anthropogenic methane emissions in the United States (EPA, 2017b), and production is confined to a few regions of the country. Globally, however, rice cultivation is responsible for approximately 10 percent of total emissions.[1]

Methane emissions from rice cultivation are the result of anaerobic decomposition of organic material (i.e., methanogensis), which escapes to the atmosphere primarily by diffusive transport through the rice plants during the growing season, when soils are waterlogged. In the United States, a combination of Tier 1 and 3 methodologies (IPCC, 2006) is used to estimate methane emissions from rice cultivation (EPA, 2014). The activity data are represented by the rice paddy annual harvested area taken from the National Resources Inventory (USDA-NRCS, 2015). Most of the estimates use a Tier 3 approach, where a process-based model (DAYCENT) is used to simulate rice cultivation and associated methane emissions. In instances where DAYCENT cannot be used because of lack of representation of production systems (e.g., when rice is grown in rotation with crops that are not included in DAYCENT, such as vegetables and perennial/horticultural crops, and for organic soils), an Intergovernmental Panel on Climate Change (IPCC) Tier 1 emission factor is employed using a default base estimation rate. This estimation rate assumes a continuously flooded field with no organic amendments and scaling factors to represent water management regimes that differ from this base case, as outlined by IPCC (2006). According to EPA (2017b), extensive improvements have been planned to update time-series management data, which is expected to improve methane emission estimates by more accurately reflecting fertil-

[1] See http://www.globalmethane.org/documents/analysis_fs_en.pdf.

izer rates, updated tillage and water management practices, organic amendments, and planting/harvesting dates. Uncertainties related to estimating emissions from rice cultivation (±28 percent in the GHGI) are largely due to their high spatial heterogeneity and data scarcity on field irrigation, soil properties, rice variety, and rice production systems. Improving data availability for the variables used in process-based models could significantly reduce uncertainties in emission estimates.

WASTEWATER

Methane from wastewater is currently estimated to contribute about 2 percent of anthropogenic methane emissions in the United States (EPA, 2017b). Wastewater channeled to septic systems and via sewers to centralized wastewater treatment facilities can produce methane as a result of methanogenesis when anaerobic conditions develop during transport and treatment steps. Methane can also be emitted due to fugitive emissions from anaerobic digesters or from anaerobic conditions developing in residual biosolids following land disposal. The principal factors used in current IPCC (2006) emission estimates are population, the estimated quantity of degradable organic carbon, assumed temperature, and the type of treatment system. For septic systems, the U.S. population is multiplied by the estimated fraction of wastewater treated in septic systems (about 19 percent) and an emission factor. For centralized systems, the organic carbon fraction of the wastewater is estimated using biochemical oxygen demand (an estimate of the amount of oxygen needed to degrade the waste aerobically, thereby avoiding methane emissions) and chemical oxygen demand (amount of material available for chemical oxidation). Then, 81 percent of the U.S. population is multiplied by factors indicating the amount of waste entering the system, the relative use of aerobic versus anaerobic treatment systems, and system-specific emission factors. In general, systematic accounting of degradable carbon to anaerobic pathways through the various process steps for individual treatment facilities is lacking, as is process-specific modeling for fugitive methane generation and emissions, leading to very high uncertainties regarding methane emissions from wastewater treatment. A limited body of recent research currently exists on methane production and emissions from wastewater systems in the United States. Bellucci (2010) concluded from a field and laboratory study of three wastewater plants in the Chicago area that IPCC (2006) methodologies yielded reasonable values when compared to field observations. However, many researchers point to very high uncertainties for methane emissions from these systems (−26 to +22 percent in the GHGI), as well as the paucity of field studies

of U.S. systems. Complications include fossil carbon, which is unavailable to anaerobic microbial pathways (Tseng et al., 2016), and/or sequestered carbon through wastewater treatment steps (Rosso and Stenstrom, 2008). In addition to direct emissions from sewers and during treatment steps, there can also be methane emissions from residual biosolids (Tian et al., 2009).

APPENDIX D

U.S. Greenhouse Gas Inventory Development

PRINCIPLES OF GREENHOUSE GAS INVENTORY DEVELOPMENT

Key to understanding the emission numbers contained in the annual U.S. Greenhouse Gas Inventory (GHGI) is understanding the principles upon which the inventory is developed:

- **Inclusion of anthropogenic emissions from sources and removals by sinks:** The GHGI covers all human-induced greenhouse gas (GHG) emissions not controlled by the Montreal Protocol; at a minimum, the inventory must include emissions of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3) across all sectors of the economy (energy; industrial processes and product use; agriculture, land use, land use change, and forestry [LULUCF]; and the waste sector). In the case of the LULUCF sector, anthropogenic emissions and removals are considered to be those arising from managed lands, while those arising from unmanaged lands are considered natural emissions and therefore excluded from the GHGI.
- **Reporting of actual emissions:** The inventory methods result in an estimate of the GHG emissions in the year in which they occur; that is, the methods result in actual emissions to the atmosphere and not potential emissions that may be released from the source over a period of years.
- **Full territorial coverage:** The GHGI covers the entire United States and its territories.
- **Use of the 2006 IPCC Guidelines:** The 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines outline a tiered approach for estimating GHG emissions from each source or sink of anthropogenic emissions. There are generally three tiers for estimating emissions for each category:
  - Tier 1 broadly relies on multiplying activity data (AD) by an international default factor representing emissions per unit of activity;
  - Tier 2 approaches generally involve the application of a region- or country-specific emission factors to national- or regional-level AD;

  - Tier 3 approaches are more detailed, involving further stratification of the AD, estimates from process-based models, plant-level emission estimates, direct measurement, or other equivalent country-specific approaches.
- Ensuring the inventory is transparent, accurate, consistent, comparable, and complete.
  - Transparency: The data sources, assumptions, and methodologies used in the inventory should be clearly explained to enable a third party to reproduce the estimates.
  - Consistency: The same methods and data sources should be used for all years in the time series.
  - Comparability: Countries should estimate emissions using the methods in the 2006 IPCC Guidelines and report using the commonly agreed-upon reporting format.
  - Completeness: The inventory must report emissions from all categories and gases for which methods are included in the 2006 IPCC Guidelines.
  - Accuracy: Emissions and removals should not be overestimated or underestimated, as far as can be judged, and uncertainties should be reduced as far as practical.

The U.S. inventory development process includes a 30-day expert review period that includes a group of non-EPA technical experts who are not involved in constructing the inventory. Once their comments are reviewed and addressed, the U.S. Environmental Protection Agency (EPA) releases the draft inventory for a 30-day public review. After comments from the public and expert reviews are taken into consideration, the EPA finalizes the inventory and the U.S. Department of State officially submits the U.S. annual GHGI to the United Nations Framework Convention on Climate Change (UNFCCC) in April of each year.

INSTITUTIONAL ARRANGEMENTS IN THE UNITED STATES

Developing the GHGI involves the cooperation of many individuals at various levels of government and in the private sector, including federal and state government authorities, research and academic institutions, industry associations, and private consultants (see Figure D.1). The inventory is produced, and reviewed, annually and is constantly being updated and improved.

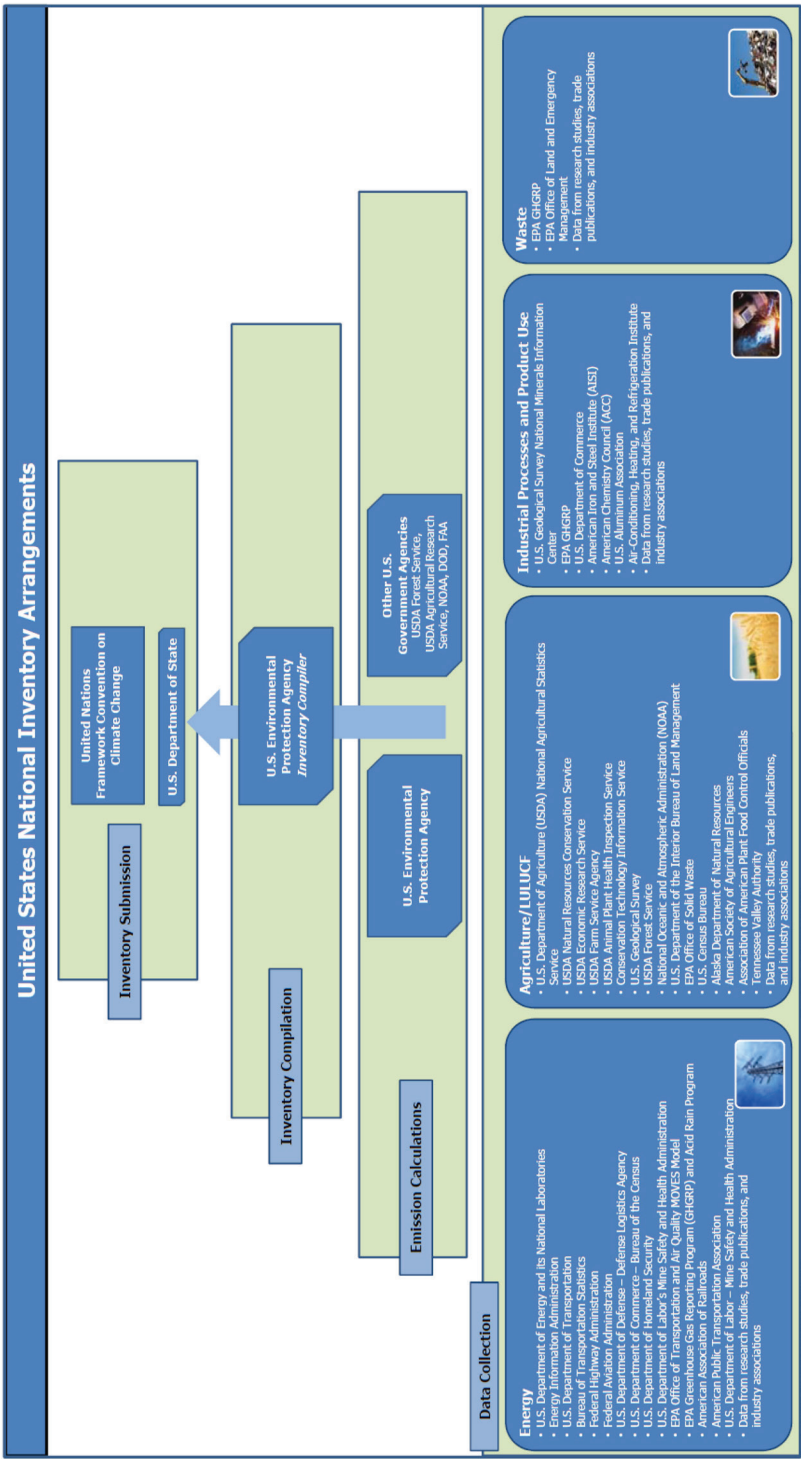

FIGURE D.1 National inventory arrangements. SOURCE: EPA, 2017b.

APPENDIX E

Acknowledgment of Those Who Provided Input to the Committee

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Marc Fischer, **Lawrence Berkeley National Laboratory**
Johannes Friedrich, **World Resources Institute**
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APPENDIX E

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Dan Zimmerle, **Colorado State University**

APPENDIX F

Common Units for Reporting Methane Concentrations and Emissions

Methane concentrations, emissions, and flow rates (metered sources) are commonly reported using a wide range of units. This appendix focuses primarily on units used in this report.

METHANE CONCENTRATIONS

Volumetric mixing ratio (v/v or l^3/l^3): Parts per million (ppm), parts per billion (ppb), and parts per trillion (ppt); 1 ppm = 1,000 ppb; 1 ppm = 1,000,000 ppt.

Mass per unit volume (m/v or m/l^3) at standardized temperature and pressure: milligrams or grams per cubic meter (mg m^{-3}, g m^{-3}) at standardized temperature and pressure conditions (commonly 0°C and 101.325 kilopascals)

Note: Conversions from volumetric to mass-based units require use of the ideal gas law equation: $PV = NRT$, where

P = pressure in atm,

T = temperature in Kelvin [=deg C + 273],

R = molar gas constant, where $R = 0.082058$ L atm mol^{-1} K^{-1}

1 mole methane = 16.04 g.

METHANE EMISSIONS

Mass per time (m/t): megagrams, or terragrams per year (Mg yr^{-1}, Tg yr^{-1})

Mass per unit area per time ($m/(l^2$ t): grams per square meter per day (g m^{-2} d^{-1}). Used for area sources (i.e., manured soils; landfills).

Mass CO_2 equivalents per time: Requires multiplication of mass methane by global warming potential (GWP) for methane. GWP varies through time (=28 per IPCC 5th Assessment Report).

METHANE FLOW RATES (METERED SYSTEMS)

Standard cubic feet per minute: Cubic feet per minute at 60°F and 14.7 pounds per square inch (psi) pressure.

Standard cubic meters per minute: Cubic meters per minute at 15°C and 100 kilopascal pressure.

Normal cubic meters per minute: Cubic meters per minute at 0°C and 101.325 kilopascal pressure.

Multiplication factors for common metric units

1,000,000,000,000	10^{12}	tera
1,000,000,000	10^{9}	giga
1,000,000	10^{6}	mega
1,000	10^{3}	kilo

APPENDIX G

Biographical Sketches of Committee Members

James W. C. White (*Chair*) is interim dean of the College of Arts & Sciences and a professor of geological sciences at the University of Colorado Boulder. He is a climate scientist with experience working with ice cores from Greenland and Antarctica. His areas of focus are global change, paleoclimate dynamics, and biogeochemistry, and his specific interests include global-scale climate and environmental dynamics; carbon dioxide concentrations and climate from stable hydrogen isotopes, peats, and other organics; climate from deuterium excess and hydrogen isotopes in ice cores; isotopes in general circulation models; and modern carbon cycle dynamics via isotopes of carbon dioxide and methane. Dr. White received his Ph.D. from Columbia University. He has participated in numerous National Research Council study committees, including chairing the Committee on Understanding and Monitoring Abrupt Climate Change and Its Impacts, and recently completed a term as chair of the Polar Research Board.

David Allen is the Gertz Regents Professor of Chemical Engineering, and the director of the Center for Energy and Environmental Resources, at the University of Texas at Austin. He is the author of seven books and over 250 papers, primarily in the areas of urban air quality, the engineering of sustainable systems, and the development of materials for environmental and engineering education. Dr. Allen has been a lead investigator for multiple air quality measurement studies, which have had a substantial impact on the direction of air quality policies. He directs the Air Quality Research Program for the State of Texas, and he is the founding editor-in-chief of the American Chemical Society's journal *ACS Sustainable Chemistry & Engineering*. The quality of his work has been recognized by the National Science Foundation, the AT&T Foundation, the American Institute of Chemical Engineers, the Association of Environmental Engineering and Science Professors, and the State of Texas. In 2017, he was elected to the National Academy of Engineering. He has served on a variety of governmental advisory panels and from 2012 to 2015 chaired the U.S. Environmental Protection Agency's Science Advisory Board. Dr. Allen received his B.S. degree in chemical engineering, with distinction, from Cornell University in 1979. His M.S. and Ph.D. degrees in chemical engineering were awarded by the California Institute of Technology in 1981 and 1983. He has held visiting faculty appointments at the California Institute of Technology, the University of California, Santa Barbara, and the U.S. Department of Energy.

Praveen K. Amar is an independent consultant working in the areas of environment (air), energy, and climate change strategies. He recently served as a member of the Technical Experts Group for the United Nations Environment Programme (UNEP) that developed UN-written guidelines on best available technologies and best engineering practices for mercury control from industrial sources. These guidelines were required under the UN global treaty known as the Minamata Convention. From May 2011 to May 2013, he was the senior policy advisor of technology and climate policy at the Clean Air Task Force, an environmental organization with a focus on protecting the environment through research, advocacy, collaboration, and innovation. From 2007 to 2011, he served as a member of U.S. Environmental Protection Agency's (EPA's) Clean Air Scientific Advisory Committee (CASAC) panel on review of Secondary National Ambient Air Quality Standards for SO_2 and NO_x. Since 2015, he has been serving on the reconstituted CASAC review panel on the same subject. He recently completed his service on the EPA's Clean Air Act Advisory Committee Climate Change Work Group that addressed approaches the EPA may take to control greenhouse gas emissions from large industrial sources. He served as a member of the National Academies Board on Environmental Studies and Toxicology from 2010 to 2016, and as a member of the National Academies Committee on Scientific Tools and Approaches for Sustainability for use in the EPA's decision making. He is currently serving on the National Academies' Committee on the Review of Environmental Protection Agency's Science to Achieve Results' Research Grants Program. He received his Ph.D. in engineering from the University of California, Los Angeles, and is a registered professional engineer in California.

Jean Bogner is research professor emerita at the University of Illinois at Chicago (UIC), Department of Earth and Environmental Sciences. Previously she worked more than 20 years at Argonne National Laboratory (ANL) focusing on applied geochemical research for mined land reclamation, groundwater remediation, and the recovery and utilization of landfill biogas. Subsequent U.S. and international projects at ANL, her consultancy Landfills +, Inc. (1997-2013), and UIC have focused on fundamental field and laboratory investigations related to landfill CH_4 generation, transport, soil oxidation, and emissions. Recent publications focus on field-validated modeling for site-specific landfill CH_4 emissions inclusive of local soils and climate, spatial and temporal variability of emissions, and alternative emission measurement strategies. During 2004-2007 she was the coordinating lead author for the "Waste Management" chapter of the Intergovernmental Panel on Climate Change (IPCC) 4th Assessment Report for Working Group III ("Mitigation of Climate Change"). She holds B.A., M.S., and Ph.D. degrees in geoscience, focusing on hydrogeology, geochemistry, and soils.

Lori Bruhwiler is a physical scientist in the Global Monitoring Division of the National Oceanic and Atmospheric Administration's Earth Systems Research Laboratory (ESRL) in Boulder, Colorado. Dr. Bruhwiler received her Ph.D. and master's of astrophysical, planetary, and atmospheric sciences from the University of Colorado in 1992 and 1988, respectively. Prior to her work at ESRL, Dr. Bruhwiler was a physical scientist for the Geophysical Fluid Dynamics Laboratory in Princeton, New Jersey. Her research interests include understanding the budgets of CO_2 and CH_4 using atmospheric transport models, observations, and assimilation techniques.

Daniel Cooley is an associate professor in the Department of Statistics at Colorado State University. Dr. Cooley received his Ph.D. in applied mathematics from the University of Colorado at Boulder in 2005. Apart from being an associate professor, Dr. Cooley is also a faculty member at the Colorado State University School of Environmental Sustainability. Dr. Cooley's research interests include extreme value theory, modeling multivariate extremes, heavy-tailed phenomena, spatial statistics, Bayesian modeling, and the meteorological/environmental and ecological applications of these. He has published many articles and has given several short courses on extremes. Dr. Cooley is currently chair of the American Statistical Association's Advisory Committee on Climate Change Policy. In 2017, Dan was named a professor laureate of CSU's College of Natural Sciences.

Christian Frankenberg is a scientist at the Jet Propulsion Laboratory at California Institute of Technology in Pasadena, focusing on the remote sensing of atmospheric trace gases (with particular focus on greenhouse gases), biogeochemical cycles (through observations of greenhouse gases and chlorophyll fluorescence), hydrological cycle and distribution of water isotopes, inverse methods, and applied spectroscopy. Dr. Frankenerg received his Ph.D. in environmental physics from Ruprecht-Karls-University in Heidelberg, Germany, in 2005 where he was also a postdoctoral researcher. Dr. Frankenerg was also a VENI Postdoctoral Researcher (in conjunction with a personal fellowship from the Dutch Science Foundation) until December of 2009. Most recently he was awarded the NASA Early Career Achievement Medal and the Lew Allen Award for Excellence in 2012.

Fiji George is the director of Regulatory Policy at Southwestern Energy and has more than 23 years of experience related to energy–environmental and sustainability science and policy issues spanning natural gas production, processing, transmission, and liquid natural gas. His current focus is on characterizing methane emissions from the natural gas value chain through collaborative research and developing sound policies to meet the challenge of reducing methane emissions from the natural gas sector. He also focuses on identifying solutions for prudent natural gas development in a low-

carbon economy, including assessing the impact of carbon budgets on oil and gas development. His experience includes leading the development of comprehensive methane emission inventories and protocols, development of methane measurement programs, and participation in scientific studies with academia, nongovernmental organizations, and other industry partners. He has been involved in several multi-stakeholder studies, including the 2010-2011 National Petroleum Council, the University of Texas studies on methane emissions from the production sector, the Stanford University–led Energy Modeling Forum, and methane studies in collaboration with the Colorado School of Mines, the National Renewable Energy Laboratory, and the National Oceanic and Atmospheric Administration. He holds a master's in civil (environmental) engineering from Texas A&M University and a bachelor's in mining engineering from Anna University, India.

Lisa Hanle is an independent consultant who has been active in the reporting and review of greenhouse gas (GHG) inventory information at the project, facility, national, and international levels for 19 years. Among other initiatives, she is currently serving as the director of the MRV Support Program at the Greenhouse Gas Management Institute, supporting developing countries in GHG inventory-related issues in the context of implementation of the Paris Agreement. Previously, she served as a Programme Officer at the United Nations Framework Convention on Climate Change (UNFCCC) in Bonn, Germany, where she supported the international negotiations to develop the latest guidelines for reporting and review of GHG inventories under the Convention and the Kyoto Protocol, for use by developed countries. On a technical level, while at the U.S. Environmental Protection Agency, she supported development of the annual U.S. GHG inventory to the UNFCCC (responsible for generating emission estimates for industrial processes and fugitive emissions from coal, oil, and natural gas). Ms. Hanle was also a core member of the team that developed the United States' first mandatory, facility-level GHG reporting program, and served as a lead author in the development of the 2006 Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories. She holds a master's degree from the Johns Hopkins University School of Advanced International Studies, where she focused on international economics with a concentration in energy, environment, science, and technology.

Alexander Hristov is a professor of dairy nutrition in the Department of Animal Science at The Pennsylvania State University and is a member of several professional societies and of the Feed Composition Committee of the National Animal Nutrition Program. He has a Ph.D. in animal nutrition from the Bulgarian Academy of Agricultural Sciences. Dr. Hristov is chair of the Network on Feed and Nutrition in Relation to Greenhouse Gas Emissions, which is an activity of the Livestock Research Group within the

Global Research Alliance on Agricultural Greenhouse Gases. Dr. Hristov's main research interests are in the areas of protein and amino acid nutrition of dairy cattle and mitigation of nutrient losses and gaseous emissions from cattle operations.

Ermias Kebreab is a professor of animal science and holds the Sesnon Endowed Chair in Sustainable Animal Agriculture at the Department of Animal Science, UC Davis. He is the deputy director of Agricultural Sustainability Institute and he was appointed associate vice provost at UC Davis Global Affairs in 2016 to advance the university's engagement in international education. Dr. Kebreab conducts research on reducing the impact of animal agriculture on the environment, particularly greenhouse gas emissions. He has served on several national and international committees including those organized by the Intergovernmental Panel on Climate Change, United Nations Food and Agriculture Organization, and National Academies of Sciences, Engineering, and Medicine. He has mentored or hosted over 30 scholars in his laboratory, authored more than 200 peer-reviewed articles and 34 book chapters, and edited 5 books. Dr. Kebreab received several awards including the AFIA Ruminant Nutrition Award from the American Society of Animal Science. Dr. Kebreab received his B.Sc. degree from University of Asmara, Eritrea, and his M.Sc. and Ph.D. from University of Reading, United Kingdom.

April Leytem is a research scientist at the U.S. Department of Agriculture (USDA) Agricultural Research Service with the Northwest Irrigation and Soils Research Laboratory in Kimberly, Idaho. For the past 11 years she has been working in the area of on-farm emissions of ammonia and greenhouse gases from the livestock sector, including animal housing, manure storage, and land application of manures. Studies have focused on development of techniques for measuring/monitoring on-farm emissions and development of baseline emission factors. In particular, her focus has been on emissions from western dairy production systems. She was a contributing author for the USDA report, *Quantifying Greenhouse Gas Fluxes in Agriculture and Forestry: Methods for Entity-Scale Inventory*; in particular, she co-authored the chapter on "Quantifying Greenhouse Gas Sources and Sinks in Animal Production Systems." In addition she has been involved in helping to improve whole-farm modeling efforts to estimate emissions from dairy production systems and efforts to quantify emissions for carbon credit applications.

Maria Mastalerz is a senior scientist with the Indiana Geological and Water Survey and adjunct associate professor with the Department of Geological Sciences, Indiana University, Bloomington. Dr. Mastalerz received her Ph.D. in mining geology from Silesian Technical University in Gliwice and her M.Sc. in geology from Wroclaw University, both in Poland. She did postdoctoral research at the University of British Columbia in Vancouver, Canada. Dr. Mastalerz's area of expertise is coal geology and organic petrol-

ogy and geochemistry of hydrocarbon source rocks. She has conducted research on coal and kerogen in sedimentary basins of Poland, Canada, Australia, New Zealand, and the United States. She also has wide laboratory-oriented experience; she has developed and applied electron microprobe and reflectance micro-FTIR to study light element composition and functional group distributions in organic matter. Her current projects include characterization of Indiana Basin coals, investigation of coal-bed methane potential, and CO_2 sorption into organic matter–rich formations, and oil and gas shale characterization. She has authored more than 200 papers related to fossil fuels published in peer-reviewed journals and is a recipient of national and international awards for her contributions to coal geology and organic petrology. Dr. Mastalerz serves as an associate editor of the *International Journal of Coal Geology*, and is an active member of American Association of Petroleum Geologists, Geological Society of America, International Committee for Coal and Organic Petrology, and the Society for Organic Petrology.

Steven Wofsy is the Abbott Lawrence Rotch Professor of Atmospheric and Environmental Science at Harvard University. His research emphasizes sources and distributions of greenhouse gases on urban, regional, and global scales and the impacts of climate change and land use on ecosystems and atmospheric composition. Dr. Wofsy's extensive research interests include terrestrial carbon, effects of forests on climate, and climate in forests; inference of large-scale carbon budgets from atmospheric and land surface data; CO_2 as a tracer of atmospheric transport in the upper troposphere and stratosphere; and new instrumentation for measuring atmospheric carbon cycle species (CO_2, CO, and CH_4). Dr. Wofsy has published over 300 journal articles during a career spanning four decades. His awards include the American Geophysical Union's Macelwane prize and NASA's Distinguished Public Service Medal. In 2011, he was elected to the National Academy of Sciences. He earned his B.S. in chemistry from the University of Chicago and his M.A. and Ph.D. in chemistry from Harvard University. He has served on the NASA Earth System Science and Applications Advisory and on the NASA Advisory Council as well as on the Carbon Cycle Science Plan Working Group and North American Carbon Program writing group. His recent National Research Council service includes the Committee on Indicators for Understanding Global Climate Change, the Panel on Atmosphere, the Committee on Methods for Estimating Greenhouse Gas Emissions, and the Committee on Ensuring the Utility and Integrity of Research Data in a Digital Age.

APPENDIX H

Disclosure of Conflict of Interest

The conflict-of-interest policy of the National Academies of Sciences, Engineering, and Medicine (www.nationalacademies.org/coi) prohibits the appointment of an individual to a committee like the one that authored this Consensus Study Report if the individual has a conflict of interest that is relevant to the task to be performed. An exception to this prohibition is permitted only if the National Academies determine that the conflict is unavoidable and the conflict is promptly and publicly disclosed.

When the Committee that authored this report was established, a determination of whether there was a conflict of interest was made for each Committee member given the individual's circumstances and the task being undertaken by the Committee. A determination that an individual has a conflict of interest is not an assessment of that individual's actual behavior or character or ability to act objectively despite the conflicting interest.

Mr. Fiji George was determined to have a conflict of interest because of his employment with Southwestern Energy.

The National Academies determined that the experience and expertise of the individual was needed for the Committee to accomplish the task for which it was established. The National Academies could not find another available individual with the equivalent experience and expertise who did not have a conflict of interest. Therefore, the National Academies concluded that the conflict was unavoidable and publicly disclosed it through the National Academies Current Projects System (www8.nationalacademies.org/cp).