Probabilistic, Measurement-Informed Greenhouse Gas Emissions from Global Liquefied Natural Gas Supply Chains Reveal Wide Country-Level Variation

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Abstract

Growth in liquefied natural gas (LNG) demand has been accompanied by debates about its greenhouse gas (GHG) emissions impact. Studies have shown that activity-based inventory accounting methods in the oil and gas sector significantly underestimates methane emissions. As a result, target-based policies and voluntary initiatives are moving towards adopting direct measurements to assess the GHG emissions intensity (EI) of LNG supply chains. Yet, most supply chain assessments of LNG do not incorporate measurement data. In this work, we develop a probabilistic, geospatial, and measurement informed life cycle assessment model to estimate the GHG EI of global LNG supply chains covering over 90% of LNG trade. We find a ~5x range in supply chain GHG EI from 8.6 g CO_2e/MJ in Qatar to over 39 g CO_2e/MJ in Algeria. Overall, our work suggests supply chain-weighted GHG EI of global LNG trade is underestimated by up to 31% compared to prior estimates that did not incorporate measurements. Probabilistic models of GHG EI of LNG exhibit a heavy tailed distribution, revealing the importance of low likelihood but high emitting supply chains. Incorporating direct measurements in supply chain assessments is necessary to avoid underestimation from activity-based inventories and increase confidence in target-based policies to address methane.

Main

Global liquefied natural gas (LNG) trade routes are undergoing significant shifts following the reduction in Russian pipeline exports to Europe and the rise of the United States (US) as the largest exporter[1, 2]. In parallel, the liquefied natural gas (LNG) industry is poised for substantial growth, with global liquefaction capacity projected to expand from 580 billion cubic meters (bcm) today to 850 bcm by 2030 [1]. Despite benefits from clean combustion and contributions to national security, [3, 4, 5] this growth has been accompanied by debates about the GHG emission intensity of LNG [6, 7, 8]. Methane and carbon dioxide emissions along the LNG supply chain reduce the climate benefits of LNG over more carbon intensive fuels such as coal [9, 10]. A lack of global standards in assessing climate impacts of LNG supply chains have led to studies that span both sides of this debate – from LNG being worse than coal to LNG significantly reducing global greenhouse gas emissions [9, 11].

Regulatory policies and voluntary initiatives to address GHG emissions from the LNG supply chain have converged on the importance of direct measurements [12]. Accurate measurement informed supply chain GHG emissions information is a key building block for these voluntary and regulatory programs. The European Union's (EU) methane regulations scheduled to require natural gas importers to Europe to provide monitoring, reporting and verification (MRV) information and future contracts will be subject to a methane intensity import standard [13]. To implement this, the EU is relying on measurement and reporting guidance documents from the Oil and Gas Methane Partnership (OGMP 2.0), despite concerns about transparency and completeness [14, 15]. Even regulatory reporting programs such as the United States Greenhouse Gas Reporting Program (GHGRP) have been recently revised to incorporate more empirical elements in developing emission inventories [16]. The US, along with other major LNG exporting and importing countries, is developing a monitoring, measurement, reporting, and verification (MMRV) framework for consistent, global GHG emissions assessment of LNG supply chains [17]. Similarly, Japan and South Korea have launched the methane emission reduction (CLEAN) initiative, a demand-side program that requires suppliers to submit information related to GHG emissions of LNG cargo [18].

Numerous life cycle assessment (LCA) studies that investigate the LNG supply chain GHG emissions intensity (EI) of LNG have been published in the literature [19, 20, 21, 22, 23]. An overwhelming majority of these studies use life cycle inventories constructed from process-level, bottom-up inventory estimates. Even in the US, the use of empirical data in GHG LCAs for the LNG supply chain are limited to the incorporation of official inventory estimates [9, 13, 17]. However, the past decade of measurement campaigns at oil and gas facilities have consistently demonstrated that official inventories underestimate emissions [24, 25, 26]. Such underestimation has been demonstrated at upstream production sites, midstream facilities, liquefaction terminals, and LNG shipping vessels, resulting in a potential of 22-54% underestimation in life-cycle carbon footprint estimates [27, 28, 29, 30, 31]. In addition, recent studies based on top-down (TD) observations show that "so-called" ultra-emitters contribute 8–12% of global O&G methane emissions [32], yet these emissions are not leveraged into existing LCA frameworks,. Although several recent studies that incorporated measurements within LNG LCAs have provided key insights into spatial variation in

GHG EI of LNG, these studies have been restricted to a few key oil and gas basins in the US [33, 34, 35].

A further challenge with contemporary LCA of LNG supply chains is that they are deterministic, often producing a single static GHG intensity metric that does not evolve with new evidence [7, 21, 33, 36, 37, 38]. The use of such metrics in policy development or compliance monitoring is problematic as it does not account for the rapidly changing emission landscape. New methane regulations, advances in technology, and consumer demand could likely result in large short-term variability in emissions at different spatial scales. Furthermore, recent evidence of sub-national variability in GHG emissions across the LNG supply chain as well as the presence of methane ultra-emitters suggest that we should expect significant variability in GHG EI of LNG across global supply chains [21, 32, 33, 39, 40]. Thus, a probabilistic supply chain assessment that accounts for the variability in emissions can appropriately account for changing global LNG supply chain GHG EI. It can also ensure that target-based policies do not inadvertently penalize low emissions supply chains or conversely incentivize high emission supply chains.

In this work, we develop the first probabilistic, geospatial, measurement informed life cycle assessment (GM-LCA) to estimate well to gate GHG EI of LNG production from twelve major LNG exporters, accounting for over 90% of the global LNG supply in 2023 [41]. Our work represents two new advances: a geospatial LCA model that directly incorporates remote sensing measurements of GHG emissions within lifecycle inventories and a probabilistic framework to quantify variability in GHG EI distributions of major LNG global LNG supply chains. This method results in global LNG supply chain emissions intensity that is about 31% greater than conventional inventory-based supply chain assessments with wide inter-country variability Furthermore, our probabilistic models show that GHG EI of every LNG supply chain is log-normally distributed, indicating the impact of low likelihood but high EI supply within countries. Probabilistic LCA tools that account for empirical GHG observations could increase trust between industry stakeholders, government, and civil society by providing a nuanced and verifiable view of progress towards GHG emission reduction across LNG supply chains.

Results

GHG Intensities of LNG Exporting Countries

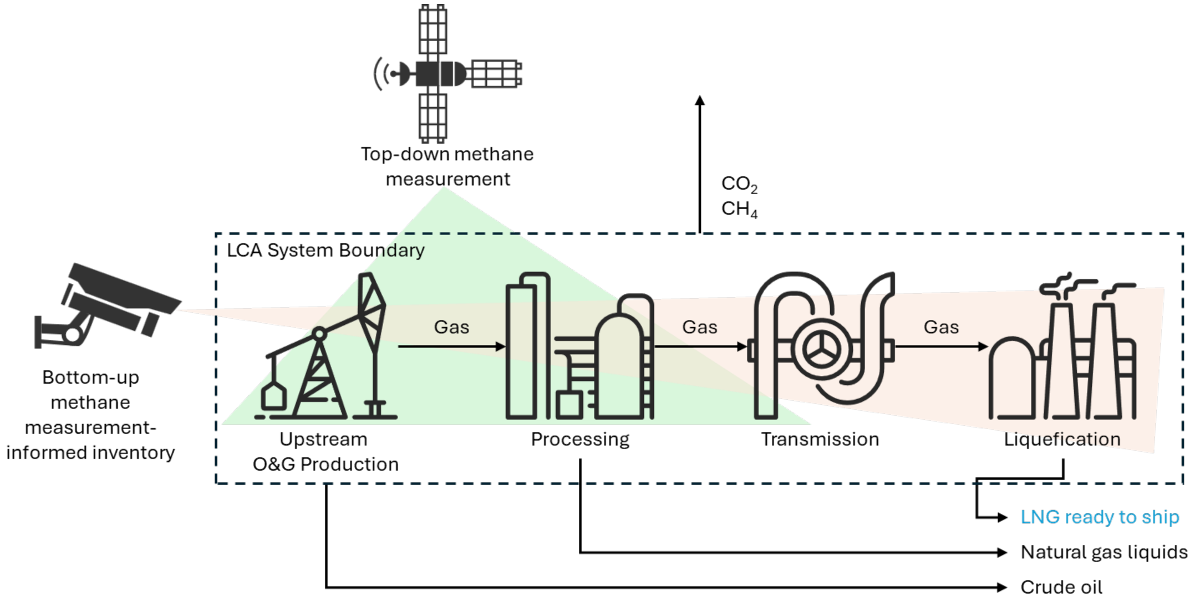


Figure 1 The system boundary of GM-LCA for the LNG supply chain. Bottom-up life cycle emission inventories are supplemented with top-down measurements to develop a measurement-informed life cycle inventory. Emissions are allocated based on energy content and assigned to different co-products in the production and processing stage.

Figure 1 illustrates the GM-LCA system boundary and material flows for LNG production across four key stages: upstream oil and gas production, natural gas processing, pipeline transmission, and LNG liquefaction. This analysis adopts a functional unit of 1 MJ (g CO_2e/MJ) of LNG ready for shipping at the liquefaction terminal, with GHG EI estimated and aggregated for each stage. GHG emissions are allocated on an energy content basis between natural gas and its co-products at each stage (see methods and SI section S2) based on their lower heating values (LHV) [42]. Emissions are aggregated using both 100- and 20-year global warming potential (GWP) values for CO_2 and CH_4, based the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) [43]. CO_2 emissions are calculated based on energy consumption at each stage of the supply chain. Methane emissions within the LNG supply chain are modeled based on bottom-up (BU) empirical inventories at the process level for the reference year 2023, following methodologies from prior studies, which have been closely validated with conventional lifecycle inventory development used in the National Energy Technology Laboratory (NETL) US LNG LCA model [20, 34]. Additionally, TD methane emission inventories are collectively harmonized from recent peer-reviewed studies based on either satellite observations or aerial field campaigns between 2010 and 2019, representing the latest publicly accessible data, for each of the exporting countries [26, 44, 45, 46, 47, 48, 49]. These TD estimates were used to calculate the discrepancy between observed emissions and the BU emissions inventory. This discrepancy is taken as a best estimate of the contribution to the GHG EI that is not represented in conventional BU life cycle inventories and can range from 2 to 11 g CO_2e/MJ as noted in Figure 2a. Country-specific BU activity data are obtained from the International Energy Agency (IEA) [50]. When data for a particular country is not available, proxy parameters based on similar resource characteristics in other regions are used to estimate emissions (see Methods).

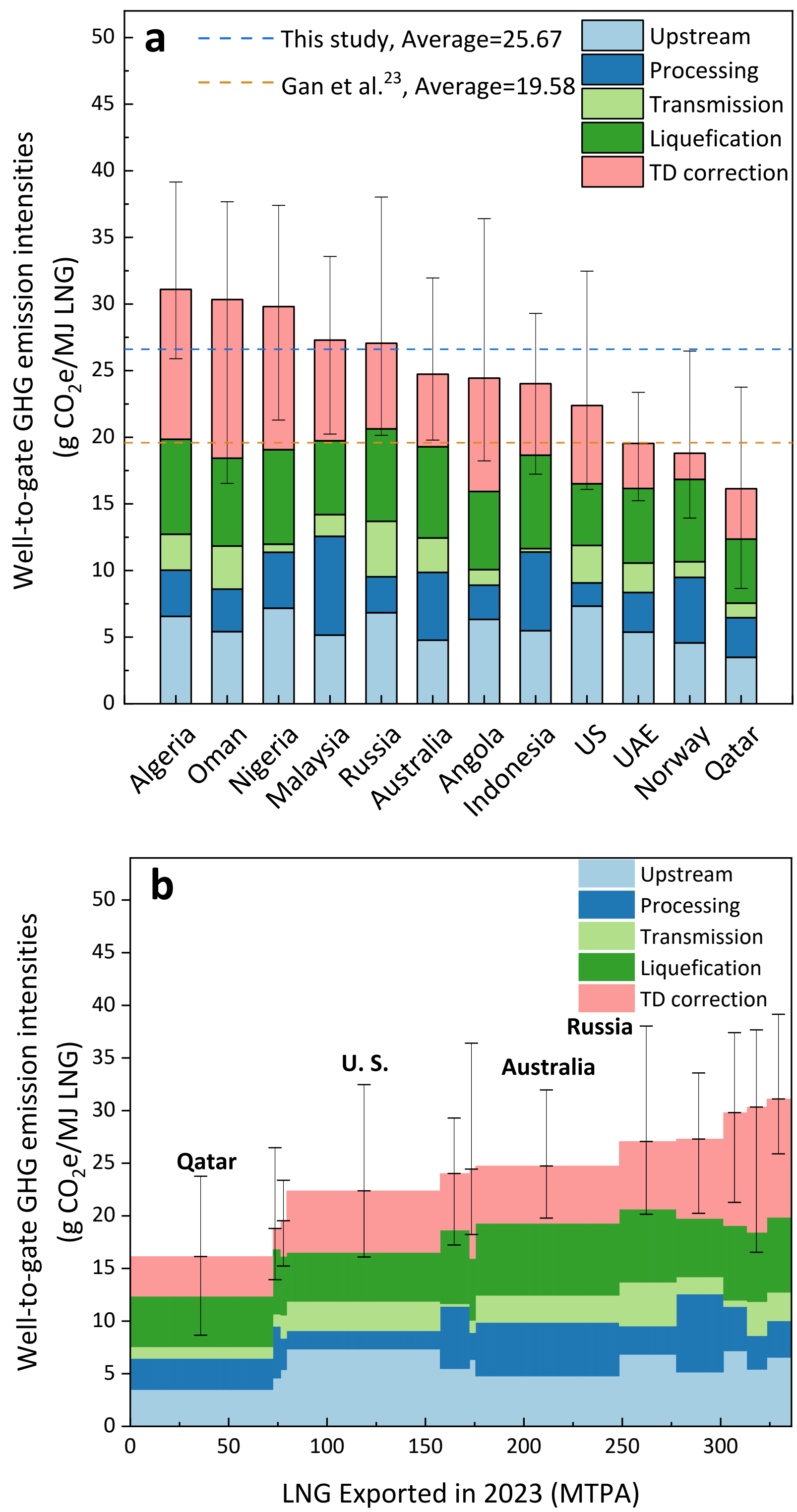


Figure 2 Country-level average GHG EI for LNG supply chain of major exporting countries based on GWP-100, AR6. ***a*** *Breakdown of GHG EI (g CO_2e/MJ LNG) across well-to-gate system boundary including upstream (light blue), processing (dark blue), transmission (light green), liquefaction (dark green) and a corrected TD EF (pink) for the top twelve major LNG-exporting*

countries. The global weighted average GHG EI is 25.7 [16.4, 31.3] g CO_2e/MJ LNG (this study, blue dashed line), compared to a previous estimate of 19.6 g CO_2e/MJ LNG (Gan et al.[23], orange dashed line). Error bars represent 95% CI based on 500 Monte Carlo simulations. ***b*** *The ranked GHG EI values matching with the LNG export volumes in 2023, representing 91.4% of total global LNG trade [41]. Country-specific average GHG EI contributions are weighted by trade volumes, with Qatar, the United States, Australia, and Russia identified as leading exporters. Detailed percentage contributions of CH_4 and CO_2 emissions are provided in SI Section S4. GHG EI results based on GWP-20 (AR6) are discussed in SI Section S5.*

Figure 2(a) presents the well-to-gate, measurement-informed GHG EI for LNG supply chains from twelve major LNG-exporting countries across four stages of the supply chain. TD measurements are incorporated as a correction to the BU life cycle inventory-based EI to account for persistent underestimation in BU inventories. While root causes for this underestimation can vary by region and resource type, the key drivers, such as outdated emission factors, global observation of large intermittent emission sources, and unaccounted-for sources (e.g. dry gas seals) created the knowledge gaps in official inventory estimates, representing commonly understood sources of underestimation [32, 40, 51, 52]. The GHG EIs across countries exhibit a wide range, varying from a best-case scenario (i.e., lowest GHG EI across all country's 95% confidence interval) of about 8.6 g CO_2e/MJ in Qatar to a over 39 g CO_2e/MJ in Algeria, representing nearly a five-fold difference. The global energy-supply-weighted average GHG EI from this study (25.7 [16.4, 31.3] g CO_2e/MJ LNG) is about 31% higher than a prior estimate by Gan et al. [23] (19.6 g CO_2e/MJ LNG), driven by the inclusion of TD measurement estimates within life cycle inventories. The uncertainty range, shown by error bars, highlight the variability in emission factors and TD measurement within countries, representing a wide range of observed variability in input parameters (SI section S2).

Figure 2(b) shows the rank-ordered GHG EI of LNG exports weighted by their global trading volumes in 2023. According to the 2024 annual report from the international association of LNG importers (GIIGNL) [41], the twelve countries represented in this study collectively account for 91.4% of global LNG trade, with the United States, Australia, Qatar, and Russia leading in export volumes. While Qatar exhibits a relatively low trade-weighted average GHG EI of about 16 g CO_2e/MJ, Australia's trade-weighted average GHG EI of about 25 g CO_2e/MJ is over 50% higher, highlighting the variability in emission intensities across global LNG supply chains. The trade-weighted GHG EIs shown in Figure 2(b) contextualize the impact of global LNG market share on overall GHG emissions profile from major suppliers. A 1 g CO_2e/MJ increase in GHG EI for the United States would result in a 0.32 g CO_2e/MJ rise in the global weighted average GHG EI, whereas an identical GHG EI increase in Angola would not have a measurable impact on the global weighted average (i.e., less than 0.01 g CO_2e/MJ). This has important implications for the GHG emissions profile of LNG – not only does the total volume of traded LNG matter for global GHG emissions, the origin of a marginal ton of LNG can be the difference between an LNG supply chain that lowers global carbon emissions versus one that does not.

The variation in GHG EI values across countries, reflect differences in supply chain characteristics, technological constraints, and emissions estimation techniques. Countries with higher proportions of onshore gas production tend to have higher emissions in the upstream production stage compared with offshore production. While there is some evidence for lower flaring intensity from offshore production compared to onshore production, accurate estimates of GHG EI from offshore operators is limited by a lack of empirical observations. Additionally, gas composition plays a predominate role in GHG emission estimation in the upstream stage. For instance, a higher CO_2 content in produced gas is correlated with higher energy consumption for acid gas removal, thereby generating more GHG emissions.

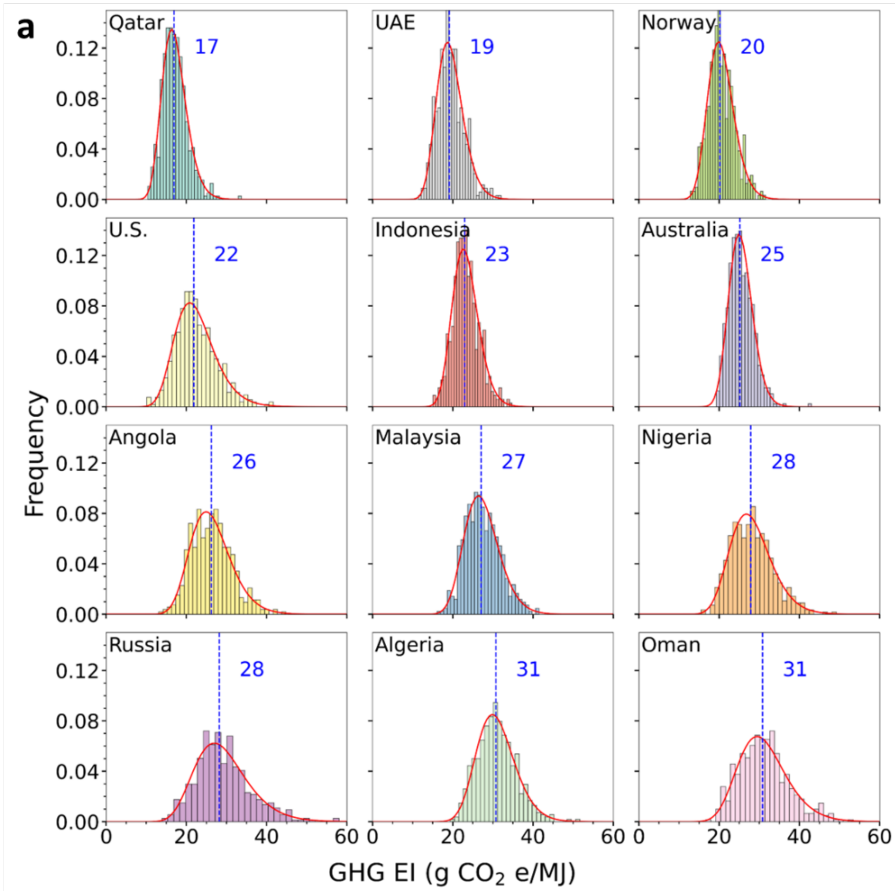
Processing stage emissions are also influenced by gas composition and the carbon intensity (CI) of the electricity grid, when processing plants are electrified. While we make country-level assumptions about the level of electrification at the processing stage, differences within geographic regions such as the Permian and Marcellus shale basins in the US can result in significant subnational differences in GHG EI of LNG supply chains [33]. Recent work has even identified large differences in GHG EI based on the gas pathway between production regions and liquefaction terminals [34]. Countries with significant offshore production, such as Australia, Indonesia, Malaysia, and Norway, tend to exhibit higher GHG emissions during the processing stage due to longer transportation distances from offshore production facilities to onshore processing plants, which require more energy compared to onshore production.

Transmission stage emissions, on the other hand, are directly related to pipeline length; longer distances necessitate more compressors, leading to higher CO_2 emissions from fuel consumption and increased CH_4 emissions from leakage and venting. By contrast, the liquefaction stage GHG EI are similar across countries, as most emissions at this stage are CO_2 emissions from combustion. Minor variations in liquefaction stage GHG EI arise primarily due to differences in gas composition and the need for additional acid gas removal prior to liquefaction.

Uncertainty in TD measurements used to correct the BU inventory estimates further influences GHG EI estimates. Methane emissions derived from different remote sensing technologies show substantial variability. Chen et al. [44] reported 0.0033 g CH_4/MJ for Qatar using TROPOMI, while EDGAR v4.3.2 estimated 0.148 g CH_4/MJ using GOSAT [45], a two-order-of-magnitude difference. These discrepancies highlight the need to accurately reconcile across TD methane measurement techniques as well as with the established BU emission inventories. Without incorporating top-down data, our estimates closely align with Gan et al. [23], with the top-down correction contributing an additional 6.1 g CO_2e/MJ. Additionally, smaller differences are attributed to uncertainties arising from variation in the reference year (we used data from 2023, while Gan et al. [23] used data from 2012) and differences in geospatial LCA system boundary coverage. For example, Gan et al. [23] assumed natural gas transport from Russia to China via pipelines, excluding liquefaction emissions for Russian gas. Furthermore, while Gan et al.'s [23] analysis was conducted at the field level, our assessment uses a national-level approach to ensure consistency across all major LNG suppliers and to better match spatial resolution of publicly available TD measurement data. Our study's limitation lies in relying on U.S.-based life cycle inventory methodological approaches (see SI section S3); datasets to estimate detailed and consistent process-level emission factors for all countries are not currently available. In addition, we rely on reported TD measurements for the countries investigated, which span measurements collected in the past decade. As technologies evolve, more rapid availability of TD data could enable timely updates to GHG EI.

Field-level assessments using our proposed GM-LCA framework would require more granular methane emissions inventory data for all major exporters. For instance, in prior analysis by Zhu et al. [33], GHG EI of LNG produced from the Permian and Marcellus basins differed significantly [35]. In these two basins, methane emissions are well-documented using both BU and TD approaches, which would enable us to conduct a more detailed sub-national assessment. Our country-level results for the U.S. in this study are consistent with a weighted average of basin-level US LNG emissions intensity available from prior studies [20, 33, 34]. Compared to the harmonized LCA model by Heath et al. [19], which performed a meta-analysis of eight peer-reviewed studies, our study improves accuracy by incorporating top-down measurements within life cycle inventories and down-scaling input parameters to enable global comparison. In comparison to Roman-White et al. [39], which used supplier-specific data, our analysis retains some uncertainty that could be addressed through enhanced spatial and temporal resolution of LCA inventories. In addition, recent work on estimating GHG EI of specific pathways for natural gas from production regions to liquefaction terminals in the US reveal significant sub-regional disparity across supply chains [34]. However, such analysis is limited by data availability and is not well suited for global comparative analysis. A lack of standardized measurement, reporting, and verification protocols for methane emissions and unknown data quality in existing datasets remain a significant challenge to global harmonization of LNG supply chain GHG EI assessment.

GHG EI Probabilistic Distributions



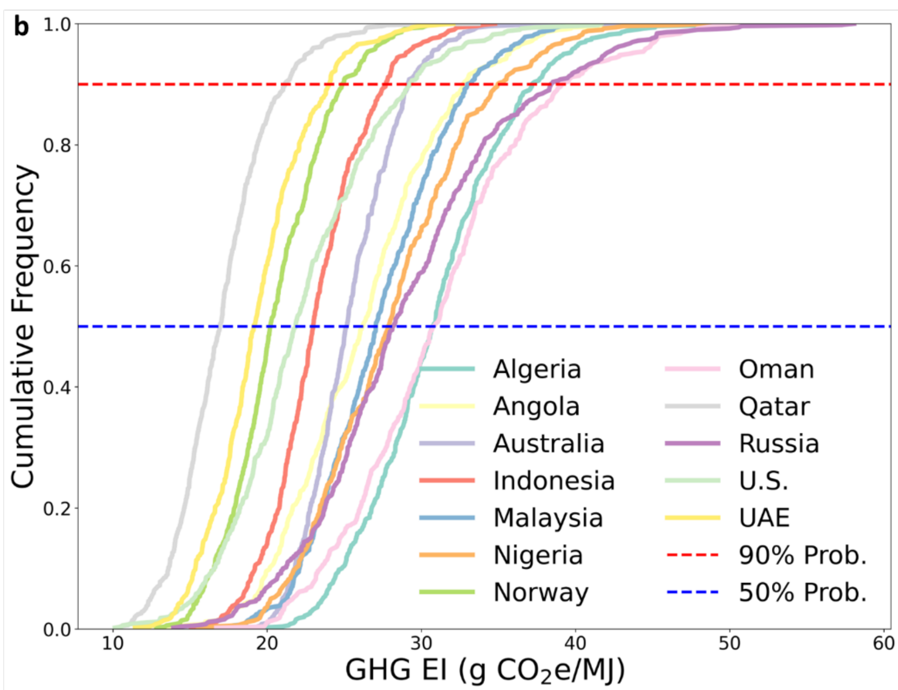


Figure 3 Probabilistic distributions of the GHG EI of country-level LNG supply chains. (a) GHG EI distributions for each country derived using Monte-Carlo based uncertainty modeling across 85 parameters of the GM-LCA model. Median values are labelled for each country in blue vertical lines. (b) Cumulative probability distributions of supply chain GHG EI, including markers for 50% and 90% likelihood thresholds.

Figure 3 displays the results of Monte Carlo simulations, presenting both histograms and cumulative probability distributions for the GHG EI of LNG production across the twelve analyzed countries. For each country, 500 iterations were run, accounting for variability in 85 input parameters, randomly sampled based on triangular or uniform distributions informed by peer-reviewed literature (see SI Table S7). The histograms reveal that GHG EIs follow a log-normal distribution for each country, with noticeable variations in median and spread. A log-normal fit indicates the importance of heavy-tailed distribution in GHG EI for LNG supply chains, an observation that was previously only limited to the scale of individual facilities and equipment [19, 20, 23]. This suggests that supply chain specific life cycle assessments and not national-level assessments will be necessary to develop realistic estimates of LNG GHG EI.

The differences across countries predominately reflect variability in reported TD methane emissions in each country, with higher variability yielding a wider GHG EI range. Similar Monte Carlo simulations on life cycle GHG EI based only on BU emission inventories demonstrate a significantly lower range and is best fit with normal distributions (see SI section S7) – an indication that BU life cycle inventory-based supply chain assessments are blind to the tail risks of high-emitting LNG supply chains. Based on this analysis, Algeria and Oman have a higher probability of LNG supply chain EI exceeding 30 g CO_2e/MJ compared to the US or Norway. While the above distributions allow one to visualize variability in supply chain GHG EI, it does not account for uncertainty in parameter estimates. However, ignoring uncertainty is a reasonable approach for two reasons: first, the uncertainty in BU life cycle inventory parameters is much lower than the variability in those parameters, which are better modeled through Monte Carlo simulations, and two, the variability in measured estimates used for the TD correction is also much larger than measurement uncertainty [27, 53]. The cumulative probability distributions in Figure 3(b) illustrate the range and likelihood of GHG EI values. Countries with flatter curves exhibit higher variability, indicating less consistency in GHG EI, while steeper curves indicate lower variability which, at present, arise from limited availability of TD measurement data. The distribution of supply chain GHG EI represents known variability in parameter values across each stage of the supply chain.

Global Supply Chain Analysis

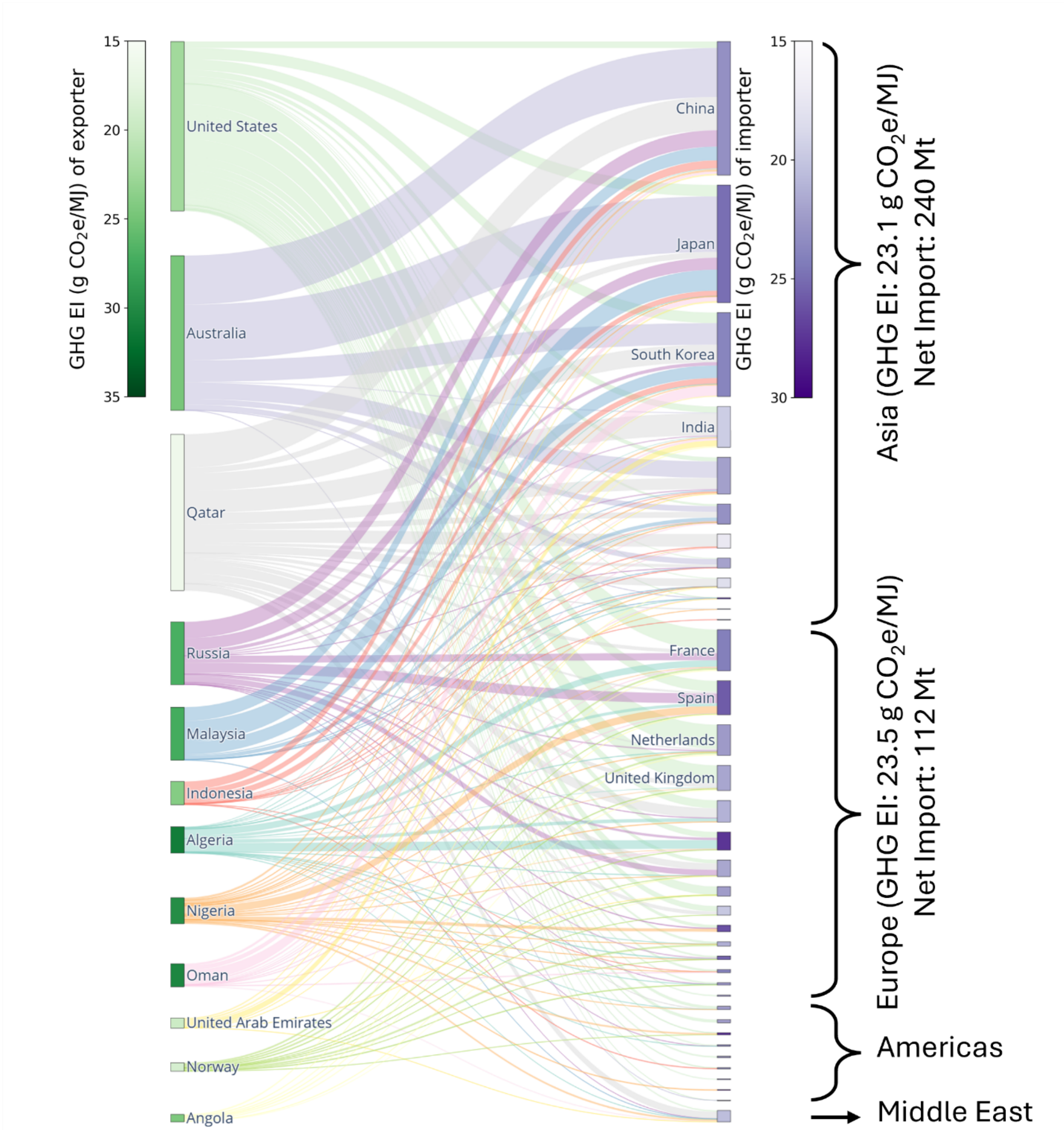


Figure 4 Sankey diagram of global LNG trade flows, export volumes, and associated GHG EI from 12 major exporting countries, accounting for over 91% of market share [38]. Bars (left) for each exporting country are scaled by total volume exported with colors representing production through liquefaction supply chain GHG intensity. Bars (right) for each importing country are scaled by total volume imported with colors representing weighted average GHG EI of imported LNG (shipping and regasification are excluded).

Figure 4 shows a Sankey diagram of the GHG EI associated with global LNG trade flows. Global trade flows in 2023 are estimated to generate 303 to 579 million tonnes (Mt) of GHG, of which methane contributes 110 to 242 Mt CO_2e (mean: 37.5%, range: 36.2% - 41.9%). Regionally, Europe and Asia are the primary LNG importers, with Asia importing 240 Mt and Europe importing 112 Mt compared to a global net trade volume is 401 Mt [41]. On the supply side, Australia and Qatar collectively hold over 50% of the Asian LNG market, while the United States dominates the European market, also with over a 50% market share [41]. Despite differences in trade flows, the weighted average GHG EI of LNG shows limited variation between regions: 23.1 g CO_2e/MJ for Asia vs. 23.5 g CO_2e/MJ for Europe. However, Asia's higher import volumes result in a larger aggregated GHG footprint from LNG imports compared to Europe. Thus, GHG emissions from regional LNG trade are heavily influenced by the emissions intensity of exporting regions and their market shares. However, significant changes in regional GHG EI could occur if the composition of imports change significantly. The difference between US and Russian LNG supply chain suggests that Europe's shift away from Russia-derived natural gas (whether transported by pipeline or LNG) likely resulted in a significant reduction in supply chain GHG EI for Europe. For example, the US increased its LNG exports to Europe by 4.86 Mt from 2022 to 2023 [41]. Assuming this increment entirely displaced Russian natural gas, it results in an emission reduction of 0.3 g CO_2e/MJ in 2023, based on the difference GHG EI between U.S. and Russia. Similarly, future shifts in production mix including from expanded capacity in the US, Qatar, and Australia and new capacity in Canada or countries in North Africa could significantly impact regional GHG EI of landed LNG. Such trade- and production-driven dynamics of the global LNG market requires that the analysis presented here is updated on a periodic basis to inform policy discussions.

Potential Impact on GHG Mitigation

One implication of the present study is to put GHG mitigation efforts in new perspective. The Global Methane Pledge [50] aims to reduce global methane emissions by 30% by 2030. Prior to this study, the global, activity-based GHG EI baseline was 19.6 g CO_2e/MJ; by incorporating latest measurements, global measurement informed GHG EI is now estimated to be 30% higher, 25.7 g CO_2e/MJ. Applying the 30% emission reduction goal to countries party to the Pledge implies the Pledge aimed to reduce GHG EI to 13.7 g CO_2e/MJ. However, based on our study, we estimate that the Pledge would only achieve a GHG EI of 21.1 g CO_2e/MJ, which is 7.6% higher than even prior activity-based baseline estimates. Putting the GHG EI in the context of expected LNG production increases, this implies that if every party to the Pledge is successful, GHG EI of global LNG will be 4.6 g CO_2e/MJ less compared to current measurement informed baseline. This corresponds to a total global GHG reduction of 62 Mt CO_2e or 14% by 2030. Consequently, additional GHG EI reduction of 46.7% would be needed to achieve the level of GHG EI that had been previously implied by the Pledge using activity-based baseline GHG EI.

Discussion and Conclusion

This study provides a comprehensive global analysis of the GHG EI of LNG production across twelve major exporters, utilizing a GM-LCA framework that integrates BU and TD methane measurements and inventories. The analysis highlights geospatially differentiated LNG production and emissions, quantifying country-level variation in GHG footprint associated with the

LNG trading market. The findings provide a more accurate understanding of GHG emission sources within LNG markets, suggesting that strategies be tailored to regional and supply chain-specific contexts. Three key conclusions are outlined.

First, incorporating TD measurements of GHG emissions across global LNG supply chain stages within an LCA framework is critical to develop an accurate supply chain GHG EI. Using publicly available satellite and aerial datasets, we find that up to 31% of supply chain GHG EI is not accounted in assessments that only use BU approaches to build a life cycle emission inventory. Without supplementing traditional life cycle assessments with GHG measurement data, supply chain analyses risk underestimating GHG EI to varying but potentially significantly degrees. Furthermore, as the magnitude of the discrepancy between inventories and measurement vary across regions and countries, ignoring measurements in life cycle inventories could result in misleading conclusions about relative GHG EI of LNG sources, especially when GHG attributes are of public or corporate policy concerns Recent advances in high spatial and temporal resolution methane monitoring technologies can further enable measurement informed and near-real time assessments of GHG EI of global LNG supply chains.

Second, geographic variation in GHG EI of LNG supply chains revealed here demonstrate the benefits of regional and supply chain-specific assessments. GHG EI across exporting countries for LNG production range from a low of 8.6 to a high of 39.2 g CO_2e/MJ, a nearly five-fold difference, primarily driven by variations in methane emissions. Globally, the GHG footprint of LNG trade is estimated at 303 to 579 Mt CO_2e in 2023, with methane emissions contributing up to 41% of the total.

Third, probabilistic modeling of life cycle GHG EI of global LNG supply chains reveal a log-normal distribution indicating the importance of low likelihood but high EI supply chains. The wide range of EIs within individual countries suggests recasting the issue of GHG emissions of LNG within a risk assessment framework. Corporate entities and countries that are developing target-based approaches to emissions mitigation would benefit by focusing on parameters like exceedance probabilities instead of finding a *single* GHG EI for a specific supply chain.. For example, in this work, we find that the probability of LNG supply chain GHG EI being greater than 30 g CO_2e/MJ is less than 15% for the US while it is greater than 30% for Nigeria. Thus, the distribution of life cycle GHG EI across global supply chains can be used as inputs to assess risk that emissions intensities exceed specified thresholds. This probabilistic framework avoids creating false certainty in typical life cycle GHG EI estimates. Furthermore, such a probabilistic framework further builds trust in a global measurement-informed supply chain assessment as snapshot observations of high emissions using satellites or other technologies can be discussed in the context of these heavy-tailed distributions.

The study discussed several limitations throughout the analysis, including assumption constraints and the inherent variability in LNG trade flows. In addition, developing internationally recognized and standardized approaches for incorporation of top-down measurements within life cycle inventories can lead to increased confidence in their expanded use. The success of target-based methane mitigation policies or implementation of a differentiated gas market relies on building trust in supply chain carbon accounting systems. Without rigorous ways to update priors about the GHG EI of supply chains using empirical measurements, continued reliance on accounting-based approaches to GHG EI estimation risk devolving into a low-trust and unreliable system similar to the voluntary carbon offset market [54].

Methods

LCA – Goal & Scope, System Boundaries, Functional Unit, Attributional Method

In this study, we developed a geospatial, measurement-informed LCA (GM-LCA) framework that integrates multi-scale methane inventories included both bottom-up (BU) and top-down (TD) methane measurement technologies. The primary goal is to establish the GHG emission intensities (GHG EI) of LNG produced from twelve major exporting countries, by incorporating these multi-scale methane measurements into an attributional LCA framework, and therefore, improve the overall accuracy of the estimate. Additionally, we performed the global analysis based on LNG trade flows for 2023 [41] to derive a global supply- weighted average GHG EI. The well-to-gate (WtG) system boundary of LNG production covers four stages as shown in Figure 1, which presented the material flows, and the integration of methane data from both inventory approaches. The detailed description for each stage, including inputs and outputs of the BU methane inventory can be found in the supporting information (SI) section S2. For consistency and comparability, we adopted a functional unit of 1 MJ of LNG at the liquefaction terminal ready for shipping. Methane and CO_2 emissions are allocated between LNG and its co-products according to the energy allocation method, based on the lower heating values (LHV) of each product, according to the International Standards Organization (ISO) 14040/44/67 [55, 56, 57]. The allocation factors for each country are derived from national production data [58] for crude oil, natural gas, and lease condensate, along with their composition-based LHVs [42]. This allows us to determine, for each of the 12 investigated countries, how much crude oil and lease condensate is co-produced per MJ of LNG production from upstream and processing stages, ensuring a consistent country-specific energy allocation approach. We adopted global warming potentials (GWP) over 100-year and 20-year timeframe (results based on GWP-20 can be found in SI section S4), according to the Intergovernmental Panel on Table 7.15, Chapter 7 of Climate Change 6th Assessment Report (IPCC, AR6) [43] to estimate the GHG EI in the unit of g CO_2-equivalent per functional unit (g CO_2e/MJ).

$$EF_{LNG} = \frac{EF_T}{LHV_T} \times \frac{LHV_{LNG}}{LHV_T}$$

where EF can represents either methane EF or GHG EI and LHV_T is the total energy content of LNG and its co-products at each stage.

Methane Inventories

Bottom-up emissions inventory: We empirically simulated BU methane emission inventories [59, 60, 61, 62] at the process-level across four stages for each country for 2023 (see SI section S4 for detailed process-level description). [33, 35]. Emissions from onshore and offshore production are differentiated using separate emission factors (EFs) for processes such as flaring from the NETL report on (name the report here) [61]. The aggregated BU methane inventory for each country was cross validated with the IEA methane tracker for the year 2023 [50].

Top-down emissions inventory: The TD methane emission inventories (see Table S6, which converted annual methane emission rate into energy basis) are collected and harmonized from multiple studies [26, 44, 45, 46, 47, 48, 49], including the aerial and satellite surveys (e.g., TROPOMI, GOSAT) for the countries investigated. Reported TD methane emission estimates can vary significantly, up to an order of magnitude, depending on the measurement technique and survey year. For example, Maasakkers et al. [45] reported methane emissions of 0.18 Tg a^{-1} for Algeria based on GOSAT measurements in 2012, while Scarpelli et al. [48] estimated emissions at 1.11 Tg a^{-1} using the 2019 TROPOMI data. To ensure consistent temporal alignment with the latest BU modeling approach, we adopted the most recent TD emission estimates available. Furthermore, when multiple studies utilized the same measurement technique and survey year, we performed temporal alignment by averaging their reported values. For instance, both Chen et al. [44] and Scarpelli et al. [48] provided emission estimates using TROPOMI data from 2019, and thus their values were averaged for the overlapping countries (e.g., Qatar and United Arab Emirates) in our analysis. The methane EFs derived from these top-down studies are then allocated to natural gas, crude oil and lease condensate based on the aggregated energy content [42]. To avoid double counting between BU and TD emission estimates, we estimated a TD correction for country-level emission estimate by calculating the marginal difference in emissions from the BU and TD estimates. Thus, the net emissions between BU and TD inventories are assumed to account for the abnormal emission events [28, 32] that are typically not captured in our BU estimate. Because the BU estimates for upstream and processing emissions are established at the process level, they inherently provide stage-specific details. In contrast, the higher spatial coverage of TD estimates (e.g., from aerial or satellite data) encompasses multiple engineering activities within a single survey region, making it difficult to disaggregate emissions by individual supply chain stages. Moreover, natural gas production survey regions typically include both upstream and processing operations, which the TD observations can cover simultaneously.

$$TD\ correction = TD_{CH_4} - BU_{CH_4,upstream} - BU_{CH_4,processing}$$

where $TD\ correction$ is the EF that needs to be corrected in the unit of g CH_4/MJ LNG, and $BU_{CH_4,upstream}$, and $BU_{CH_4,processing}$ are simulated EF from the existing LCA and incorporated to the GM-LCA framework. Therefore, the overall GHG EI can be estimated as follows by aggregating the CO_2 and CH_4 emissions of each stage.

$$GHGEI_T = \sum EF_{CO_2} + \left(BU_{CH_4,total} + TD\ correction\right) \times GWP_{CH_4}$$

where $GHGEI_T$ is the total GHG EI across its system boundary after allocation, and EF_{CO_2} is the total CO_2 emission for each stage. The GWP_{CH_4} is the GWP factor according to IPCC, AR6 [43]. Proxy parameters are used for a particular country when TD information is not available – these are based on similarity in resource characteristics in other regions. For example, there are limited TD observations of methane emissions from countries with significant offshore production such as in Norway. In these cases, TD discrepancy is estimated as a production weighted average of the discrepancy between BU and TD measurements in other countries (see SI section S5).

Uncertainty Analysis via Monte Carlo Simulation and Statistical Modeling

The GM-LCA of LNG in this study comprises of 85 independent input parameters (Table S1-S6 outlined unique input parameters for each country and Table S7 listed common input parameters for developing the GM-LCA) related to activity and emissions data, each contributing to the overall uncertainty of the model output. The base case value of each input parameter was used to calculate the baseline GHG EI for each of the twelve investigated countries, while the lower and upper bounds of each input parameter were incorporated to quantify the uncertainty range. Specifically, the input parameters were modeled using either triangular or uniform probability distributions to represent the likelihood of values within their specified lower and upper bounds. To propagate the input uncertainties through the GM-LCA model and evaluate their impact on the output, we performed a Monte Carlo simulation with 500 model iterations. In each iteration, random values for all 85 input parameters were independently sampled from their respective probability distributions. These sampled values were input into the GM-LCA model to compute the corresponding output for that iteration. This process was repeated 500 times, generating a dataset of 500 output values that reflect the combined effect of input parameter uncertainties. The resulting statistical distribution was characterized by conducting the statistical analyses on the ensemble of 500 model outputs to capture the probability of the GHG EI for each LNG-exporting country. For each country, a log-normal distribution was fitted to the outputs using the Maximum Likelihood Estimation (MLE) method. Key statistical metrics, including the mean, 5th percentile (P5), and 95th percentile (P95), were reported and compared across the twelve major LNG exporters.

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Conflicts of Interest

The authors declare the following competing financial interest(s): A.P.R. is currently a member of the Gas Pipeline Advisory Committee of the US Department of Transportation; in this role, he is a Special Government Employee. A.P.R. has current research support from the US Department of Energy, Environmental Defense Fund, and sponsors of the Energy Emissions Modeling and Data Lab (EEMDL). P. B. has been funded by several sources including oil and gas companies, UK Government, United Nations Environment Programme and various environmental NGOs.

Data Availability

All data necessary to replicate the results presented in this study are provided along with the paper. Additional data tables and figures are available in Supplementary Information. The development of measurement-informed emissions inventories is based on peer-reviewed and publicly available data. Corrections to published estimates to be incorporated in this work are described in Supplementary Information, whereas the original measurement data can be found in the peer-reviewed literature.

References

1. International Energy Agency. World Energy Outlook 2024; 2024.

2. Ravikumar AP, Bazilian M, Webber ME. The US role in securing the European Union's near-term natural gas supply. Nature Energy 2022, 7(6): 465-467.

3. U.S. Department of Energy. Natural Gas Benefits and Considerations. Alternative Fuels Data Center; 2025 Available at https://afdc.energy.gov/fuels/natural-gas-benefits.

4. International Energy Agency. Natural Gas; 2025; Available at: https://www.iea.org/energy-system/fossil-fuels/natural-gas.

5. International Energy Agency. The Role of Gas in Today's Energy Transitions: World Energy Outlook special report, 2019.

6. Yang S, Hastings-Simon S, Ravikumar AP. Pipeline Availability Limits on the Feasibility of Global Coal-to-Gas Switching in the Power Sector. Environmental Science & Technology 2022, 56(20): 14734-14742.

7. Tanaka K, Cavalett O, Collins WJ, Cherubini F. Asserting the climate benefits of the coal-to-gas shift across temporal and spatial scales. Nature Climate Change 2019, 9(5): 389-396.

8. Yang S, Hastings-Simon S, Ravikumar AP. Global liquefied natural gas expansion exceeds demand for coal-to-gas switching in paris compliant pathways. Environmental Research Letters 2022, 17(6): 064048.

9. Howarth RW. The greenhouse gas footprint of liquefied natural gas (LNG) exported from the United States. Energy Science & Engineering 2024.

10. Gordon D, Reuland F, Jacob DJ, Worden JR, Shindell DT, Dyson M. Evaluating net life-cycle greenhouse gas emissions intensities from gas and coal at varying methane leakage rates. Environmental Research Letters 2023.

11. Mallapragada DS, Naik I, Ganesan K, Banerjee R, Laurenzi IJ. Life Cycle Greenhouse Gas Impacts of Coal and Imported Gas-Based Power Generation in the Indian Context. Environmental Science & Technology 2019, 53(1): 539-549.

12. Ravikumar AP, Tullos EE, Allen DT, Cahill B, Hamburg SP, Zimmerle D, et al. Measurement-based differentiation of low-emission global natural gas supply chains. Nature Energy 2023.

13. European Commission. New EU methane regulation to reduce harmful emissions from fossil fuels in Europe and abroad. 2024 [Accessed January 26, 2025] Available from:

https://energy.ec.europa.eu/news/new-eu-methane-regulation-reduce-harmful-emissions-fossil-fuels-europe-and-abroad-2024-05-27_en

14. United Nations Environment Programme. The Oil and Gas Methane Partnership 2.0 (OGMP 2.0): A Framework for Action. 2021 [Accessed December 2, 2024] Available from: https://ogmpartnership.com/

15. Tullos E, Cahill B. To Meet Global Methane Goals, Improve Gas Data. Center for Strategic and International Studies. 2023 [Accessed January 26, 2025] Available from: https://www.csis.org/analysis/meet-global-methane-goals-improve-gas-data

16. U.S. Environmental Protect Agency. Greenhouse Gas Reporting Program: Revisions and Confidentiality Determinations for Petroleum and Natural Gas Systems (89 FR 42062). [Final Rule]. To be codified at 40 C.F.R. pt. 98, subpt. W. 2024.

17. U.S. Department of Energy. Greenhouse Gas Supply Chain Emissions Measurement, Monitoring, Reporting & Verification Framework. 2024 [Accessed January 26, 2025] Available from: https://www.energy.gov/fecm/greenhouse-gas-supply-chain-emissions-measurement-monitoring-reporting-verification-framework

18. International Energy Agency. Coalition for LNG emission abatement towards net zero clean. 2024 [Accessed January 26, 2025] Available from: https://www.iea.org/policies/18350-coalition-for-lng-emission-abatement-towards-net-zero-clean

19. Heath GA, O'Donoughue P, Arent DJ, Bazilian M. Harmonization of initial estimates of shale gas life cycle greenhouse gas emissions for electric power generation. Proceedings of the National Academy of Sciences USA 2014, 111(31): E3167-3176.

20. Roman-White S, Rai S, Littlefield J, Cooney G, Skone TJ. Life cycle greenhouse gas perspective on exporting liquefied natural gas from the Unites States: 2019 update. United States; 2019 12.

21. Nie Y, Zhang S, Liu RE, Roda-Stuart DJ, Ravikumar AP, Bradley A, et al. Greenhouse-gas emissions of Canadian liquefied natural gas for use in China: Comparison and synthesis of three independent life cycle assessments. Journal of Cleaner Production 2020, 258.

22. Mukherjee M, Littlefield J, Khutal H, Kirchner-Ortiz KM, Davis KG, Jing L, et al. Greenhouse gas emissions from the US liquefied natural gas operations and shipping through process model based life cycle assessment. Communications Earth & Environment 2025, 6(1).

23. Gan Y, El-Houjeiri HM, Badahdah A, Lu Z, Cai H, Przesmitzki S, et al. Carbon footprint of global natural gas supplies to China. Nature Communication 2020, 11(1): 824.

24. Brandt AR, Heath GA, Kort EA, O'Sullivan F, Pétron G, Jordaan SM, et al. Methane Leaks from North American Natural Gas Systems. Science 2014, 343(6172): 733-735.

25. Rutherford JS, Sherwin ED, Ravikumar AP, Heath GA, Englander J, Cooley D, et al. Closing the methane gap in US oil and natural gas production emissions inventories. Nature Communication 2021, 12(1): 4715.

26. Sherwin ED, Rutherford JS, Zhang Z, Chen Y, Wetherley EB, Yakovlev PV, et al. US oil and gas system emissions from nearly one million aerial site measurements. Nature 2024, 627(8003): 328-334.

27. Wang JL, Daniels WS, Hammerling DM, Harrison M, Burmaster K, George FC, et al. Multiscale Methane Measurements at Oil and Gas Facilities Reveal Necessary Frameworks for Improved Emissions Accounting. Environmental Science & Technology 2022.

28. Riddick SN, Mauzerall DL. Likely substantial underestimation of reported methane emissions from United Kingdom upstream oil and gas activities. Energy & Environmental Science 2023, 16(1): 295-304.

29. Brown JA, Harrison MR, Rufael T, Roman-White SA, Ross GB, George FC, et al. Informing Methane Emissions Inventories Using Facility Aerial Measurements at Midstream Natural Gas Facilities. Environmental Science & Technology 2023, 57(39): 14539-14547.

30. Zhu Y, Ross G, Khaliukova O, Roman-White SA, George FC, Hammerling D, et al. Multiscale Measurements of Greenhouse Gas Emissions at U.S. Natural Gas Liquefaction Terminals. Environmental Science & Technology Letters 2024.

31. Balcombe P, Heggo DA, Harrison M. Total Methane and CO2 Emissions from Liquefied Natural Gas Carrier Ships: The First Primary Measurements. Environmental Science & Technology 2022, 56(13): 9632-9640.

32. Lauvaux T, Giron C, Mazzolini M, d'Aspremont A, Duren R, Cusworth D, et al. Global assessment of oil and gas methane ultra-emitters. Science 2022, 375(6580): 557-561.

33. Zhu Y, Allen DT, Ravikumar AP. Geospatial Life Cycle Analysis of Greenhouse Gas Emissions from US Liquefied Natural Gas Supply Chains. ACS Sustainable Chemistry & Engineering 2024.

34. Roman-White SA, Mallikarjuna Prasanna D, McCullagh A, Ravikumar AP, Allen DT, Chivukula K, et al. Gas Pathing: Improved Greenhouse Gas Emission Estimates of Liquefied Natural Gas Exports through Enhanced Supply Chain Resolution. ACS Sustainable Chemistry & Engineering 2024.

35. Vallejo V, Nguyen Q, Ravikumar AP. Geospatial variation in carbon accounting of hydrogen production and implications for the US Inflation Reduction Act. Nature Energy 2024.

36. Abrahams LS, Samaras C, Griffin WM, Matthews HS. Life cycle greenhouse gas emissions from U.S. liquefied natural gas exports: implications for end uses. Environmental Science & Technology 2015, 49(5): 3237-3245.

37. Jaramillo P, Griffin WM, Matthews HS. Comparative Life-Cycle Air Emissions of Coal, Domestic Natural Gas, LNG, and SNG for Electricity Generation. Environmental Science & Technology 2007, 41(17): 6290-6296.

38. Jordaan SM, Ruttinger AW, Surana K, Nock D, Miller SM, Ravikumar AP. Global mitigation opportunities for the life cycle of natural gas-fired power. Nature Climate Change 2022, 12(11): 1059-1067.

39. Roman-White SA, Littlefield JA, Fleury KG, Allen DT, Balcombe P, Konschnik KE, et al. LNG Supply Chains: A Supplier-Specific Life-Cycle Assessment for Improved Emission Accounting. ACS Sustainable Chemistry & Engineering 2021, 9(32): 10857-10867.

40. Schuit BJ, Maasakkers JD, Bijl P, Mahapatra G, van den Berg AW, Pandey S, et al. Automated detection and monitoring of methane super-emitters using satellite data. Atmospheric Chemistry and Physics 2023, 23(16): 9071-9098.

41. International Group of Liquefied Natural Gas Importers. The LNG industry GIIGNL Annual Report; 2024.

42. Masnadi M, El-Houjeiri H, Schunack D, Li Y, Englander J, Badahdah A, et al. Global carbon intensity of crude oil production. Science 2018, 361(6405): 851-853.

43. Intergovernmental Panel on Climate Change. Chapter 7: The Earth’s Energy Budget, Climate Feedbacks, and Climate Sensitivity. In Climate Change 2021: The Physical Science Basis. Cambridge, United Kingdom and New York, NY, USA; 2021.

44. Chen Z, Jacob DJ, Gautam R, Omara M, Stavins RN, Stowe RC, et al. Satellite quantification of methane emissions and oil–gas methane intensities from individual countries in the Middle East and North Africa: implications for climate action. Atmospheric Chemistry and Physics 2023, 23(10): 5945-5967.

45. Maasakkers JD, Jacob DJ, Sulprizio MP, Scarpelli TR, Nesser H, Sheng J-X, et al. Global distribution of methane emissions, emission trends, and OH concentrations and trends inferred from an inversion of GOSAT satellite data for 2010–2015. Atmospheric Chemistry and Physics 2019, 19(11): 7859-7881.

46. Janssens-Maenhout G, Crippa M, Guizzardi D, Muntean M, Schaaf E, Dentener F, et al. EDGAR v4.3.2 Global Atlas of the three major greenhouse gas emissions for the period 1970–2012. Earth System Science Data 2019, 11(3): 959-1002.

47. Lu X, Jacob DJ, Zhang Y, Maasakkers JD, Sulprizio MP, Shen L, et al. Global methane budget and trend, 2010–2017: complementarity of inverse analyses using in situ (GLOBALVIEWplus CH₄ ObsPack) and satellite (GOSAT) observations. Atmospheric Chemistry and Physics 2021, 21(6): 4637-4657.

48. Scarpelli TR, Jacob DJ, Grossman S, Lu X, Qu Z, Sulprizio MP, et al. Updated Global Fuel Exploitation Inventory (GFEI) for methane emissions from the oil, gas, and coal sectors: evaluation with inversions of atmospheric methane observations. Atmospheric Chemistry and Physics 2022, 22(5): 3235-3249.

49. Foulds A, Allen G, Shaw JT, Bateson P, Barker PA, Huang L, et al. Quantification and assessment of methane emissions from offshore oil and gas facilities on the Norwegian continental shelf. Atmospheric Chemistry and Physics 2022, 22(7): 4303-4322.

50. International Energy Agency. Global Methane Tracker Documentation 2024 Version; 2024.

51. Irakulis-Loitxate I, Guanter L, Maasakkers JD, Zavala-Araiza D, Aben I. Satellites Detect Abatable Super-Emissions in One of the World's Largest Methane Hotspot Regions. Environmental Science & Technology 2022, 56(4): 2143-2152.

52. Jong TAd, Maasakkers JD, Irakulis-Loitxate I, Randles CA, Tol P, Aben I. Daily global methane super-emitter detection and source identification with sub-daily tracking. EarthArXiv preprint 2024.

53. Johnson MR, Conrad BM, Tyner DR. Creating measurement-based oil and gas sector methane inventories using source-resolved aerial surveys. Communications Earth & Environment 2023, 4(1).

54. Trencher G, Nick S, Carlson J, Johnson M. Demand for low-quality offsets by major companies undermines climate integrity of the voluntary carbon market. Nature Communication 2024, 15(1): 6863.

55. ISO14040. Environmental management - life cycle assessment principles and framework. European Committee for Standardisation (ISO 14040:2006); 2006.

56. ISO14044. Environmental management – Life cycle assessment – Requirements and guidelines. European Committee for Standardisation (ISO 14044:2006); 2006.

57. ISO14067. Greenhouse gases — Carbon footprint of products — Requirements and guidelines for quantification. European Committee for Standardisation (ISO 14067:2018); 2018.

58. Energy Institute. Statistical Review of World Energy; 2024.

59. Zimmerle DJ, Williams LL, Vaughn TL, Quinn C, Subramanian R, Duggan GP, et al. Methane Emissions from the Natural Gas Transmission and Storage System in the United States. Environmental Science & Technology 2015, 49(15): 9374-9383.

60. Allen DT, Torres VM, Thomas J, Sullivan DW, Harrison M, Hendler A, et al. Measurements of methane emissions at natural gas production sites in the United States. Proceedings of the National Academy of Sciences USA 2013, 110(44): 17768-17773.

61. Mallapragada DS, Reyes-Bastida E, Roberto F, McElroy EM, Veskovic D, Laurenzi IJ. Life cycle greenhouse gas emissions and freshwater consumption of liquefied Marcellus shale gas used for international power generation. Journal of Cleaner Production 2018, 205: 672-680.

62. Littlefield J, Augustine D, Pegallapati A, Zaimes GG, Rai S, Cooney G, et al. Life Cycle Analysis of Natural Gas Extraction and Power Generation: National Energy Technology Laboratory (NETL); 2019.