ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP (SECOND EDITION)

CHAPTER 12:

GREENHOUSE GAS EMISSIONS MONITORING

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Good information on the sources of greenhouse gas (GHG) emissions is essential for responding to climate change. Accurate and timely data are needed to design mitigation strategies, prioritize abatement opportunities and track the effectiveness of climate policies. Historically, however, data concerning sources of GHG emissions have often been partial and approximate, with significant time lags. In many cases, a lack of definitive information on GHG emissions has been an important hurdle to climate action.

Artificial intelligence (AI) is helping address this challenge. AI tools are now analyzing vast amounts of data from Earth-observation satellites, airplanes, drones, land-based monitors, the Internet of Things (IoT), social media and other technologies. This capability dramatically improves our ability to monitor GHG emissions from specific sources accurately in near real-time.

AI's impact on GHG emissions monitoring will likely grow in the near future as machine learning (ML) algorithms used to analyze and process satellite imagery at scale continue to evolve from relatively early-stage computer vision technologies to powerful deep learning (DL) models trained on ever-growing amounts of data. In addition, large language models (LLMs) and generative AI may play an important role in building detailed and comprehensive asset databases (needed to attribute GHG emissions to their sources), while making it easier for end-users to use digital data.

A. Background

i. From GHG concentrations to emissions

Scientists began regularly measuring GHG concentrations in the atmosphere in the 1950s. These measurements, from ground-mounted instruments and Earth-observation satellites, have shown a steady increase in GHG concentrations and been foundational for climate science (see Figures 12-1

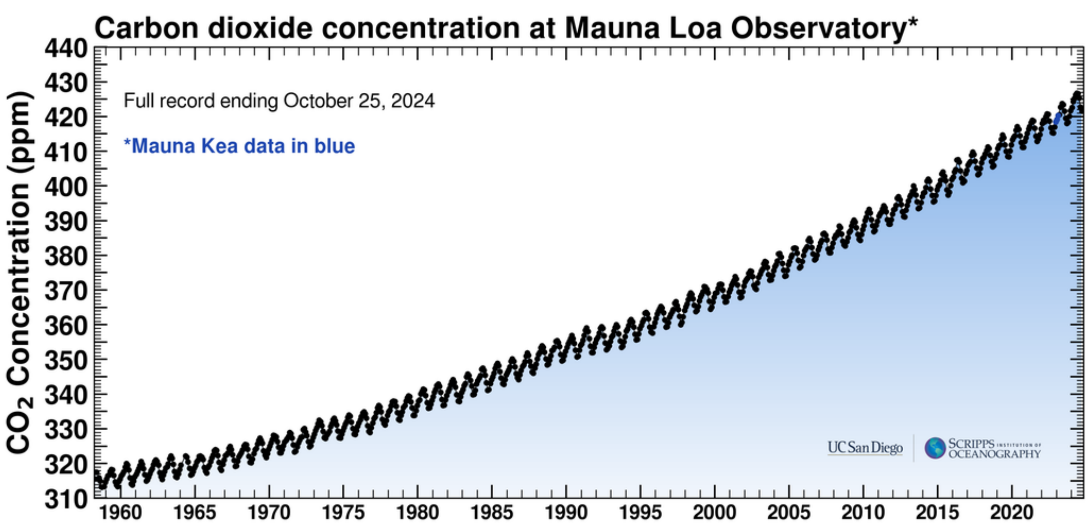


Figure 12-1. The Keeling Curve, showing measurements of CO_2 concentrations at the Mauna Loa Observatory in Hawaii since 1958, is named after the scientist Charles David Keeling who started the monitoring program.
Source: https://keelingcurve.ucsd.edu/

and 12-2). However, the data on GHG concentrations provide very limited or no information on the sources, location, timing and rates of GHG emissions.

To understand sources and amounts of GHG emissions, the climate community has often relied on estimated emission factors based on categories of equipment and processes. Unfortunately, these emission factors often systematically underestimate real emissions.[1-5] (This is especially true of anthropogenic methane emissions, which unlike CO_2 emissions are not a necessary byproduct of fossil fuel combustion.) In addition, the use of emission factors creates no incentive for improving operational performance. For example, a natural gas pipeline operator will be assigned the same level of methane emissions—based on pipeline length and diameter—whether or not it engages in routine venting, flaring or other climate-adverse, high-emitting and avoidable practices.

Different GHGs pose very different detection and measurement challenges:

- CO_2 emissions are mainly caused by fossil fuel combustion and deforestation. CO_2 emissions from fossil fuel combustion can be estimated with reasonable accuracy using fuel-consumption data, while deforestation emissions can be estimated with a lower level of accuracy using land-use-change data. However, neither fuel-consumption nor land-use-change data are readily available in all jurisdictions with sufficient frequency and granularity.
- Methane (CH_4) emissions, in contrast, come from a range of anthropogenic sources (the energy sector, food system and waste management) in addition to natural sources, such as melting of the permafrost, and are less correlated with consumption. Energy-related methane emissions are largely avoidable byproducts of fossil fuel production and transport, uncorrelated with consumption rates and unevenly distributed across fossil-fuel supply chains. Agriculture-related methane emissions are mainly a result of livestock biology and rice cultivation. They have long been deemed relatively difficult to avoid, although emerging technologies may change that. Technologies also exist to reduce waste methane emissions through better landfill management practices.

Figure 12-2. *Japan's Greenhouse gas observing satellite "IBUKI-2" (GOSAT-2).*
Source: https://global.jaxa.jp/projects/sat/gosat2/

ii. AI-enabled greenhouse gas (GHG) emissions monitoring

The use of satellites, drones and ground sensors to monitor GHG emissions at the source has increased significantly in recent years. These instruments produce vast amounts of data that can be processed and analyzed with AI algorithms to yield accurate emissions measurements.

A growing constellation of government and private satellites now monitors GHGs. Japan launched the first such satellite in 2009—the Greenhouse Gases Observing Satellite "IBUKI" (GOSAT).[6] Other government satellites include the European Space Agency's (ESA's) Copernicus Sentinel program; NASA's Landsat, OCO-2 and-3, EMIT and GOES missions; the German Space Agency's (DLR) Environmental Mapping and Analysis Program (EnMAP)[7]; the Italian Space Agency's (ASI) PRISMA[8]; China's Gaofen, Ziyuan and Huanjing missions[9]; and many others.

On the private-sector front, GHG-tracking satellites include, *inter alia*, the GHGSat constellation and Maxar's WorldView program. Several private start-ups, such as the French company Absolut Sensing, are planning to launch new Earth-observation nanosatellites. Oil and gas companies, including Exxon Mobil[10,11] and Saudi Aramco,[12] have announced plans to operate their own GHG monitoring satellites.

Non-governmental organizations (NGOs) have recently been adding to this ecosystem of Earth-observation satellites. The Environmental Defense Fund (EDF), a US NGO, launched MethaneSat in March 2024. Carbon Mapper, a public-private coalition composed of Planet, NASA's Jet Propulsion Laboratory (JPL), the State of California, the University of Arizona, Arizona State University, the Rocky Mountain Institute, the High Tide Foundation and other sponsors launched Tanager-1 in August 2024,[13] the first of several dedicated GHG-tracking satellites.

AI technologies are essential for processing the vast amount of imagery these satellites generate, analyzing it at scale and speedily converting it into precise, accurate and actionable data. Thanks in part to the falling cost of data storage and the dramatic increase in compute power achieved in recent years, scientists have developed powerful algorithms to process and analyze terabytes of raw satellite imagery and other data at scale in near-real time. This “software” development is a critical enabler of advances on the “hardware” side.

Further progress in AI, together with new satellites, will continue to improve methane emissions monitoring and will open up new abatement opportunities. Progress in real-time CO_2-emissions monitoring, as well as in measurement and monitoring of natural carbon sinks—such as vegetation—offers the same potential.

B. Methane Emissions

Methane has more than 80 times the warming power of CO_2 in the first 20 years after release and is as big a source of near-term warming as CO_2.[14] Although methane emissions account for an estimated 30% of global warming to date, the lack of good information on sources of methane emissions has limited the ability of policymakers and emitters to address this problem.

In recent years, the convergence of AI and satellite imagery has significantly improved methane-emissions monitoring. ML algorithms now make it possible to analyze raw satellite imagery at scale in record time. This is accomplished in three main stages. First, AI tools help identify abnormal concentrations of methane. Next, AI tools convert these static measurements into dynamic emissions events. Finally, detailed databases of infrastructure and industrial assets and advanced emissions dispersion models are used to connect (“attribute”) these emission events to their point sources. These tools provide policymakers and emitters with important new information for methane abatement by attributing observations of excess methane in the atmosphere to the specific sources that are responsible.

i. Processing data at scale

AI algorithms that process large amounts of remote-sensing data related to methane have been developed by scientists at research institutions, such as the Netherlands Institute for Space Research (SRON), the French Laboratory for Climate and Environmental Science (LSCE) and the Wofsy group at Harvard University (to name just a few), often working in partnership with private actors, such as French environmental intelligence firm Kayrros SAS or Canadian company GHGSat. (One co-author of this chapter is a principal of Kayrros.) Kayrros has been particularly active in further developing and operationalizing research advances, which has enabled automatic detection and measurement of large methane emissions events at scale on a global basis (Figure 12-3). The International Methane Emissions Observatory (IMEO), established in 2021 by the United Nations Environment Programme (UNEP) and the European Union, has been using methane detection data from Kayrros, SRON and GHGSat as feeds for its Methane Alert and Response System (MARS), which collects and disseminates information on super-emitters and works with the responsible parties and their governments to reduce emissions. More recently, the IMEO has been developing its own capability to process and analyze satellite imagery in-house.[15]

Advances in AI-enabled image-processing capacity help squeeze ever more methane information from satellite imagery, including from sensors that may not have been originally designed for that purpose. Thanks to this progress, satellites can now detect methane at the same spatial resolution and emission threshold as aerial surveys (down to 3 meters and 100 tons per hour or less), at a much lower cost and higher temporal resolution (frequency).[16] The combination of new satellites and increased processing capacity results in a growing number of GHG emission detections and facilitates their attribution to point sources on the ground. There is a trade-off among spatial resolution, temporal resolution (frequency) and spectral resolution (sensitivity) in most satellites—optimizing for two of these variables usually comes at the expense of the third. However, integrating inputs from multiple sensors (often called "data fusion") can overcome these limitations by creating an ideal, multi-scale monitoring platform that combines the best of all instruments.

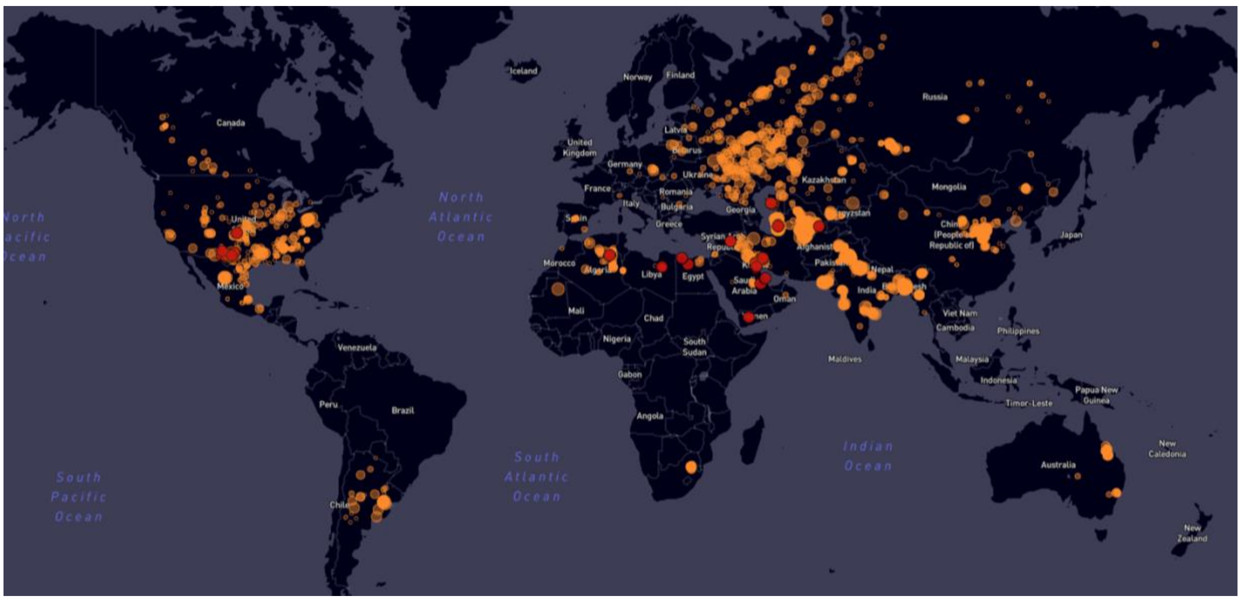


Figure 12-3. Methane super-emitters identified from satellite data processed with AI algorithms. Source: Kayrros.

ii. Use cases and takeaways

AI-enabled methane monitoring can be used in two ways: to identify large but sporadic emissions events, known as "super-emitters," or to assess total overall methane emissions from a country, sub-national region or fossil-fuel basin over a more prolonged period of time.

The transparency provided by AI and satellites has already significantly changed our understanding of anthropogenic methane emissions. For example, large emissions events from fossil fuel extraction and transportation have been shown to be far more ubiquitous than previously thought. Eliminating these super-emitters is "low-hanging fruit" for climate action: their eradication could be achieved at a relatively low cost,[17-19] significantly reducing anthropogenic methane emissions and cutting the increase in global average temperatures by 0.3 °C by 2045 and by 0.5 °C by 2100.[20,21] This set of abatement measures—the fastest known way to reduce global warming—is entirely dependent on the use of AI.

AI-enabled monitoring also has revealed large-scale, chronic methane emissions from landfills, with a disproportionate share in South Asia (India, Bangladesh and Pakistan)—another promising abatement opportunity.[22] In these countries, methane abatement could also provide substantial health benefits and reduce the need for imported, high cost liquefied natural gas (LNG). Similarly, AI-enabled monitoring using airborne detectors has uncovered large, ongoing methane emissions from US landfills.[23] In addition, AI can be used to analyze satellite imagery to track methane emissions from cattle feedlots.[24]

Basin-level or regional methane emission assessments can also help establish national or subnational methane inventories, set abatement targets and monitor the effect of mitigation policies. Saudi Arabia's King Abdullah Petroleum Research and Studies Center (KAPSARC), a government think-tank, conducted an AI-enabled study of Saudi methane emissions from oil and gas production and landfills. Their findings have confirmed the accuracy of earlier government assessments compared to those of the International Energy Agency (IEA) and the European Commission's Emissions Database for Global Atmospheric Research (EDGAR).[25]

C. Carbon Dioxide (CO_2) Emissions

AI is increasingly used to better understand and quantify sources of CO_2 emissions. At present, CO_2 emissions are monitored by assessing levels of carbon-emitting activities, such as industrial production and deforestation. AI helps build on existing datasets and dramatically improves the timeliness, granularity, comprehensiveness and accessibility of CO_2 emissions information.

i. Methodology: Bringing granular, real-time accountability to carbon emissions

AI can analyze and integrate large quantities of data from highly diverse real-time or near-real-time datasets from industry, power generation, ground transportation and other sectors. This approach has produced near-real-time trackers of CO_2 emissions by sector, company or even individual asset, with continuous improvements made to the underlying datasets and AI-based emissions analysis methods.[26,27]

ii. Current applications and emerging opportunities

AI-enabled CO_2 emissions data allow policymakers, industries and other carbon-market participants to monitor demand for carbon allowances in near real-time, better understand the drivers of carbon emissions and assess the effectiveness of emissions-abatement policies with timeliness and precision. For example, AI can model and monitor CO_2 emissions from urban environments with high spatial and temporal resolution, helping city managers and urban planners assess the effects of abatement measures, sharpen their toolkit and respond to changing circumstances in a timely manner.[28-30]

More use-cases for AI-enabled CO_2 emissions data will undoubtedly emerge as AI algorithms continue to improve, helped in part by new underlying data from Earth-observation satellites scheduled to be launched soon.

iii. Use case: Providing near-real-time information on CO_2 emissions from transport and industry

Climate Trace, Carbon Monitor and other organizations are using AI to more accurately monitor CO_2 emissions. Their methods include combining computer vision with data from remote-sensing satellites, such as detecting water vapor (a proxy for CO_2 emissions) released from large natural-draft cooling towers at power plants[31,32]; measuring daily vehicle traffic on roads over large regions and GHG emissions these vehicles collectively produce[33]; and improving plume-inversion techniques to translate direct CO_2 concentration measurements into estimates of CO_2 emissions rates at large power plants.[34]

Related work has used AI to create a much more accurate estimate of GHG emissions per nautical mile from cargo ships and has combined this information with satellite-relayed ship tracking data from automated identification system (AIS) transponders.[35]

Such transparency carries far-reaching consequences for carbon abatement. In particular, AI-enabled measurements can support and improve carbon markets, such as the EU Emissions Trading System or the California Cap-and-Trade Program, amplifying their impact by providing carbon-market participants with up-to-date information on implied demand for carbon credits.

In operational contexts, AI tools are increasingly able to make real-time predictions of the CO_2 emissions that will result from different vehicle duty cycles,[36] industrial process changes[37] and industrial boiler use.[38] This can help optimize operations to reduce on-site emissions and can highlight specific operating conditions that lead to excessive emissions.

AI-enabled measurement of carbon emissions could also help assess lifecycle emissions of commodities and other products. This type of information may be critically important for carbon border adjustment mechanisms. For example, AI-enabled measurements could be used to assess the amount of carbon (and methane) emissions embedded in products (e.g., crude oil, gasoline, LNG, electric vehicles (EVs) or wind turbines) by collecting data on emissions associated with each link of their respective supply chains. Countries importing the product could use this information to assess its GHG intensity and any associated GHG tariff.

Finally, AI tools can provide policymakers with a powerful resource for tracking effects of emissions regulations, identifying and prioritizing CO_2 abatement opportunities, detecting swings in CO_2 emissions and crafting appropriate reaction measures in a timely manner. This is particularly the case for urban CO_2 emissions, which are estimated to account for up to 60% of total CO_2 emissions and which can be analyzed with AI technologies in great detail.[39]

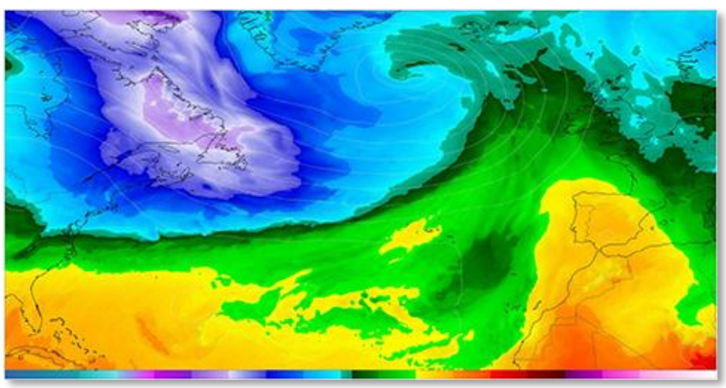
iv. Use case: Achieving near-real-time transparency on negative CO_2 emissions and carbon credit demand

In its Sixth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) highlights the importance of vegetation to achieving our climate goals. Forestry and other forms of vegetation constitute a vital carbon sink. Monitoring this carbon sink has been challenging with traditional techniques. However, AI algorithms can be trained to survey the world’s vegetation at high spatial resolution with radar and optical satellite imagery and can precisely measure the amount of biomass carbon sequestered in forestry and other forms of vegetation, at scale and at reasonable cost.

Traditional monitoring of forest projects involves sending teams of inspectors on the ground at large intervals of 5 to 10 years to inspect sample sections of the forests, measure the circumference of their tree trunks, and extrapolate from those measurements. Inspections are (1) too few and far between to detect deforestation or degradation in time to take corrective measures, (2) do not account for carbon leakage (whereby deforestation is pushed from carbon-offset projects to surrounding areas) and (3) do not provide sufficient data to assess the baselines used to set the number of carbon credits issued (i.e., the assumed growth trajectory of the forest parcel in the absence of a carbon offset project).

In contrast, AI can be used to process radar and optical satellite imagery to survey forests and build a strong monitoring, reporting and verification (MRV) architecture around carbon-offset projects. AI technologies make it possible to monitor entire projects comprehensively, cost-efficiently and non-intrusively at relatively high frequency. They are also able to detect carbon leakage virtually from the onset and to test the projects' baselines by using archival imagery to observe underlying trends in their respective areas over extended periods of time.[40] This transparency has the potential to rebuild confidence in carbon-offset projects, prevent and crack down on unsavory practices in nature-based solutions (NBS) markets, set strong safeguards around our shared forestry endowment and safely channel capital from North to South.

Many start-up companies are currently engaged in AI-assisted biomass carbon monitoring, competing commercially in this emerging sector. As with monitoring positive carbon emissions, this application of AI technology has several use cases. These include strengthening forest protection through robust MRV of carbon offsetting projects, supporting carbon markets with provision of near real-time data on the supply of carbon credits and facilitating implementation of anti-deforestation policies.



These AI-assisted technologies are a potential game changer for developing a robust and transparent NBS sector. NBS projects have been plagued by a lack of transparency that has shielded dubious and sometimes fraudulent business practices, caused market inefficiencies and failures, and severely undermined market confidence in NBS as a viable climate tool.[41,42] AI technologies can provide carbon traders with near-real-time information about the supply of carbon offsets, supplementing implied demand data produced from monitoring carbon emissions. Near-real-time transparency on carbon-credit supply and demand fundamentals can facilitate price formation in carbon markets and can help send price signals needed to support investment in offset projects.[43]

D. Policy and Market Impacts

Policymakers and private-sector companies around the world are already beginning to avail themselves of AI-enabled emissions-tracking tools. This is especially true of EU and US methane policies.

i. Methane

By shining a light on methane emissions, AI has sparked a revolution in global governance of these emissions. The full impact of such changes have yet to be felt, but they have the potential to start reducing global methane emissions relatively soon.

In the United States, these policies include both new methane regulations of the US Environmental Protection Agency (EPA) and the methane provisions of the Inflation Reduction Act of 2022. Both sets of rules recognize AI-enabled satellite technologies as a way to independently track the methane footprint of oil and gas operators without having to rely on their self-reporting. To that end, and in a departure from past practice, the US EPA has invited third-party notifiers to provide methane detection data that may be used as a basis for enforcement actions and other measures. These third-party agents, which will be subject to formal EPA certification, may include users of AI-enabled satellite monitoring technologies.

The US Government has also tasked NASA with supervising the launch of the US GHG Center, a multi-agency unit of NASA, the US EPA, the National Institute of Standards and Technology (NIST) and the National Oceanic and Atmospheric Administration (NOAA).[44] The US GHG Center is expected to provide a wealth of information on GHG emissions, including AI-enabled methane measurements.

Similarly, the EU Methane Strategy is imposing both new methane reporting standards for European energy producers and new due-diligence requirements for European importers of fossil energy. It has considered a “border adjustment mechanism” that would place a tariff on methane emissions associated with EU imports from countries that do not already penalize methane emissions. Companies may use AI-enabled satellite monitoring technologies for compliance purposes, and EU member countries may use them for enforcement.

Meanwhile, as noted above, the IMEO has been developing the MARS platform, which uses AI and satellite imagery to track global methane emissions.

In parallel with these developments, AI-enabled satellite monitoring of methane emissions has been instrumental in the birth of multilateral coalitions and initiatives to reduce methane emissions from the oil and gas sector, such as the Global Methane Pledge, launched at COP26 in Glasgow in 2022 and joined by more than 155 participants.[45] AI-enabled detections of large methane emissions in Turkmenistan played a role in getting Ashgabat to agree to work with the United States and other countries to reduce its methane footprint.

AI-enabled satellite monitoring can empower countries to report their methane emissions to the United Nations Framework Convention on Climate Change (UNFCCC) more accurately than is possible with the prevailing method of emission factors. However, while this use of AI technology for GHG inventories or “stocktake” purposes is not expressly disallowed by the United Nations, it is not explicitly encouraged. This is unfortunate, since satellite studies often show large discrepancies between “bottom up” inventories based on emission factors and “top down” measurements with AI and satellites. On rare occasions, AI monitoring has made it possible to validate the accuracy of national inventories and disprove higher third-party estimates (see, e.g., KAPSARC 2023 study).[26]

Once methane abatement policies have been adopted by countries and/or corporations, AI technologies can help verify their implementation, assess their effectiveness and evaluate what works best or what does not work. For example, the Permian basin (the United States’ most prolific oil and gas basin) straddles the line between Texas and New Mexico, two states with very different methane regulations. Here, AI monitoring could help empirically measure the impact of these policies on the basin’s GHG footprint.[46]

In commodities markets, methane emissions (or the lack thereof) are becoming an important differentiating factor, with products deemed “clean” or “low emissions” already commanding or set to command a premium. AI-enabled technologies hold promise as a key tool for helping establish the methane footprint of individual oil and gas producers or cargoes of oil or LNG and could become an important building block in “responsible gas“ certification.[47]

In equities and fixed-income markets, several banks and asset managers have announced AI-assisted initiatives to factor methane measurements and other climate-related metrics into their decision-making for investments or loans. Here too AI-assisted technologies could prove pivotal in helping financial actors integrate climate considerations into their workflows.

ii. Carbon dioxide (CO_2)

Policymakers are increasingly considering the need to adjust international trade practices to avoid “carbon leakage” (i.e. “imported emissions” from exporting countries with loose carbon regulations to importing economies with more stringent rules). At the national level, this can mean a “carbon border adjustment mechanism” (CBAM) – a carbon tariff on imported goods from countries with lower carbon emissions standards than the destination market.

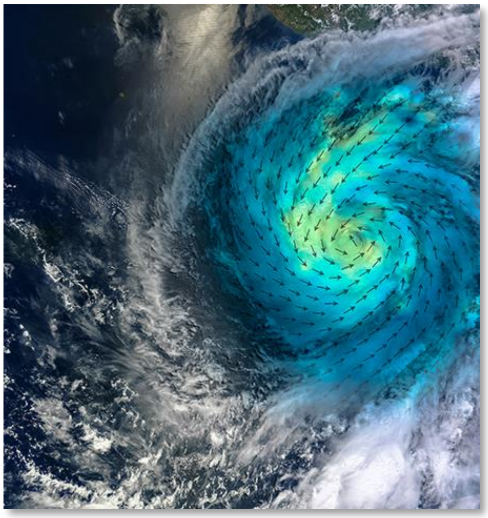
An EU CBAM is due to take effect in its definitive regime in 2026. In the United States, there is bipartisan support for a proposed US version of the European CBAM. (In California, a CBAM is already effectively in place regarding the inter-state movement of electricity from neighboring states under the California Air Resources Board’s Cap-and-Trade Program.)

One of the challenges raised by proposed CBAM regulations is to accurately assess the carbon footprint of internationally traded commodities and goods—a challenge that AI-enabled technologies might help to overcome. Not surprisingly, there is strong interest in both the European Union and the United States in studying the usefulness of these technologies for determining the carbon intensity of imports.

E. Barriers

The use of AI to harness satellite imagery and other data sources is one of the most promising developments for GHG emissions monitoring. However, there are important barriers.

i. Lack of AI literacy



Lack of AI literacy limits the ability of data users to analyze GHG data, integrate these data into their operations and generate customized products and applications based on these data. Lack of AI literacy could also inhibit the willingness of national governments to avail themselves of AI-enabled Earth-observation tools in the absence of guidelines from the UNFCCC, even if these technologies could greatly enhance the accuracy of their GHG inventories and support their stocktake efforts. Finally, lack of AI literacy could also adversely affect public trust in AI-enabled GHG data and create a fertile ground for misuse of data. To realize the full potential benefits of AI for GHG emissions monitoring, AI literacy must be broadly improved, including in developing economies.

The growth of generative AI and large language models (LLMs) could help overcome this barrier by making it easier for users to leverage AI-enabled data. This could however prove to be a double-edged sword. Distrust of generative AI and the tendency of some LLMs to "hallucinate" could undermine user confidence and emerge as barriers to adoption in their own right.

ii. Sovereignty concerns

Sovereignty concerns may emerge as a significant impediment to using AI-enabled GHG emissions data. Some countries may object to foreign monitoring and analysis of emissions within their territories. AI-enabled analysis of GHG emissions data may face a trust deficit if it is perceived as biased in favor of certain economic actors, especially if these data are used as the basis for imposing international tariffs or trade restrictions.

Independent verification of global GHG data and international consensus about the accuracy of AI-enabled analyses will be required to fully realize the potential benefits of AI tools in GHG emission monitoring.[48]

iii. Emitter pushback

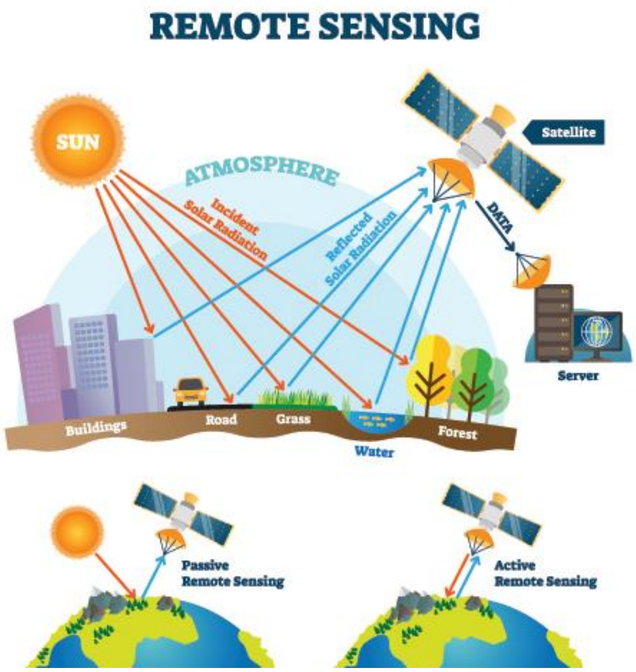
Industry participants whose true climate footprint might be exposed by AI technologies as larger than reported or whose short-term interests might otherwise be harmed by the transparency brought by AI technologies might be naturally inclined to push back against these measurements. National governments whose GHG inventories might be shown as understating actual emissions might be inclined to react by challenging the maturity and reliability of AI-enabled monitoring technologies.

iv. Uncertain financial models

A tension exists in current development of AI-enabled GHG monitoring tools. While these tools rely strongly on data provided by publicly funded satellites, much of their technological innovation is the result of intense competition between private-sector companies, including many start-ups. These companies are profit-seeking and must generate revenue from the sale of data to recoup their investments and fund further research and development (R&D). At the same time, the data must be shared as widely as possible and ideally made publicly available in open access to maximize their impact and facilitate global acceptance of their accuracy. Protecting the intellectual property in many AI-enabled technologies is essential to the financial success of these private-sector enterprises and thus to innovation in AI technologies but may limit public acceptance of GHG emissions data.

F. Risks

Risks with respect to using AI for GHG emissions monitoring are modest. Safety and bias concerns that arise with using AI in other sectors are not major issues when using AI for monitoring GHGs. However, two categories of risks require attention.



Privacy concerns may arise when AI enables remote monitoring. For example, manufacturers may be concerned that AI-enabled remote GHG emissions measurements could provide confidential information about factory operations to competitors. However, the technologies underlying AI-enabled emissions data (high-resolution remote sensing and advanced AI algorithms) can be used to obtain competitive industrial information regardless of whether they are also used to assess emissions. Mitigation of this concern ultimately relies on policies that address those underlying technologies.

Lack of confidence arising from data inconsistency. Lack of confidence in AI-enabled data could emerge among key stakeholders due to a variety of factors, such as naturally occurring differences in GHG emissions detections and measurements, inaccurate measurements or seemingly conflicting results. Natural differences in data could be misconstrued as conflicting when they in fact simply stem from the intermittency of some emissions and timing differences in collecting satellite imagery. Inaccurate or conflicting results could result from the proliferation of imagery transmitted by a growing constellation of Earth-observation satellites, as well as from new start-up companies competing in the AI-for-climate space, with different providers releasing different measurements.

G. Recommendations

Several measures could help address the barriers and overcome the risks described above, promoting the use of AI tools for GHG emissions monitoring.

1. *National governments should encourage the UNFCCC to update guidance on preparing national emissions inventories to explicitly allow the use of AI-enabled data rather than primarily emissions factor–based assessments. This would provide for more accurate baselines and thus make it easier to optimize climate policies and to better tailor them to specific national conditions, while also better recognizing the progress of countries in reducing their climate footprint.*
2. *Carbon accounting bodies, such as the GHG Protocol of the World Resources Institute (WRI) and World Business Council for Sustainable Development (WBCSD) or the Science Based Targets Initiative (SBTI), should develop rules for including AI-enabled data as part of corporate carbon footprints, supply chain emissions estimates and related emissions-tracking efforts. When feasible, they should encourage or prioritize the use of validated AI-enabled emissions data over generic emissions factors. In tandem with this, other relevant multilateral institutions, such as the World Trade Organization (WTO) and IEA, should continue[49] explicitly addressing the topic of using AI-enabled emissions data and should identify roles they can productively play in advancing its use in a scientifically robust manner.*
3. *National governments and appropriate international bodies should consider how best to set up the housing and governance regime of AI-enabled emissions data, including such questions as whether one or several national or international organizations or private entities should function as de facto or de jure central data repositories or clearinghouses. Clear options should be defined and decisions made in the short-term. To the extent that the market or regulations require information on GHG emissions in supply chains, the quality of emissions data will be of paramount importance. To be effective, emissions data will need buy-in from as many stakeholders as possible and must be independently replicable. Governments and multilateral organizations should consider the role of existing institutions, such as the IMEO, the World Meteorological Organization and the Food and Agriculture Organization, as well as major philanthropic organizations and for-profit companies, in providing repository and clearinghouse services for AI-enabled GHG emissions data.*
4. *National governments and appropriate international bodies should continue ongoing efforts toward standardizing AI-enabled emissions data and should consider whether to set up formal processes to certify AI-assisted emissions data and data providers. In the last two years, NIST at the US Department of Commerce and the UK Space Agency have spearheaded a series of brainstorming workshops and consultations with leading scientists and industry participants from around the world, with the goal of achieving greater standardization and consistency in AI-assisted measurements of methane and other GHG emissions and of preempting the risk of future conflicting data.[50] These efforts are highly worthwhile and ought to be continued so as to guarantee the scientific integrity and comparability of emissions data and to build public trust. To*

the extent possible, participation should be broadened to include more representatives from emerging and newly developed economies and major exporters of commodities and manufactured goods.

5. *National governments, philanthropic organizations and private-sector companies should support ongoing "ground truthing" efforts by research universities and scientific organizations that aim to independently assess the performance of AI-assisted GHG monitoring technologies. Because AI-enabled GHG monitoring technologies often detect and measure emissions that cannot be otherwise detected or measured, proving their accuracy can be challenging. Hence, there is a need to support public research to develop ways of independently replicating and corroborating AI-enabled data and verifying their accuracy based on well-calibrated ground-truth experiments.*
6. *National governments and private-sector organizations should enhance their in-house AI proficiency, whether by requiring minimum AI literacy standards from a broad cross-section of employees or by building up dedicated AI-focused units and data-science centers within their organizations. Minimum AI literacy may be essential for these organizations to deploy AI-enabled GHG emissions data and to integrate those data into public and proprietary databases and operational systems. Professional standards bodies should update accreditation requirements for professions, such as public accounting and civil engineering, to require demonstration of minimal AI proficiency and the ability to use basic AI technologies. This would serve as a step to support adoption and implementation of emissions abatement targets by industry and carbon accounting by corporations. Trade and professional organizations, such as the Society of Petroleum Engineers (SPE) or the International Association for Energy Economics (IAEE), should support AI literacy among their members and the adoption of AI-enabled GHG monitoring, including through training programs in countries where these technologies are not widely available.*
7. *Banks, asset managers and other private-sector actors should use AI-enabled methane emissions data to quantify the embedded emissions of fossil fuel shipments, following the lead of some financial institutions who have already begun this practice.*

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