ROADMAP FOR U.S.-CHINA METHANE COLLABORATION: SPATIAL ANALYSIS OF METHANE EMISSIONS

KEY MESSAGES

- Joint U.S. and China efforts to reduce methane emissions are critical for limiting near-term warming. China and the U.S. are the first and third largest methane emitters, and collectively account for a quarter of global methane emissions today.
- One key challenge for methane mitigation is uncertainties in historical anthropogenic methane emissions inventories. Evaluating the spatial distribution of methane emissions can help improve historical emissions estimates and inform policy targets and mitigation strategies.
- This analysis compared gridded emissions data from four inventory sources for both the U.S. and China. Our results suggest that while there are similarities in estimates of total emissions by region across inventories, the spatial distribution of those emissions across regions varies. Major differences between inventories are likely caused by differences in emission factors and proxy geospatial information used to disaggregate national emissions. These differences are important when gridded emissions data are used by top-down inventories to verify bottom-up estimates.
- This analysis highlighted a number of high-emitting grids, largely in major agricultural and energy producing regions, and highly populated urban areas, suggesting that a number of sites may be contributing to the bulk of emissions in both countries. Targeting sources of methane emissions from facilities with outsized methane emissions could have a significant impact on overall emissions reduction.
- Policy implications from this research include:
  - Local, flexible, and targeted policies in major emitting regions may be more cost-effective and may more accurately and effectively measure and reduce emissions compared to blanket policies
  - Subnational actors and collaborations may be able to contribute significantly to methane emissions reductions
  - Increased accessibility and transparency of facility-level data and improved monitoring methods may facilitate better identification of super-emitting facilities
  - More detailed emission factors to increase confidence in bottom-up inventory estimates require more detailed, facility level emissions and infrastructure geospatial data
  - Consistent application by the private sector of rapidly improving satellite technologies for Leak Detection and Repair (LDAR) programs may improve the accuracy of emissions monitoring

INTRODUCTION

Methane has a global warming potential that is 25 times more potent than CO_2, making methane emissions reduction critical to keeping the world on a path to 1.5°C (IPCC, 2007). According to existing estimates, China and the U.S. are the first and third largest methane emitters and collectively account for roughly one-quarter of total global methane emissions (GMI, 2022). Joint efforts by the U.S. and China to reduce methane emissions can accelerate methane mitigation in both countries.

However, there is uncertainty in current historical estimates of methane emissions in both countries, making setting quantitative policy targets, evaluating mitigation potential, and developing sectoral strategies difficult. Estimating historical anthropogenic methane emissions is challenging due to the fact that sources of emissions are largely processes where emission rates depend on site-specific conditions and operational procedures, leading to high levels of uncertainty. There are two commonly used approaches for estimating historical methane emissions: 1) bottom-up calculations, which use emission factors or process models to estimate emissions from historical activity levels, and 2) top-down calculations, which use atmospheric measurements, generally combined with atmospheric model calculations, to estimate emissions from a given region.

While bottom-up methods are used by countries for greenhouse gas (GHG) reporting, top-down estimates can serve as an important verification tool for bottom-up methodology (Brandt et al., 2014; Jacob et al., 2016; Kirschke et al., 2013). Top-down estimates, based on atmospheric observations, can accurately capture global emissions, but attributing these emissions to regions and/or sectors is difficult, due in part to limited satellite observation data, uncertainties in atmospheric transport and chemistry models, and overlapping sources of emissions in the same region (Dlugokencky et al., 2011; Kirschke et al., 2013). Top-down inventories rely on bottom-up emission estimates to attribute emissions to regions and sectors. Gridded emissions data, or emissions data reported spatially by grid cells, is critical for developing top-down estimates that accurately reflect the spatial distribution of methane emissions (Feng et al., 2020; Jacob et al., 2016). This report evaluates differences among gridded emissions data from several inventories to better understand uncertainty in historical methane emissions distribution and identify areas for methane mitigation in both the U.S. and China.

GEOSPATIAL DISTRIBUTION OF METHANE EMISSIONS

We compared gridded emissions data for total, total agricultural, total waste and total energy from EDGARv6.0 (EDGAR), CEDSv2021_04_21 (CEDS), and GAINSv4 (GAINS), and sub-energy sectors of coal, oil and gas exploitation from EDGAR and GFEIv2 (GFEI) (Höglund-Isaksson et al., 2020; Janssens-Maenhout et al., 2019; McDuffie et al., 2020; Scarpelli et al., 2020). We define a "hotspot" in this analysis as any gridded cell that is above 50 Gg a^{-1} at 0.5° or above 30 Gg a^{-1} at 0.1° resolution, and major hotspots as a grid cell with emissions above 80 Gg a^{-1} at 0.5° or above 50 Gg a^{-1} at 0.1°. This analysis was limited to spatial distributions from bottom-up inventories, as these were available for the regions considered. A similar analysis could be applied to comprehensive spatial data from remote sensing methods once that becomes available.

High Emitting Areas in the U.S. and China Across Sectors

There are a number of major hotspots largely in major energy production regions, in both countries (Figure 1). Major hotspots for total emissions and energy emissions are almost identical, suggesting that the major sources of concentrated emissions are in the energy sector. While most major hotspots are attributed to the energy sector, there are still significant hotspots in the waste and agriculture sectors. Although agriculture emissions are higher than waste emissions in both countries, waste emissions are highly concentrated in urban areas, such as New York City, Los Angeles, Beijing, Shanghai, and Hong Kong, leading to more concentrated emissions than in agriculture (Figure 1).

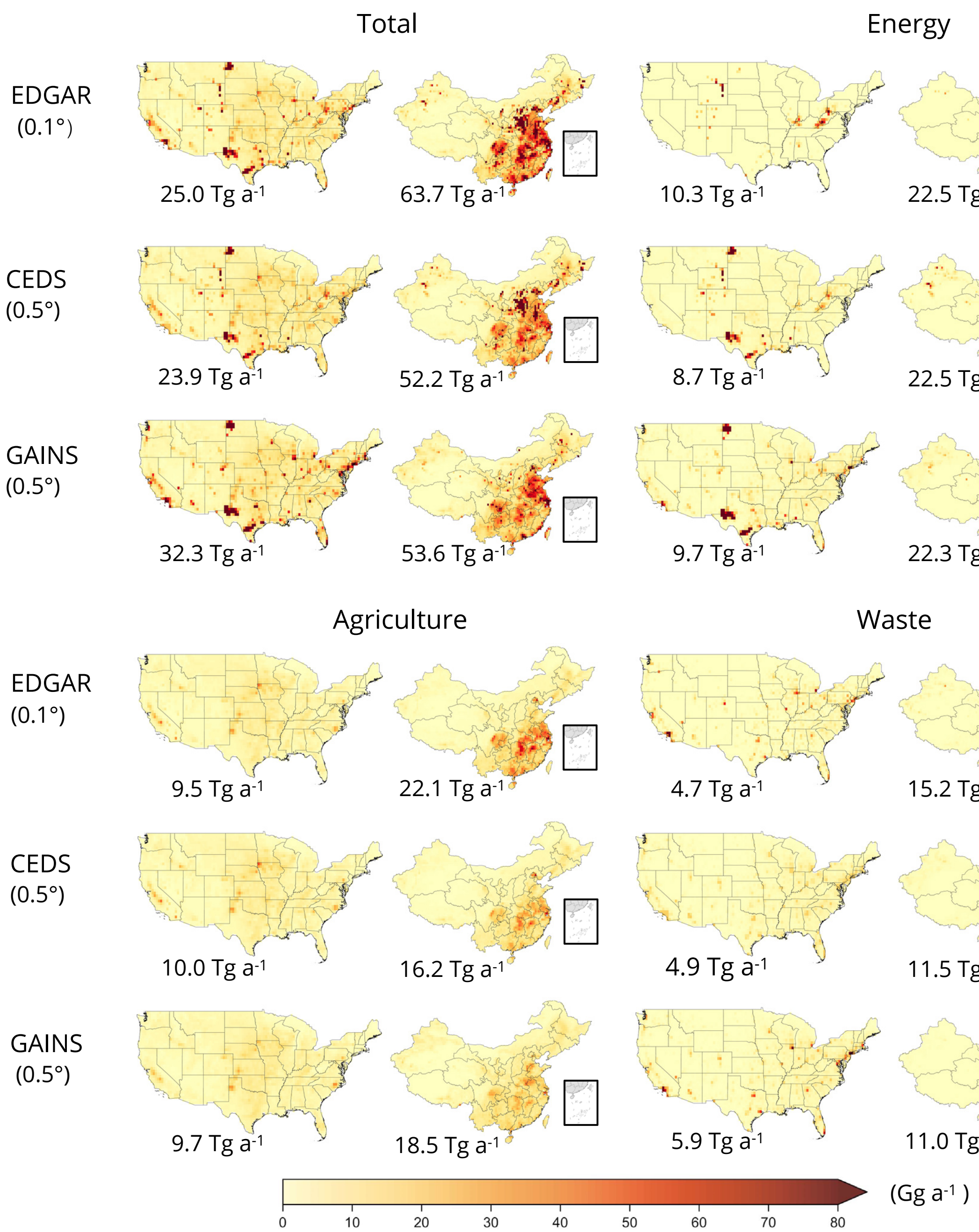
The location of hotspots across sectors can vary significantly by country. In the U.S., energy, agriculture and waste hotspot locations vary, as energy and agriculture production regions are typically located far from major urban centers. Energy and agricultural production do not often coincide within the same state, although there is some overlap in Texas and California. Hotspots in the agriculture, waste and energy sectors in China are largely concentrated in the eastern part of China. Energy emissions are concentrated in the northeast, while agriculture production is primarily located in the southeastern portion of China.

Hotspot variation across inventories highlights areas of uncertainty in geospatial distribution (Figure 1). Differences across inventories can be partially explained by the adoption of different approaches to calculate bottom-up emission estimates, and the use of different geospatial proxy data to attribute bottom-up calculations to grid-cell level. CEDS shows fewer concentrated waste hotspots in eastern China than other inventories, but this may be from unintentionally using agriculture waste burning as proxy data for all of waste. EDGAR adopted a higher methane correction factor for wastewater treatment plants (Peng et al., 2016), which might partially explain why waste emissions are higher in EDGAR. U.S. agriculture emissions are fairly similar across inventories, because all three inventories use activity data from the Food and Agriculture Organization (FAO) and default IPCC emission factors. Inventories largely agree on the distribution of agriculture emissions in China, but magnitude varies significantly across inventories because of different approaches to estimating rice cultivation emissions. EDGAR assumes a higher proportion of continuous floods relative to other bottom-up inventories (Cheewaphongphan et al., 2019), which might explain higher total estimate and concentration of emissions in southeastern China.

Total emissions in the energy sector are consistent across inventories, but distribution, especially in China, varies significantly, highlighting the need for additional data collection and verification of global inventory geospatial proxy data. Inventories largely agree on the major hotspot regions, with a few exceptions. Not all inventories demonstrate high energy emissions in Shanxi - GAINS total energy emissions are highly concentrated in cities and have additional hotspots in the southeast U.S. and California, whereas EDGAR and CEDS show a wider range of areas with reduced emissions concentration.

FIGURE 1: TOTAL, ENERGY, AGRICULTURE AND WASTE METHANE EMISSIONS IN THE U.S. AND CHINA.

GAINS data is from 2020 and CEDS and EDGAR data is from 2018. Each cell represents 0.5x0.5° resolution for CEDS and GAINS, while EDGAR cells are at 0.1x0.1° resolution, which is a limitation of this comparison.



Coal, Oil and Gas Major Hotspots

Increasing certainty around the location of emissions, particularly emissions from energy, is important for informing policies that have a local or regional focus and for identifying the heaviest emitting sites for facility-level mitigation implementation.

Coal Mining Emissions

The magnitude of energy total and coal emissions in coal producing regions that have reduced production relatively recently, like the Appalachian region in the U.S. and Guizhou in China (Figure 1 and Figure 2), varies across inventories and may be attributed to a difference in the underlying geospatial information used across inventories. GFEI shows more hotspots for coal emissions in both the U.S. and China, especially in Appalachia, Guizhou, Liaoning, and Hunan than EDGAR. In the U.S., GFEI uses state-level estimates for proxy spatial data, which can include methane recovered or destroyed, post-mining emissions (Maasakkers et al., 2016). GFEI is based on a 2013 EIA report, which might explain why some coal emissions are identified in areas with reduced coal production in recent years. For China, GFEI uses 2011 geospatial data from the Chinese State Administration of Coal Mine Safety (SACMS) (Scarpelli et al., 2020; Sheng et al., 2019). Thus it is unclear whether these regions are currently major sources of emissions due to abandoned coal mine methane or whether the results are an indication of out of date data.

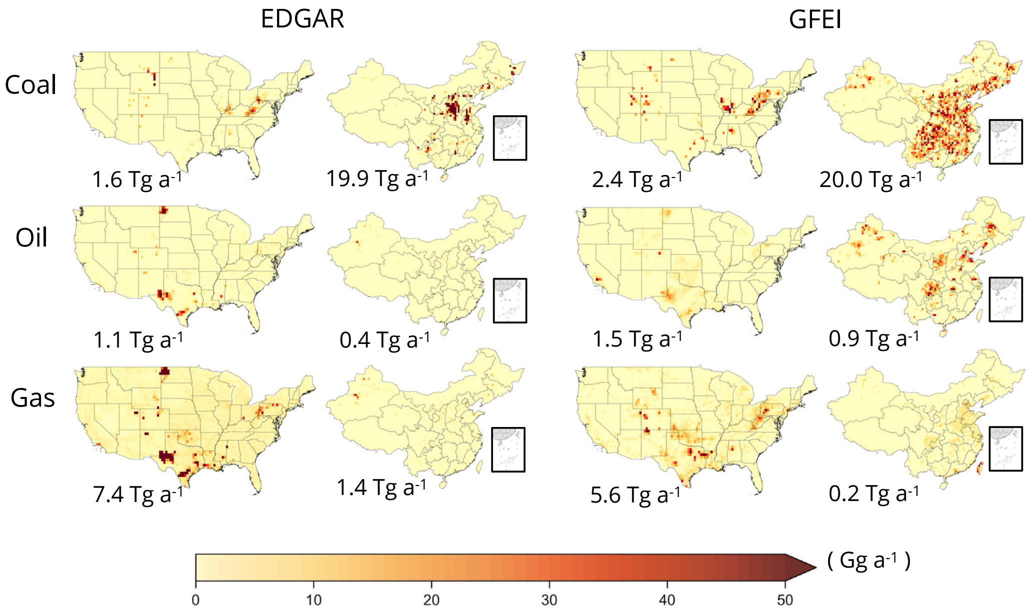
Another major difference between inventories is the relative concentration of coal emissions in Shanxi province. Another study found that the number of coal mines included in EDGARv4.3.2 was about 2.5 times less than the actual number of mines in China, and may have been disproportionately placing mines in certain regions, including Shanxi (Sheng et al., 2019). Though this may have been partially updated in EDGARv6.0, there are still significant emissions concentrated in Shanxi, while GFEI results suggest much more widespread sources of coal mining methane emissions throughout eastern China and Xinjiang.

Oil and Gas Production Emissions

Differences across the inventories for the oil and gas sector indicate differences in assumptions about oil and gas infrastructure in China, and sources of emissions in the U.S. (Figure 2). Oil emissions in EDGAR are more concentrated in both the U.S. and China than in GFEI, though GFEI total emissions are higher. However, gas emissions are much higher in EDGAR than in GFEI in both countries. In GFEI, gas emissions along pipelines are generally lower and emissions from production fields are generally higher but EDGAR tends to allocate midstream emissions to pipelines rather than to specific facilities (Scarpelli et al., 2020). Although these pipelines are not showing up as hotspots on the EDGAR emissions map, EDGAR assumes <5 Gg a^{-1} emissions across a large portion of the U.S. That may explain why GFEI shows more hotspots for methane emissions than EDGAR in oil and gas exploitation sectors, while EDGAR has a wider geographic range of emissions outside of production areas (Maasakkers et al., 2016). EDGAR shows that gas emissions are higher in gas production-dense areas like Texas, Louisiana, Alabama, North Dakota and Xinjiang in China. GFEI shows less emissions in Xinjiang and transmission from the province to eastern China, and that while there are some gas production emissions in the eastern part of China, near the Beijing-Hebei-Tianjin region, emissions are limited. GFEI also suggests oil and gas production emissions are not just in a few high-producing states, but also from Wyoming, Colorado, Kansas, Oklahoma, West Virginia, Pennsylvania, and New York, and are more spread out across key production states, like Texas.

FIGURE 2: METHANE EMISSIONS IN THE U.S. AND CHINA FROM COAL, OIL AND GAS EXPLOITATION.

GFEI and EDGAR data is from 2018. Each cell represents 0.1x0.1° resolution.



POLICY OPPORTUNITIES

Super-emitters: While this analysis evaluated emissions at the grid-cell level, we assume that major emitting grid cells can indicate super-emitting facilities. Targeting sources of methane emissions from facilities with outsized methane emissions could have a significant impact on overall emissions reduction. Our results suggest that a limited number of sites are contributing the bulk of emissions. Other research has found that global "super-emitter" sites (>25 tons/hour), primarily located in major oil and gas production fields in Russia, Turkmenistan, the U.S., the Middle East, and Algeria, contribute 8% to 12% of global methane emissions from oil and gas production annually (Lauvaux et al., 2022). Geospatial emissions analysis helps us to better understand hotspots for methane emissions, identify potential regions for early actions or pilot projects, as well as understand some of the differences in inventory estimates, as the location of emission sources impacts methane emission estimates. This variability in the concentration of sites can potentially be resolved through flexible policy mechanisms that account for regional differences and can be more cost-effective than blanket policies (Ravikumar and Brandt, 2017). Research has also found that mitigation costs for ultra-emitting sites are relatively low (Lauvaux et al., 2022). These large emitting sites also present an opportunity for significant methane mitigation, if methods for monitoring and reducing emissions from these sites are developed and deployed (Brandt et al., 2014).

Local and more frequent monitoring of major emission sites: In order to implement any policies to reduce methane emissions, frequent, or preferably continuous, monitoring mechanisms are needed to effectively identify super-emitting sites (Zavala-Araiza et al., 2015, 2017). Fugitive methane emissions from oil and gas production are often intermittent, meaning that average parameters to estimate emissions may substantially underestimate total emissions (Brandt et al., 2016; Irakulis-Loitxate et al., 2021). Heterogeneity in emissions across facilities also presents a significant challenge, since emission factors are usually based on a sample of facilities, or an average rate of emissions (Brandt et al., 2014). Improvements in monitoring and data collection, including remote sensing techniques, can help to better capture super-emitting sites or large emission events. Frequent or continuous monitoring could provide the necessary insight to improve the equipment, system design, and operations that would reduce the frequency of large emission events or target and repair super-emitters (Zavala-Araiza et al., 2017).

Need for consistent application of technologies to monitor super-emitters: Internal documentation shows that methane emissions from oil and gas companies are likely much higher than what is officially reported due to their failure to monitor massive methane leaks from super-emitting sites using Leak Detection and Repair (LDAR) technologies (Committee on Science, Space, and Technology, 2022). Current operator-led LDAR systems are insufficient to mitigate super-emitter sites due to LDAR's inability to define the size of super-emitting leaks, track super-emitting leaks when they occur, assess the contribution of super-emitting leaks to overall methane emissions, or use observations on super-emitters to inform their approach to leak detection in the future. Commercially available LDAR technologies are capable of quantifying the size of methane leaks from oil and gas operations, but oil and gas companies are largely not incorporating methane quantification data into their LDAR programs for operational and analytical purposes. Comprehensive and consistent application of LDAR technologies can significantly improve methane mitigation in the oil and gas sector; however, most existing applications are deployed at varying scales and frequencies and/or with a scope too narrow to address methane emissions at the scale of urgency necessitated by the climate crisis (Committee on Science, Space, and Technology, 2022).

Subnational impacts and policy actions: In addition to the need for national-level improvements, subnational efforts are also critical to refine the spatial elements of methane emissions monitoring, given the wide variation of methane emissions across states and provinces. A research partnership between NASA, CARB, and the California Energy Commission flew a plane equipped with the Airborne Visible InfraRed Imaging Spectrometer-Next Generation (AVIRIS-NG) instrument over nearly 300,000 facilities and infrastructure components in California. The study found that 10% of monitored sources qualified as super-emitters and contributed the majority of the emissions detected and estimated that super-emitters are responsible for about a third of California's total methane budget (California Air Resources Board, 2021). Project Astra, another subnational partnership that includes researchers at the University of Texas at Austin, Environmental Defense Fund, ExxonMobil, Gas Technology Institute (GTI) and the Pioneer Natural Resources Company is creating a surface-based methane sensor network designed for use in areas with potential leaks to improve monitoring of oil and gas wells in the U.S. by detecting leaks and issuing alerts for repair (University of Texas at Austin, 2021).

Improved standards for measurement: Methane emissions are dependent on a number of highly localized, and often seasonal, characteristics, such as the flooding rates of rice paddies or the gas content of coal mines. To reduce uncertainty, research should use locally optimized emission factors, technology and operational data, and geospatial infrastructure data, as well as make data publicly available for comparison (Lin et al., 2021). Addressing uncertainty in emissions estimates from variable sources like coal mines and landfills necessitates site-specific measurements, such as mine-specific data on methane ventilation and utilization rates, and a focus on the largest sources (Gao et al., 2020). Increasing consistency not only in bottom-up calculations across inventories, but also across proxy data used to distribute emissions is needed. Our research suggests that the geospatial proxy data used across inventories can significantly impact policy approaches, especially in the coal, oil and gas exploitation sectors. Making geospatial data publicly available, and frequently updated, would help to improve the accuracy of emission estimates.

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