Scientific Roadmap for Advancing Agricultural Nitrous Oxide MMRV and Modeling

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Note to Readers

This roadmap reflects a yearlong collaboration among more than two dozen U.S.-based scientific experts with broad experience measuring agricultural nitrous oxide (N_2O) emissions. Drafting took place over several virtual sessions in 2025 and culminated in an informational event at the 2025 American Geophysical Union (AGU) Conference, one of the nation's largest scientific gatherings. During this session, we presented the roadmap for public comment and invited additional expert input. These comments have since been incorporated and are summarized in Appendix B.

The intended audience includes stakeholders, decision makers, and scientists working in N_2O measurement. This roadmap aims to inform science policy, guide research prioritization, and support funding decisions across the research ecosystem. The goal is to help farmers, NGOs, businesses, and governments ask and answer the right questions as they work to reduce agricultural N_2O emissions.

Core Message

Reducing agricultural nitrous oxide (N_2O) emissions offers substantial economic, health, and climate benefits and requires accurate and dependable measurement systems to track progress. Recent advances in computation, sensing technologies, data infrastructure, and modeling make meaningful progress in N_2O emissions tracking possible today. Coordinated efforts across research communities, funders, and industry are essential to build trustworthy, scalable N_2O measurement, monitoring, reporting, and verification (MMRV) systems that reinforce national and global climate and socioeconomic goals.

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How Should This Document Be Used?

This research roadmap positions improved agricultural N_2O MMRV and modeling as central to sustainable agriculture, efficient on-farm nitrogen management, and emerging environmental markets. Based on the collective expertise of researchers and experts, it is intended as a strategic tool for funders, policymakers, and practitioners seeking to align investments and standards around robust, science-based N_2O measurement.

Advancing science and method development

Current N_2O quantification approaches remain challenging to scale and integrate, limiting capacity to meet the needs of national inventories, private climate commitments, and high-integrity crediting programs. By identifying key priorities, including sensor development, multi-scale measurements, integration of process-based and empirical models, and improved data infrastructure, this roadmap provides a shared agenda to accelerate research and practical adoption of N_2O measurement across regions and systems.

Enabling robust MMRV systems

Public and private entities increasingly recognize the need for N_2O monitoring networks that can enable both beyond CO_2 GHG monitoring strategies and improved tools to bolster agricultural MMRV. This roadmap can directly support these efforts by clarifying the targeted research investments and technological advances required for credible N_2O MMRV at field, regional, and national scales.

Informing standards, policy, and markets

By outlining the current state of N_2O research and the research areas with the greatest potential for advancement, this roadmap can guide the development of future certification schemes, standardized methodologies, and regulatory guidance for agricultural N_2O.

Guiding investment and collaboration

Given the scale of N_2O emissions from agricultural soils and their relevance to global climate goals, targeted investment in N_2O MMRV and modeling is essential. The roadmap can enable coordination among public agencies, philanthropic funders, and private-sector actors. The roadmap recommends pathways to de-risk innovation and establish shared platforms, such as open datasets, experimental networks, and benchmarking initiatives, that no single actor could develop alone.

Providing a platform for advocacy and alignment

This document can also serve as an advocacy tool to brief decision makers, support funding proposals, shape calls for research, and convene cross-sector coalitions. By articulating both the urgency and a concrete path toward credible N_2O MMRV and modeling, it can help move the field from fragmented pilots to an integrated, trusted evidence base that underpins effective policy, resilient farms, and high-integrity climate action.

The Importance of N_2O Measurement

"Understanding nature (natural carbon cycle) and mimicking it for our food systems, using practices such as circular-regenerative agriculture, is the transformation we need in our food systems, not the current linear wasteful approach. Improvements in N_2O emissions MMRV and modeling are needed to deepen this understanding."

—Isaac Mpanga, Executive Director, Circular Planet Institute and Former Sustainable Food Solutions Director, Yara North America

"For the fertilizer industry, reliable and scalable methods for measuring agricultural nitrous oxide emissions are essential. The fertilizer industry operates within complex supply chains and reporting frameworks, and the lack of consistent, science-based N_2O modeling tools creates unnecessary burdens on both companies and farmers. Improved monitoring methods and models would not only strengthen the accuracy of sustainability reporting but also support practical, on-farm decision-making aligned with the principles of 4R Nutrient Stewardship. Advancing nitrous oxide research is critical to advancing lower-emission agricultural practices."

—Leanna Nigon, Director of Agronomy, The Fertilizer Institute

"This roadmap arrives at a critical moment for agriculture, when reducing emissions must go hand in hand with protecting yield and profitability. Much needed advancements in N_2O measurement and modeling can create the foundation for better nitrogen use efficiency and clearer market signals for innovations such as biofertilizers and precision nutrition. The roadmap offers a clear, timely guide for directing investment where it can deliver real impact."

—Jane Franch, Former Director of Climate Impact, Pivot Bio

"To achieve ambitious greenhouse gas reduction goals, we partner with interested farmers, agronomists, and local organizations in our key ingredient sourcing regions to improve the health of agricultural ecosystems. Nitrous oxide is a critical, yet difficult piece of the puzzle. This roadmap charts the advancements needed in measuring nitrous oxide emissions to effectively abate them, which will lead to improved nitrogen management on farms, a more stable climate, and ultimately more resilient food systems."

—Steven Rosenzweig, PhD, Agriculture Science Lead, General Mills

Why Focus on Measuring and Reducing Agricultural N_2O Emissions?

Agricultural systems support economies and communities worldwide. Practices such as tilling, irrigating, fertilizing, and grazing can improve soil health and crop productivity, but they can also release greenhouse gases (GHGs), contributing to extreme weather events and changing rainfall patterns. A growing community is mobilizing to reduce these impacts, with early efforts centered on carbon dioxide (CO_2), soil carbon, and more recently methane (CH_4). However, improving monitoring and emissions reduction of N_2O is equally vital. N_2O emissions reduction improves climate outcomes while improving nitrogen use efficiency (defined here as yield per unit of fertilizer N applied (Congreves et al. 2021)) and enabling more sustainable food systems.

Elevated N_2O emissions often indicate excess reactive nitrogen, typically from fertilizer applied in quantities beyond crop needs. Better understanding of where and when emissions occur can help farmers optimize fertilizer use, reduce input costs, and improve nitrogen use efficiency. This means that with the right tools, reducing N_2O emissions can align with more profitable and sustainable farm management.

N_2O has a global warming potential 273 times greater than CO_2 over 100 years and 9 times greater than methane (IPCC 2021). This warming has real consequences for farming communities. Keiser et al. estimated that climate change impacts from nitrogen pollution (primarily through N_2O emissions) can be as high as $3 billion per year for individual watersheds (Keiser et al. 2025). N_2O is also the primary driver of stratospheric ozone depletion (Ravishankara et al. 2009; UNEP 2024), increasing UV exposure and associated health risks (Hayashi and Itsubo 2023). Agriculture accounts for approximately 80 percent of anthropogenic N_2O emissions (Haider et al. 2020), a proportion expected to rise significantly by 2050 (Davidson and Kanter 2014; IPCC 2021). Improved N_2O MMRV can support the industry to better account for and incentivize the reduction of these environmental, economic and health impacts while also improving farm economics and productivity.

Why Invest Now in Improved N_2O MMRV?

Growing attention to agricultural nitrogen, driven by rising fertilizer costs, supply-chain decarbonization goals, and farmer concerns about nitrogen losses, is beginning to create new demand for N_2O monitoring. At the same time, advances in sensors, platforms, and modeling are making N_2O MMRV more feasible. Improvements in process-based models (e.g., DayCent, DNDC), increased instrument sensitivity, more coordination across measurement scales, and rapid progress in machine learning have expanded the ability to combine observational data with process-based modeling approaches.

Improved N_2O measurement is critical to model accuracy and vital for ensuring the success of climate initiatives. For example, increasing soil carbon storage on agricultural land is widely promoted as a strategy to mitigate CO_2 emissions. Governments and companies are developing policies and programs that link agricultural practices to greenhouse gas reduction targets, relying on detailed MMRV systems for CO_2 and soil carbon to guide interventions and verify outcomes. However, carbon sequestration efforts can unintentionally increase N_2O emissions (Niles et al. 2019). Without the ability to measure and model both CO_2 and N_2O, these policies risk creating trade-offs, reducing one greenhouse gas while increasing another, and undermining productivity and sustainability goals.

Current technologies for N_2O MMRV cannot yet meet this need and lag behind those for CH_4 and CO_2. N_2O concentrations are roughly 1,000 times lower than CH_4 and CO_2, requiring highly sensitive and expensive detectors. Emissions also occur in episodic "hot spots and hot moments," making them harder to capture than the more consistent emissions patterns of CH_4 and CO_2 (Wagner-Riddle et al. 2020). Detecting these events requires long-term monitoring, extensive instrumentation, or modeling to fill in data gaps (Butterbach-Bahl et al. 2013). N_2O also arises from multiple natural and anthropogenic pathways (H. Tian et al. 2020), with different pathways dominating in different contexts, complicating both measurement and modeling (Hensen et al. 2013).

A lack of market demand has further limited investment in cost-effective, standardized instruments and in the creation of benchmark datasets. Long-term N_2O measurement sites remain scarce, with only 17 operating across the United States today.

These converging technological and market developments provide an opportunity to chart a coordinated path forward. This roadmap outlines priority innovations needed to advance agricultural N_2O MMRV, drawing on the collective expertise of the N_2O research community.

How Do We Benefit from Improving N_2O MMRV?

Reducing farmer input costs and public remediation costs

Measuring the magnitude, sources, and drivers of N_2O emissions enables farmers to optimize nitrogen use and reduce both private and public costs associated with nitrogen losses. Between 40–60 percent of applied nitrogen is lost to the environment, with a significant portion leaving as gaseous emissions (Griesheim et al. 2019; Gardner and Drinkwater 2009). Gaseous N losses are some of the most difficult N loss pathways to quantify but can represent a major portion of a farm's climate and health externalities (S.-Y. Pan et al. 2022). Variations in fertilizer prices and risk-based overapplication exacerbate these losses (Houser 2022; Rosas et al. 2015). A 2025 estimate showed that 91 percent of the agriculture sector's crop-related emissions are as nitrous oxide from excess nitrogen application (Congressional Budget Office 2025). As commercial and regulatory incentives for managing these N_2O externalities continue to evolve (WRI & WBCSD 2026), the importance of understanding and being able to quantify them increases.

Some farmers are attempting to reduce N_2O emissions by modifying management practices, but practice impacts vary across regions and crops, and a one-size-fits-all approach is insufficient. Robust N_2O MMRV would build confidence in practice outcomes and improve decision-making support tools. This in turn would increase economic opportunities (such as Scope 3 incentives) for farmers, provide a concrete return on practice investments, and improve on-site decision making to build resilient, adaptable farms.

Increasing trust and credibility in carbon and nitrogen emission programs

Improved N_2O MMRV can enhance trust among farmers, companies, and the public in emerging climate incentives and supply-chain decarbonization programs. Many soil carbon schemes rely on the adoption of practices that may increase N_2O emissions even as they increase soil carbon. Accurate N_2O accounting strengthens the credibility of these systems.

Multinational companies require reliable N_2O estimates to meet climate goals. Enhancing site-specific models, improving their sensitivity to local conditions, and reducing the burden of data collection for farmers would remove a major barrier to scaling emissions reporting across supply chains.

Investing in N_2O MMRV establishes the rigorous evidence base for incorporating N_2O emissions reductions into existing climate programs. Enhanced N_2O measurement capabilities can also improve future sustainability frameworks, including ecosystem service markets. These improvements can expand revenue opportunities for growers, reduce the risks associated with adopting new practices, and more directly align Scope 3 decarbonization investments with emissions sources within production systems.

Driving more outcome-focused research and development

Developing technologies to reduce agricultural nitrogen losses depends on clear evidence of performance to attract customers, secure investment, and drive continued innovation. Improved N_2O MMRV establishes the baselines needed to evaluate and compare product impacts. Emerging solutions, including slow-release fertilizers, nitrification inhibitors, enhanced-efficiency crops, and biofertilizers, require substantial investment to develop and adapt to diverse conditions. Robust N_2O measurement makes it more feasible for climate and nitrogen use efficiency returns on these investments to be credibly quantified. Better MMRV also helps identify unintended effects of these technologies on nitrogen cycling, guiding product refinement.

Strengthening N_2O MMRV can additionally accelerate market growth for technologies that reduce nitrogen losses. Adoption of novel fertilizer technologies has historically been slow, partly due to uncertainty about whether benefits will materialize on a given farm. Demonstrating verified N_2O reductions of a particular technology against a baseline provides the clarity needed to meet producer, regulatory, and market expectations, ultimately improving confidence and increasing adoption. While new technologies to provide these measurements continue to appear on the market, generating robust evidence to support N2O emissions reduction claims via field trial measurements remains expensive and time consuming.

Better targeting interventions for public health and wellbeing

Rising N_2O emissions and their impact on the environment impose significant public costs, including climate effects, environmental degradation, and associated health risks. Reducing N_2O emissions is frequently intertwined with improving overall nitrogen use efficiency when designing interventions to reduce public health harms caused by nitrogen waste.

Excess nitrogen can enter waterways, contaminate drinking water with nitrates, exposure to which has been linked to cancer, birth defects, and other health impacts. N_2O contributes to stratospheric ozone depletion, increasing exposure to harmful UV radiation, and can elevate risks of skin cancer and cataracts by up to 7 percent (UNEP 2024). A recent long-term study linked elevated nitrate exposure in drinking water in the U.S. Midwest to a 73 percent increase in cancer likelihood (Mendy and Thorne 2024). These combined environmental and health burdens potentially cost the public up to $210 billion per year (Sobota et al. 2015). To ensure that public investments in N_2O emissions reductions intended to improve public health outcomes are effective, it is essential to understand current N_2O emission levels and track how they respond to relevant policy interventions over time.

Example Use Cases for Agricultural N_2O MMRV

Accurate N_2O measurement must be matched to its purpose. Different end users require different levels of accuracy, scale, and statistical rigor, depending on how measurement informs decisions. Three use cases—**Voluntary Offset Markets**, **Corporate Supply-Chain Emission Management**, and **Alignment of Incentives and Regulations with Practices**—illustrate why specific improvements in N_2O MMRV are necessary.

Key Takeaway: End user needs directly motivate the development of next-generation N_2O MMRV tools (i.e., more scalable measurement technologies, improved regionalized models, and rigorous statistical frameworks that align measurement strategy with end-user decisions). Better N_2O data are a key decarbonization lever that incentivizes product innovation by the input provider, the grower's desire to increase operational robustness, and the Scope 3 mandates of the buyer, creating a net-positive outcome for the entire value chain.

Alignment of economic incentives and regulation with practices

N_2O management is a game of maximizing efficiency, compared with the uncertain ROIs of carbon sequestration or broad regenerative transitions under the current economic system**.** Current MRV (measurement, reporting, and verification) tools often rely on static **IPCC Tier 1 factors**, which assume that emissions are a linear function of fertilizer volume. Relying solely on these factors creates a productivity penalty: When relying on tools that use static IPCC Tier 1 factors, the only way to lower field level N_2O emissions is to apply less product, a direct conflict for fertilizer producers and a yield risk for farmers.

By moving to high-fidelity measurement, sensing, and process-based modeling, we unlock another path:

- **For fertilizer producers:** Better data allow them to prove the efficacy of "premium" products (stabilizers, inhibitors, and controlled release) that reduce N losses without slashing sales volume. This protects margins while meeting decarbonization targets (Greene 2026).
- **For farmers:** Precision data removes the guessing game of nitrogen application. Instead of following generic mandates, farmers can optimize inputs based on real-time soil and weather data, improving **nitrogen use efficiency** and net profitability while minimizing the risks of total practice overhauls (AEM 2024).
- **For CPGs and food brands:** High-fidelity N_2O data allow for **environmental attribute certificates (EACs)** and shared-cost models where the financial benefit of a low-carbon product is distributed across the chain, de-risking the investment for any single entity (Bergmark 2026).
- **For policymakers:** Robust, shared N2O data can support public-private partnerships, designing fit-for purpose incentives, and grounded assessments of public spending efficiency.

Why N_2O MMRV improvement is needed:

The cost of relying on estimated data is rising. With the full implementation of European Union and California's climate disclosures in 2026, companies using generic emission factors will likely **misreport** their footprints, potentially leading to missed opportunities for emissions reduction or, if the regulatory environment strengthens, higher carbon taxes and lower market valuations. Precision modeling has been shown to reduce N_2O blind spots by up to **73 percent** compared with legacy models, turning a hidden liability into a bankable asset (Joshi et al. 2024).

Corporate supply-chain emission management (Scope 3)

Corporations sourcing agricultural commodities, especially manufacturers of consumer packaged goods (CPG), must quantify and reduce Scope 3 emissions across their supply sheds, the geographic regions from which they source raw materials, due in part to global regulations and consumer pressure.

Completeness of emissions accounting is often their biggest challenge, and currently N_2O is a major contributor to uncertainty relative to other sources (e.g., deforestation risk in beef systems).

Key end-user requirements driving MMRV needs:

- **Regionally accurate N_2O emission maps** (e.g., county-scale) to identify hot spots and prioritize interventions.
- **Models validated for local agronomic conditions**, enabling corporations to design sustainability programs that reliably reduce emissions.
- **Farm-level measurements** to demonstrate reductions in targeted programs, especially for externally funded or verified initiatives.
- **Integration with supply-shed data** (e.g., aggregated procurement flows) to link emissions to purchasing decisions.

Why N_2O MMRV improvement is needed:

Corporations increasingly commit to science-based Scope 3 targets. They need N_2O MMRV systems that produce actionable regional maps, quantify the effect of practice changes, and verify progress in demonstration projects without imposing high burdens on farmers or supply-chain partners.

Voluntary carbon offset markets

Project developers aggregate emissions impacts from many discontinuous farms and convert them into verified offsets for corporate buyers. These buyers pay a premium for accuracy because it reduces reputational risk and increases trust in long-term offtake agreements. Offsets are issued under tiered accuracy standards, from Tier 1 global emission factors to Tier 3 validated measurements, which include calibrated process-based models (e.g., DayCent). Tier 3 earns more offsets and drives market value, making improved measurement and modeling essential. However, being able to account for N_2O is a key gap in reducing the uncertainty of these model estimates.

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Key end-user requirements driving MMRV needs:

- **Program-level accuracy**, not single-farm accuracy, because offset units represent aggregated emissions across a heterogeneous set of fields.
- **Robust, regionally relevant models** capable of estimating N_2O emission impacts of farm practices.
- **Representative, scalable subsampling** to calibrate models without measuring every farm. Less accurate but scalable field-level measurement tools are valuable.
- **Statistical frameworks** to evaluate cost–accuracy tradeoffs and optimize sampling.
- **High field-count coverage**, because variation among farms dominates total uncertainty; more farms measured at moderate accuracy often produces better program-level accuracy than a few precise measurements.

Why N_2O MMRV improvement is needed:

The market financially rewards accuracy and penalizes inaccuracy through lower offset issuance. Developers must therefore improve the quality of models and the cost-effectiveness of farm-level measurement while reducing uncertainty to remain competitive.

What Kinds of Investments Are Needed to Advance N_2O MMRV and Modeling?

Top 10 Community-Consensus Priorities

1. **Build cheaper, more robust, and more portable sensors.**
   Engineering advances are needed to lower costs, increase instrument durability, and enable large-scale deployments. Opportunities include improved wireless communication, automated calibration, adaptive sampling based on environmental triggers, and lower-cost components that maintain data quality.
2. **Develop new ways of measuring N_2O.**
   Emerging technologies, such as active lidar, chemi-resistive sensors, plasmonic and nanomaterial-based detectors, and microelectromechanical systems (MEMS), could expand measurement capabilities and enable observations in challenging environments.
3. **Design multi-site measurement networks for improved coverage and benchmarking.**
   Coordinated networks would support efficient data collection and the creation of robust benchmark datasets for model development.
4. **Invest in quality assurance/quality control (QA/QC) for N_2O measurements.**
   Ground-based calibration and validation networks that feed into coordinated databases, particularly in intensive agricultural areas, can help generate higher-quality data products, improve satellite retrievals, and ensure data quality at multiple steps in the collection process.
5. **Connect N_2O measurements across scales.**
   Additional methods are needed to interpolate and extrapolate data, particularly chamber-based observations, to landscape-scale systems.
6. **Ensure collected data are usable in multiple ways.**
   Adopting semantics and ontologies aligned with FAIR principles (findable, accessible, interoperable, and reusable) will reduce bottlenecks in data sharing and enable richer, machine-actionable datasets for research and markets.
7. **Build data infrastructure to support broad use of N_2O data.**
   Sustained investment in data and model infrastructure, community coordination, and semantic resource development is critical.
8. **Get N_2O data into the hands of modelers and technical assistance providers.**
   New protocols and pipelines are needed to integrate observational data rapidly and reliably into nitrogen and GHG models.
9. **Improve models through intercomparison.**
   Regular, coordinated model cross-validation is essential for global assessment and for building trust in N_2O MMRV frameworks.
10. **Combine process models with machine learning.**
    Integrating the domain knowledge inherent in process models with machine learning architectures can improve model accuracy, interpretability, and robustness while reducing dependence on large datasets.

Call to Action

Improving agricultural N_2O MMRV offers substantial economic, agronomic, and climate benefits. Recent advances in sensing technologies, data infrastructure, and modeling now make it feasible to build the robust N_2O MMRV systems needed to integrate this greenhouse gas into emerging national and global monitoring and reporting frameworks. Achieving this requires coordinated progress on foundational measurement and modeling capabilities and stronger collaboration across research groups working at different scales and in different disciplines.

The field is well positioned to accelerate innovation. Strategic investment in the priorities outlined in this roadmap can strengthen coordination across the research and innovation ecosystem, including among public agencies, philanthropy, industry, and other nontraditional funders. This investment can also build capacity in organizations that translate research into practice and can enable partnerships that link scientific development with real-world deployment. Together, these efforts will ensure that N_2O emissions decline over time and that the benefits of improved nitrogen management are widely realized.

Sensors

Why do we need to advance sensor and platform design?

Well-designed, cost-effective sensors and flexible deployment platforms are essential for measuring and monitoring agricultural N_2O emissions. Historically, sensor systems have been tailored to a single spatial scale—farm, regional, or landscape—according to the research questions driving their development. Static (non-steady-state) chambers have been the predominant method for localized soil N_2O flux measurements since the mid-1980s. Tower-based systems (flux-gradient and eddy covariance), suitable for multi-field landscape measurements, became routine in the early 2000s with the availability of sufficiently fast and sensitive N_2O analyzers. More recently, researchers have begun deploying N_2O sensors on unmanned aerial vehicles (UAVs) and light aircraft to capture measurements at micro-regional scales. Satellite-based methods show promise for broad regional monitoring, though current instruments are not yet sensitive enough to detect small changes in lower-atmosphere N_2O concentrations.

Today's sensors provide useful data across multiple spatial scales and temporal resolutions but do not yet meet all research or operational needs. Many systems remain difficult to deploy on working farms, whether due to interference with field operations (e.g., flux chambers) or the fragility of sensors mounted on equipment. Improvements in sensitivity, accuracy, robustness, and deployment flexibility are needed to drive both routine monitoring and fundamental research into the drivers of N losses, including N_2O emissions. These improvements will also enable better process-based and hybrid modeling.

In summary, advances across sensor types and platforms, from improved data transfer in chamber systems to experimental instruments using advanced materials or spectroscopic techniques, would expand the quality and coverage of N_2O data. Some opportunities apply across measurement types, while others are specific to platforms and spatial scales.

Improving chamber-based measurements

Most soil N_2O flux measurements rely on non-flow-through static chambers because they are affordable, easy to use, and adaptable to many field conditions (De Klein et al. 2020). Chambers typically measuring less than 0.5 m^2 are inserted into the soil, sealed, and sampled over short periods to quantify headspace N_2O accumulation (Clough et al. 2020). This approach is valuable for detecting treatment differences and assessing spatial heterogeneity.

However, static chamber measurements are labor intensive and must be repeated frequently—weekly for long-term studies, or more frequently after events such as fertilization. Their small footprint and low sampling frequency limit their ability to capture the high spatial and temporal variability of N_2O emissions, including short-lived high-flux hot moments at localized hot spots where most N loss to emissions occurs (Wagner-Riddle et al. 2020; Anthony and Silver 2021; Lawrence et al. 2021; Molodovskaya et al. 2012; Parkin and Kaspar 2006; Scanlon and Kiely 2003).

Automated chamber systems address some limitations by enabling long-term, near-continuous sampling, but they remain costly. Their deployment is constrained by limits on the maximum distance between chambers and analyzers (~50 m), high power requirements, and impacts on field operations. Research groups are developing new sensor types, such as laser-based or electrochemical devices operating at chamber scales, while others are improving chamber engineering to enhance data transmission, robustness, and deployment flexibility (Bandara et al. 2021; Milam-Guerrero et al. 2022). Advancing both existing and new systems in parallel will accelerate the availability of fit-for-purpose instruments, especially those suitable for operational use beyond research stations.

How important is the detection of "hot spots and hot moments" for effective monitoring of N losses as N_2O emissions?

Scientific research shows that on an annual basis, most N_2O emissions are concentrated during a few days of the year following specific weather or management events such as fertilization, freeze-thaw, and specific summer precipitation (Molodovskaya et al. 2012; Parkin and Kaspar 2006, Scanlon and Kiely 2003)

The moment matters: One key study found that the top ~1 percent hottest moments contributed ~45 percent of the total mean annual N_2O losses (Anthony and Silver 2021).

The place matters: Another key study found locations with moderately to very poorly drained soils (which cover half the U.S. corn belt) have mean N_2O emissions that are two times those with well-drained soils when managed under corn-soybean rotations (Lawrence et. al 2021).

In short: To understand N_2O emissions and their links to agricultural practices overall, we must understand hot spots and hot moments. This implies that sensors and sensor networks should be designed to capture hot spots and hot moments, as well as baseline levels.

Key Takeaways

- Chamber-scale measurements are critical for identifying drivers of agricultural N_2O emissions and informing best management practices.
- Novel low-cost, low-power analyzers would improve the ability to conduct N_2O MMRV, especially in understudied systems.
- Alternatives to traditional chambers are emerging but not yet widely used.
- Open-source sharing of designs, firmware, and protocols can reduce barriers to global adoption and enable collaborative improvement.

High-value opportunities for improving N_2O chamber-based sensors

- **Targeted research investment:** Develop advanced sensing materials, e.g., metal-oxide semiconductors, nanomaterials (carbon nanotubes, graphene), and novel polymers, to improve N_2O sensitivity and selectivity while potentially reducing cost and power requirements (Zimbron et al. 2025).

Four sampling chambers connected to a long-term automated and solar-powered flow-through-chamber system that simultaneously measure carbon dioxide (CO_2), methane (CH4), and nitrous oxide (N_2O) concentrations multiple times per day.

- **Targeted research investment:** Advance chemi-resistive, plasmonic, and optical nanomaterial–based sensors to create inexpensive, sensitive, and robust alternatives for challenging agricultural environments (Milam-Guerrero et al. 2022).
- **Targeted research investment:** Engineer miniaturized N_2O sensors using MEMS and integrated components to reduce cost, size, and power needs, enabling incorporation into wireless networks for high- frequency distributed measurements (Bandara et al. 2021; O'Connell and Osmond 2022).
- **Research translation investment:** Improve low-power open-path and non-dispersive infrared (NDIR) sensors for long-term use in remote agricultural settings.
- **Research translation investment:** Integrate self-diagnostics and wireless calibration to enhance reliability and reduce maintenance.
- **Research translation investment:** Combine low-power wireless protocols (e.g., LoRaWAN, mesh networking) with sensors to enable scalable, low-cost monitoring networks.
- **Research translation investment:** Develop firmware that integrates sensor data with machine-learning models and farm-management platforms for more actionable outputs.
- **Research translation investment:** Engineer chambers that adjust sampling intervals dynamically based on environmental triggers (e.g., rainfall, fertilization) to optimize informational value and cost effectiveness (Lawrence and Hall 2020).

Costs of Chamber-Based Measurements

As of 2025, automated N_2O chambers can cost up to $7,000 per unit (Emily Stuchiner, pers. comm.), and the laser-based instruments required for in situ quantification can cost as much as $85,000 (O'Connell and Osmond 2022). These high costs make it difficult to deploy enough chambers to capture spatial and temporal variability in fluxes. Automated systems also require reliable power, and extending power to remote fields—or installing sufficient solar capacity—can be logistically challenging.

Efforts to reduce costs, sampling intensity, and operational complexity are therefore critical for scaling up N_2O data collection. Corteva Agriscience, for example, is developing an Automated Bulk Sampling System (ABSS) that runs on remote solar power and collects consolidated air samples from open and closed chambers into two bags over a two-week period. These systems are substantially lower in cost (~$1,200), require minimal infrastructure, and produce a manageable sampling frequency. Experimental approaches using sorbent-stabilized large-volume (400 mL) gas samples collected after a 30-minute static chamber deployment also show promise, reducing the need for multiple concentration measurements to calculate fluxes (Zimbron et al., 2025). Such emerging methods may improve affordability and usability, supporting broader spatial and temporal coverage of N_2O flux measurements.

Improving tower-based measurements

Tower-based systems are the primary tools for estimating total N_2O emissions from agricultural practices at multi-field scales (10 m–1 km) at intervals of ~30–120 minutes. They provide integrated spatial and temporal coverage and are less sensitive to localized variability than chambers. Continuous measurements across seasons enable accurate quantification of annual emissions.

The eddy covariance (EC) and flux-gradient (FG) methods are most commonly used. Both employ similar analyzers and provide comparable flux measurements (Brown et al. 2024). The FG method can be deployed flexibly, including in multi-plot configurations, where a single analyzer can monitor up to four large fields every half hour (Brown and Wagner-Riddle 2017; McMillan et al. 2014). FG systems have also been modified with low-power components to enable deployment outside research stations.

By contrast, EC systems generally require high-power, closed-path analyzers, limiting their deployment to sites with robust power access. Open-path EC sensors under development could enable off-grid operation by eliminating the need for external pumps (Valiunas et al. 2016; D. Pan et al. 2022).

An Eddy Covariance (EC) tower measuring carbon dioxide (CO_2) , methane (CH4), nitrous oxide (N2O) and water using two different analysers for comparison.

Costs of tower-based measurements

Eddy covariance and flux-gradient tower-based N_2O monitoring systems face cost and logistical barriers when one considers scaling up their deployments. Common associated costs include purchase of land, tower construction, installation of power if not already available, and instrumentation. In 2007, the IPCC estimated the costs of an eddy covariance system at $50,000, exclusive of land purchase. While tower-based methods offer spatial integration and high temporal resolution, their high cost limits the ability to conduct side-by-side comparisons across multiple fields with different management practices.

The costs associated with permanent measurement sites such as those used for regional tall towers, which have the potential to provide long-term records of atmospheric concentrations, are even higher. Consequently, tall towers equipped with instrumentation to characterize N_2O are limited to a small number of locations.

Key Takeaways

- Tower-based systems provide integrated measurements suitable for assessing total emissions from agricultural management practices, but they are less sensitive to local variability (hot spots and hot moments).
- Deployment is limited by equipment cost, power requirements, and operational complexity.
- Expanding use of both EC and multi-plot FG systems, especially when colocated, will improve comparability and support large-scale data collection.

High-value opportunities for improving N_2O tower-based sensors

- **Research translation investment:** Reduce equipment cost through engineered low-cost manifolds, Pi-based multiplexers, and low-power pumps.
- **Research translation investment:** Develop higher-precision multi-pass analyzers for detecting very small emissions (~<20 nmol m^{-2} s^{-1}), supporting more detailed quantifications to examine diurnal patterns or background measurements.

- **Research translation investment:** Create standardized EC instrument kits optimized for minimum flow restrictions and rapid sample delivery.
- **Research translation investment:** Reduce power requirements and enable low-power remote data transfer for both EC and FG systems.
- **Research coordination investment:** Expand training and develop more user-friendly equipment to address shortages of skilled technical staff.
- **Research translation and operationalization investment:** Further developing low-power open-path N_2O sensors and NDIR systems to enable long-term deployments in remote agricultural settings.

Improving aircraft-based measurements

Aircraft-based N_2O sensors enable flexible, high-resolution measurements across large geographic areas, including remote locations. Low-altitude in situ sampling (typically ~200–2,000 ft.) provides sufficient sensitivity to surface emissions and supports both in situ and remote sensing techniques (Wendisch et al. 2021).

Agricultural N_2O emissions are highly heterogeneous in space and time. Airborne sampling can provide averaged estimates over larger areas, with coverage on the order of hundreds of kilometers and sensitivity to both regional (10–100 km) and farm (~1 km) scales.

The number of airborne measurement campaigns focused on N_2O has been limited to date due to the challenge of resolving the relatively small changes in atmospheric N_2O concentrations. Historically, airborne campaigns used whole-air sampling for later laboratory analysis to overcome the difficulty of resolving small atmospheric N_2O signals in flight (Desjardins et al. 2010; Kort et al. 2008). Advances in mid-infrared lasers and spectroscopic instrumentation now support continuous, high-precision in-flight N_2O measurements (Xiang et al. 2013; Gvakharia et al. 2018; Eckl et al. 2021; Herrera et al. 2021; Dacic et al. 2024).

Examples of How Airborne N_2O Sampling Supports Emissions Quantification Across Scales and Methods

Transport Modeling:
Discrete, aircraft-based flask samples of N_2O concentrations, combined with atmospheric transport models, were used during the COBRA-NA (CO_2 Budget and Regional Airborne–North America) campaign to link observed atmospheric changes to national- and regional-scale surface fluxes. These data helped evaluate the accuracy of national N_2O emission inventories (Kort et al., 2008).

Atmospheric Inversions:
Continuous, in situ airborne analyzers have supported regional atmospheric inversions, including those conducted in California's agricultural regions during the CalNex campaign (Xiang et al., 2013). Similar in situ measurements from the ACT-America (Atmospheric Carbon and Transport–America) campaign were used to estimate regional N_2O emissions in the U.S. Midwest (Eckl et al., 2021).

Mass Balances:
The FEAST (Fertilizer Emissions Airborne Study) campaign used an in situ N_2O analyzer to perform airborne mass-balance sampling over the Lower Mississippi River Basin (~100 km) and to quantify emissions from large fertilizer production facilities (Gvakharia et al., 2020).

Regional Flux Estimates:
The MAIZE (Measurement of Agriculture Illuminating Farm-Zone Emissions of N_2O) campaign used continuous, in situ N_2O measurements within a Bayesian inversion framework to estimate N_2O fluxes in Iowa at regional to multi-field scales (Dacic et al., 2024).

Airborne N_2O observations have also been combined with atmospheric transport modeling and inversion frameworks to estimate spatially resolved fluxes, for example using a Bayesian inversion framework to obtain ~2 km resolution estimates (Dacic et al. 2024). Despite this recent progress, airborne measurement remains challenging due to instrument sensitivity requirements and the demands of operating in dynamic flight environments. To enable further progress, the FarmFlux campaign, now in planning, will provide a large observational dataset of agricultural N_2O. This new initiative is important because it will support evaluation of model treatments, help constrain emission inventories, and further refine flux parameterization schemes. Subsequent modeling and synthesis with surface information will improve links between agricultural practices and impacts on air quality, climate, and ecosystems.

Key Takeaways

- Airborne N_2O sensing is an emerging technique useful for filling gaps in tower coverage, generating large-scale, high-resolution datasets, and providing flexible coverage.
- Continued investment in instrumentation and data-analysis methods is required to fully realize airborne sensing's potential for agricultural MMRV.

High-value opportunities for improving N_2O aircraft-based sensors

- Improve flight readiness of instrumentation through better vibration and thermal stabilization; electrical isolation; and reductions in weight, complexity, and power demand (Gvakharia et al. 2018).
- Increase sensor robustness and reduce form factor to support integration with a wider range of airborne platforms.
- Develop multi-species instruments to support holistic agricultural analyses (e.g., MIRO).
- Advance alternative technologies (e.g., active lidar remote sensing) to complement extractive sampling methods (Kiemle et al. 2024).
- Continue development of UAV-compatible N_2O sensors, including both onboard and remote-sensing approaches (e.g., ARPA-E SMARTFARM program).
- Improve methods for interpreting airborne N_2O data and determine what complementary datasets most enhance interpretability.

Looking to the future: Satellite-based measurements

Interest is growing in satellite-based platforms capable of providing large-scale N_2O measurements with the spatial and temporal detail needed by farmers, modelers, and policymakers. Broader-scale measurements could improve understanding of aggregated drivers of N_2O emissions and support decision making. However, detecting agricultural N_2O emissions from space is challenging: Concentration changes are measured in parts per billion, and N_2O absorption bands are weaker than those of CO_2 or CH_4. No current satellite instrument has the necessary sensitivity and precision.

Building Scientific Foundations

Several areas of prior research may accelerate development of satellite N_2O systems, including instrument and retrieval algorithm design, existing satellite sensors collecting data in relevant spectral bands, potential proxy indicators (e.g., NO_2), and long-term surface and airborne datasets for calibration.

Sensors and Algorithms for Satellite-Based Observations

Existing satellite systems have detected N_2O in the upper atmosphere using limb and solar-occultation sounders, and more recently through nadir TIR and SWIR instruments. TIR systems have limited near-surface sensitivity, while SWIR systems provide uniform column sensitivity but insufficient N_2O signal strength for current instrumentation.

New designs combining SWIR and TIR aim to detect small (~3 ppb) concentration enhancements at scales of ~7 km (Riaz and Sun 2025; Riaz et al. 2026) but are not yet tested. Instrument designs and modeling frameworks from missions such as MethaneSAT provide useful foundations. The algorithmic models developed to translate instrument signals and noise to emissions signals and noise for MethaneSAT may also provide a foundation for the design of N_2O models and N_2O remote sensing instruments. Existing satellites such as GOSAT-2 offer relevant spectral bands for conducting sensitivity studies and refining retrieval algorithms. Ongoing launches of satellite systems targeting GHGs may provide multiple opportunities for similar studies.

Calibration Data

Long-term, ground-based measurement networks, including those hosted by the National Oceanic and Atmospheric Administration (NOAA) and the Advanced Global Atmospheric Gases Experiment (AGAGE), provide extensive time series of N_2O concentrations that support calibration, validation, and inversion modeling. The NOAA network observations, for example, span more than 40 years (since 1980).

The N_2O measurements of discrete air samples from these networks are used in inversion modeling and global trend analysis (Nevison et al. 2018, 2023; X. Tian et al. 2023). Ground-based remote sensing stations equipped with Fourier transform infrared (FTIR) instruments, such as those in the Network for the Detection of Atmospheric Composition Change (NDACC), record partial or full column N_2O concentration. These stations provide time series data for trend analysis in the troposphere and stratosphere (Angelbratt et al. 2011) and for comparison and validation of satellite retrievals (Strong et al. 2008).

Over the past 15 years, there has been much progress that could drive forward satellite-based N_2O systems. Building on these elements, there is a challenging but feasible path for the design and operationalization of satellite-based N_2O sensors capable of supporting agricultural use cases.

Key Takeaways

- Satellite systems cannot yet detect low-level agricultural N_2O emissions, and data cannot currently inform practice or mitigation decisions.
- Substantial R&D investment is needed in instrumentation, algorithm development, and calibration networks to make satellite-based N_2O monitoring viable.

High-value opportunities for developing satellite-based agricultural N_2O sensors

- **Targeted research investment:** Develop high-resolution infrared spectrometers capable of distinguishing N_2O spectral features from overlapping signals.
- **Targeted research investment:** Advance atmospheric retrieval algorithms that account for atmospheric variability and surface reflectance.
- **Targeted research investment:** Create low-cost sensors for CubeSat constellations to enable high-frequency regional observations.
- **Research coordination investment:** Expand international calibration and validation networks across chamber, tower, and airborne platforms.
- **Targeted research investment:** Investigate proxy-based methods for inferring N_2O emissions from correlated satellite observations (e.g., NO_2 (Adams et al. 2026)).

Process-Based Models

Why do we need process-based models?

Robust N_2O inventories are essential for assessing the outcomes of mitigation strategies, designing effective policies, and supporting market-based incentives. However, constructing inventories solely from direct measurements is impractical, as doing so would require sampling across large areas and long periods.

Scaling up from site-specific measurements to broader estimates can be accomplished through a range of approaches, from simple empirical models to complex, process-based models. The latter are particularly responsive to management changes because they simulate the biological and chemical processes that drive N_2O emissions, rather than relying solely on empirical relationships or correlations. They excel at ecological simulation across spatial and temporal scales, and they can explicitly incorporate environmental drivers (e.g., soil characteristics, daily weather), land history (e.g., soil organic carbon stocks), and management practices (e.g., crop types, fertilization, cultivation) (Del Grosso et al. 2006; Deng et al. 2018; Hong et al. 2025; Thorburn et al. 2010; Giltrap et al. 2020). This capability makes them useful for comparing emissions reduction and mitigation strategies, such as conducting farm-level GHG accounting (e.g., USDA COMET-Farm™) or evaluating soil-based carbon removal potential under different conservation practices.

Types of Greenhouse Gas (i.e., Nitrous Oxide) Models (Giltrap et al. 2020)

Emission factor models estimate emissions using a conversion factor (e.g., the IPCC Tier 1 conversion factor for N_2O emissions from mineral soils, which is 1 percent of applied nitrogen) with varying levels of detail (e.g., IPCC Tier 1, Tier 2 estimates). They may not capture temporal fluctuations or the impact of various environmental factors.

Empirical equation models estimate emissions as a function of environmental factors (e.g., N input, soil water content, soil temperature). They may be easier to implement than process models but may not have high temporal resolutions (e.g., regression analyses).

Process-based models estimate emissions using dynamic simulations of complex biological and geochemical processes within an agroecosystem. While able to capture temporal trends and accommodate practice changes, they are highly site-specific and require large amounts of data and expertise for calibration (e.g., DNDC, DayCent, APSIM).

Machine learning models estimate emissions using a "top down" approach to analyze datasets using algorithms that can handle nonlinear relationships between many variables. They may be able to use complex patterns in datasets to predict variable N_2O fluxes/emissions, but the underlying processes used by the model may not be clear.

Process-based models can also serve as platforms for hypothesis testing in situations where observations are limited. For example, they have been used to compare carbon and GHG responses across compost C:N ratios and application rates to evaluate the mitigation potential of compost amendments in grasslands. These results can help identify where new experimental evidence is needed. The main constraints on certainty and reliability of these models (particularly for N_2O emissions) remain limited input data, the need to calibrate and validate models across cropping systems, and gaps in mechanistic understanding.

How do we improve process-based models?

Improved Data Collection and Coordination

The data requirement for process-based models are substantial. Using these models to estimate N_2O emissions requires that values representing specific agricultural systems be entered. These values can vary quite widely—consider, for instance, a no-till wheat field in Kansas versus a cover-cropped tomato field in California—and must be obtained from field records or through model calibration.

Current U.S. inventory efforts using process-based models, such as the annual agricultural soil N_2O inventory using the DayCent model, rely on N_2O datasets from only 75 sites to represent all U.S. agricultural lands. This limited information leads to large uncertainties, approximately ±30 percent nationally, and larger at subnational scales, because of insufficient data for calibration, validation, and uncertainty analysis. Reducing this uncertainty requires longer-term data collection across a wider range of sites (Crosetto and Tarantola 2001).

However, uncertainty cannot be reduced simply by collecting more N_2O measurements. Modelers also need detailed information on management and environmental conditions that drive emissions. Advancing model development requires coordinated efforts to gather continuous, long-term N_2O measurements across diverse spatial scales and cropping systems, along with metadata on land use, management, soils, and other environmental conditions. These data in turn helps improve understanding of how parameters influence model outcomes and supports more iterative model refinement.

Data Collection Need: Land Use and Management

Land use, management, and environmental data are critical both for model calibration and for improving how these models represent the underlying processes. Compiling this data at regional or national scales is challenging, but several datasets can help address gaps. For example:

- The U.S. National Land Cover Dataset and the NASS Cropland Data Layer enable reconstruction of recent land-use histories (Yang et al. 2018; Lark et al. 2017).
- Surveys such as the USDA Agricultural Resource Management Survey provide information on fertilizer rates, timing, types, and application methods (USDA-ERS 2026).
- Local monitoring programs, such as those run by the California Central Coast Water Quality Board, supply additional fertilizer use data (CCRWQCB 2026).
- Remote sensing products, including OpTIS, support tillage and cover crop characterization (Hagen et al. 2020).
- Collect Earth is an example of an open-source system for viewing and interpreting high-resolution satellite imagery that can support land use data compilation.

Data Collection Need: Coordinated, Continuous Observations

Calibrating and validating process-based models requires an adequate number of N_2O observations for the systems being modeled. Currently, most N_2O observation networks are fragmented, uncoordinated, and biased toward particular cropping systems and regions. The lack of coordinated observations is a major limitation, especially in developing countries, where survey programs are less comprehensive.

Expanding monitoring networks and harmonizing protocols across sites and scales are essential steps. Monitoring networks must be designed to capture the high spatial and temporal variability of N_2O emissions. Approaches such as dynamically adjusting sampling frequency in response to rainfall can help capture episodic emission events. Organizations can assist by maintaining data warehouses and tools that integrate disparate datasets.

Examples of Management and Environmental Data that Need to Be Collected

Land Management Data

Fertilizer rates and types

Fertilizer application methods and timing

Land use and cropping history

Tillage practices

Irrigation management

Drainage practices

Planting and harvesting practices and timing

Grazing regimes

Cover crop management

Amendments (e.g. biochar)

Environmental and Soil Data

Temperature

Precipitation

Humidity

Wind speed

Solar radiation

Soil texture

Soil bulk density

Soil and Water pH

Soil depth

Key Terms in N_2O Modeling

Model calibration assigns initial parameter values based on prior knowledge, runs the model, and adjusts parameters by comparing predicted outputs with field measurements. This process fine-tunes the model to local conditions and improves predictive accuracy.

Validation, after calibration, compares model results against an independent dataset to ensure the model is reliable and not over-fitted. Calibration and validation both require accurate, independent measurements across spatial and temporal scales. Once complete, uncertainty and sensitivity analyses can be conducted to quantify confidence in model predictions.

Uncertainty analyses evaluate how uncertainty in model inputs, parameters, and process representations (i.e. model structure) propagates to outputs, generating confidence intervals for estimated emissions.

Sensitivity analyses determine the relative influence of individual parameters on model outputs and their uncertainty, helping to identify which factors most strongly shape model behavior.

Improved data handling can further increase the usefulness of measurements. Cloud-native formats and data architectures now enable scalable storage; interoperability; and integration of geospatial coordinates, time series, and metadata. These formats allow N_2O flux data to be combined with management records, soil chemistry, meteorology, and remote sensing datasets. Automation of data cleaning, metadata validation, and quality control can help ensure datasets are FAIR (findable, accessible, interoperable, and reusable).

High-Value Opportunities to Improve Data Collection for Process-Based N_2O Models

- **Research coordination investment:** Greater community coordination around the placement and distribution of monitoring sites would improve data collection efficiency and support robust benchmark datasets. This includes conducting research on how to locate and design multi-scale agricultural N_2O monitoring networks most effectively, and coordinating the collection of practice and field metadata associated with emissions.
- **Research coordination investment:** Integration of nonagricultural N_2O monitoring efforts, including atmospheric inversion sites, ship-based observations, and other relevant datasets, would strengthen top-down and bottom-up modeling connections.
- **Research coordination investment:** Investments in international calibration and validation networks (tower, chamber, airborne campaigns) could help improve N_2O satellite retrievals over agricultural areas, enabling usable products derived from currently noisy measurements.
- **Research translation and operationalization investment:** Stronger integration of semantics and ontologies, aligned with FAIR principles, is needed to address real-world bottlenecks in data sharing and multi-model integration. Existing efforts, such as the Crop Ontology and repositories like AgroPortal and Planteome, cover only a fraction of N_2O-related processes and lack tight links to process-based model needs.

Improving Process-Based Models: Understanding How Soil Processes Work

Reducing uncertainty in process-based model outputs requires a better understanding of soil nitrogen cycling (Butterbach-Bahl et al. 2013; Wrage-Mönnig et al. 2018; Stuchiner et al. 2025). Recent research highlights the importance of processes such as freeze–thaw dynamics and enzyme kinetics in controlling N_2O emissions, but these are not yet well represented in models. Partitioning experiments that distinguish N_2O production pathways (nitrification versus denitrification), diffusion, and consumption across soil depths are particularly valuable for disentangling complex interactions (Vogel et al. 2024; Xing et al. 2023).

A key challenge is incorporating new scientific knowledge into models without making them so complex that they become harder to calibrate or less accurate. As the number of parameters increases, calibration often becomes more demanding. Model intercomparison studies can help reconcile different scientific perspectives and highlight the most important variables or relationships to consider.

Hybrid Modeling and Model Combination

Machine learning (ML) approaches are emerging as promising tools for mapping data gaps, filling in missing information, scaling observations, and identifying key drivers of episodic N_2O fluxes (Gnisia et al. 2025). Although ML models are generally less suited than process-based models for predicting the effects of novel management changes, they can excel at pattern identification across multi-scale datasets. Combining ML-driven methods with process-based models and leveraging the mechanistic understanding embedded in the latter can improve predictions of dynamic soil biogeochemical processes.

High-Value Opportunities to Improve Process-Based N_2O Model Development

- **Research coordination investment:** Because different regions use different models, cross-validation is necessary for global assessments, regional comparisons, and building confidence in N_2O MMRV frameworks. Coordinated community efforts are needed to repeatedly update and compare models.
- **Targeted research investment:** Methods that integrate domain knowledge from process-based models with ML architectures (e.g., KGML-ag) are needed to create models that are more physically realistic, interpretable, and less dependent on large observational datasets.
- **Targeted research investment:** As agricultural management and environmental conditions evolve, continued research is needed to refine process representations in models and compare predictions with measurements.

Scaling and Integration

Why do we need to integrate N_2O measurements across scales?

Connecting measurements across N_2O measurement scales is essential for understanding the impact of local interventions and for designing policies or market-based incentives that link these local actions to broader outcomes. **Total N_2O emissions at regional or global scales** indicate the cumulative impacts of rising or falling emissions, including effects on human health and climate. **Local emissions**, measured at subplot, plot, or farm scales, provide insight into how specific management practices influence regional nitrogen cycle dynamics.

Theoretically, a sufficiently large network of local measurements could reveal regional or global trends. In practice, however, deployment of local monitoring systems is limited by accessibility, cost, and logistical constraints. As a result, the number of monitoring sites will likely remain limited. Integrating multiple measurement techniques operating at different scales is therefore necessary to capture highly variable emissions events, scale those measurements to produce regional estimates, and connect total N_2O emissions with the management practices and environmental processes that generate them.

Cross-scale integration also strengthens our conceptual models of N_2O emissions by providing consistent checks and enabling continual refinement of model assumptions. Process-based modeling approaches producing estimates over wide areas require observations at multiple scales for inputs, calibration, and validation. Emerging hybrid machine-learning/process-based models are likely to increase this need. Measurements collected at tall towers or by aircraft benefit from co-located small-tower or chamber observations for calibration and validation.

More broadly, well-constructed cross-scale linkages allow assessment of whether new policies, management strategies, or technologies are achieving intended reductions in N_2O emissions and related nitrogen losses.

Why do we need to integrate management and environmental context data across scales?

Integrating agricultural N_2O measurements with data on management practices and environmental context is essential for accurate emissions accounting, targeted reductions, and effective policy development. Management decisions, including fertilizer type, timing, and rate; manure application; tillage; irrigation; crop choice; and cover cropping strongly influence N_2O generation and release. Without linking measurements to detailed management records, it is difficult to understand what is driving emissions or to optimize reduction strategies.

Today, gaps in management data remain a practical challenge. For instance, aircraft measurement campaigns often face mismatches between the scale of N_2O observations and the resolution of on-the-ground data such as fertilizer applications, which may be available only at coarse scales (e.g., county-level annual statistics) or at high resolution only for limited research sites.

Integrating N_2O measurements with data on local environments is also important. Soil texture, moisture, organic matter, temperature, and topography interact with management choices to control nitrogen transformations and emissions timing. High-resolution environmental monitoring is critical for interpreting when, where, and why emissions occur and for identifying hot spots or high-risk periods.

Integrating emissions, management, and environmental data in model estimates can reduce excess fertilizer use and lower N_2O emissions without major yield impacts. Such integrated data are also critical for evaluating the impacts of nutrient management regulations or incentives and for verifying reported emissions reductions. Integrating environmental and management data across scales is therefore as essential as cross-scale N_2O measurement in enabling practical agricultural N_2O MMRV and modeling.

What scales should be combined for integrated N_2O MMRV?

Coordination across measurement scales supports creation of robust cross-scale datasets that advance modeling, improve local decision support tools, and inform policy and industry practices. Critical measurement scales include:

Plot Scale:
High-frequency, high-precision chamber-based measurements can capture microscale heterogeneity, including hot spots and management-driven variability.

Field Scale:
Automated chambers and mobile sensor platforms (e.g., UAV- or tractor-mounted systems) can measure emissions across diverse portions of a field, identifying spatial patterns and emission gradients.

Landscape and Watershed Scale:
Eddy covariance towers, atmospheric laser imaging systems (e.g., ARPA-E's NitroNet), and distributed sensor networks can provide continuous flux data over larger areas, linking field-level processes to regional variation.

Regional/Satellite Scale:
Remote sensing, atmospheric inversion modeling, and regional climate and crop models can support scalable aggregation for policy and MMRV. Future satellite-based N_2O measurements could provide an additional scale for comparison with regional models.

Why is cross-scale integration considered the most cost-effective approach to data collection today?

Chamber-based instruments remain essential for producing high-resolution N_2O flux data, but manual chambers are labor intensive and difficult to scale. Even with the adoption of automated chambers since the early 2000s, operational complexity, cost, and field logistics continue to limit broad deployment. Likewise, tower installations and aircraft-based measurements provide valuable insights but come with substantial capital and operational expenses.

Coordinated measurement campaigns that combine instruments across multiple spatial scales currently offer the most efficient way to expand coverage and improve data representativeness. By integrating complementary methods, these campaigns reduce per-site cost and help avoid logistical constraints associated with any single technology. Continued research to lower instrument costs, enable long-duration remote operation, and expand deployment options will further enhance the efficiency and practicality of large-scale N_2O monitoring.

Figure 1: Different instrumentation operates at distinct measurement scales. Each system has advantages and limitations, collectively providing insight into agricultural N_2O emissions and their drivers.

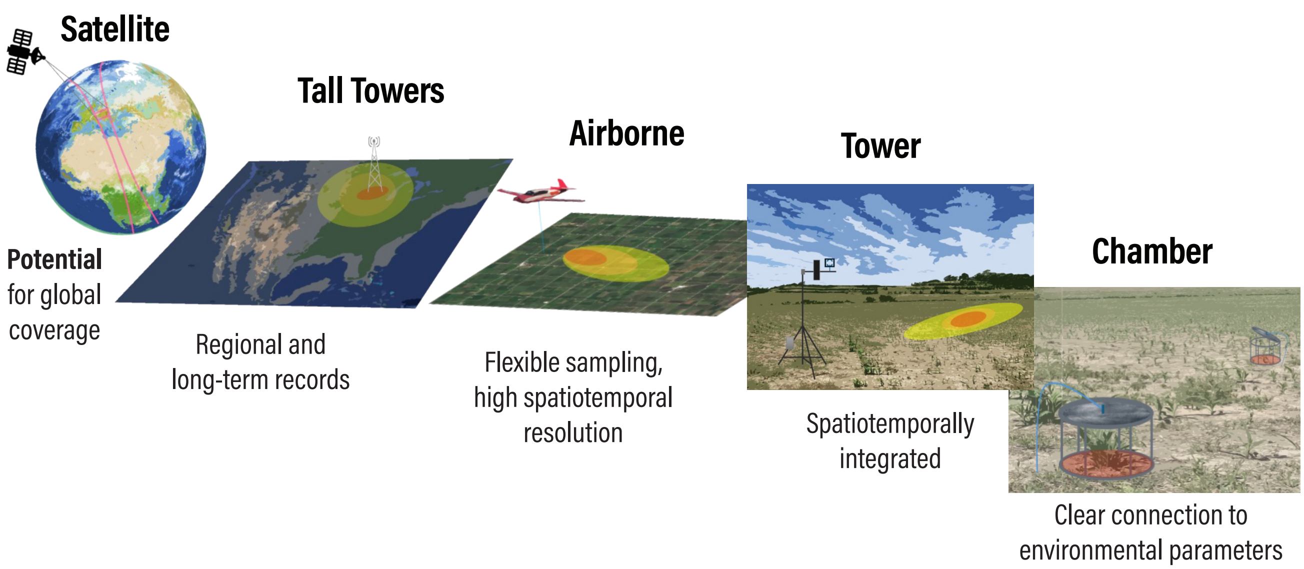

Table 1: A comparison of the strengths, weaknesses and applications of measurement platforms across different measurement scales.

Measurement Platform	Spatial Resolution (typical)	Temporal Resolution (typical)	Strengths	Weaknesses	Key Applications
Chambers	Discrete points covering up to 50 m^2	Depends on the number of chambers	▪ Long-term record ▪ Clear connection to environmental factors and drivers	▪ Sparse geographic coverage ▪ Limited operation in winter ▪ Uncertainties due to the spatial heterogeneity of N_2O hot spots	Plot-scale comparisons, process analyses (e.g., linking microbial activity, environmental factors)
Eddy Covariance/ Flux Gradient	2 to 100 ha	30-minute measurement intervals, continuous	▪ Unintrusive, lower maintenance ▪ Spatially and temporally integrated	▪ Sparse geographic coverage ▪ Limited by analyzer power requirements	Quantifying total N_2O emissions over extended periods, field-scale treatment comparisons
Aircraft	1–100 km	1s -10s measurements typical	▪ High spatiotemporal resolution ▪ Efficient and flexible sampling of large areas ▪ Access to remote locations	▪ Temporal coverage limited to length of measurement campaigns ▪ Input data for models needed at different scales	Flexible regional assessment of farm-scale emissions under real-world conditions
Tall Towers	10 km^2 (for 100–200 m towers) up to 50 km or more in radius under favorable mixing conditions	Hourly averages and 1-minute summaries are common	▪ Aggregated spatial coverage ▪ Long-term record	▪ Limited local detail ▪ Complex Interpretation: Analysis requires sophisticated atmospheric modeling ▪ Potential urban/industrial noise ▪ High costs and demanding infrastructure requirements	Support regional assessment under real-world conditions
Satellite (under development)	Unknown	Unknown	▪ Potential for global coverage	▪ Still in the research and development stage ▪ Probable weaknesses include high noise levels and uncertainty	Coverage in data-poor regions, calibration of inversion models

Improving cross-scale and cross-domain coordination of measurements

Agricultural N_2O measurement remains fragmented, driven largely by individual research projects and a limited number of long-term monitoring efforts. Without interoperable, multi-scale data, there is a risk of underestimating or misallocating emissions and mis-calibrating models (*see section on process models)*, with implications for climate policy and market mechanisms such as carbon credits or sustainable supply chains.

Challenges are intensified by limited geographic coverage and data intensity. Gaps in spatial and temporal coverage constrain our understanding of emission drivers and reduce confidence that model outputs will be locally relevant. Coordinated, systematic data collection provides policymakers, farmers, and businesses with reliable evidence to target interventions, design incentives, and support environmentally responsible practices. Closer coordination between measurement efforts and process modeling research is essential to ensure that data and models are useful beyond research settings.

Stronger integration of management and environmental data would further enhance N_2O MMRV by linking emission rates more tightly to the factors that influence them. Currently, detailed management and environmental data are often obtained on a project-specific basis. While data collection is relatively straightforward on research farms, such data on commercial farms may be proprietary, commercially sensitive, or not routinely collected. Collaboration with data aggregators, decision support tool makers and development of privacy-preserving analytics environments (e.g., data clean rooms) could help address concerns around data ownership and control while still enabling analysis.

In addition, coordination around data types, collection practices, and metadata standards would accelerate integration of datasets and support efforts to link management-scale observations with larger-scale monitoring. Community consensus around good practices and shared data standards, as well as greater emphasis on data exchange and archiving in community repositories, would facilitate this integration.

Key Takeaways for Cross-Scale Integration of MMRV and Modeling

N_2O emissions vary widely by management practices, soil type, crop choice, and climate. Collecting coordinated, interoperable agricultural N_2O data across multiple scales is therefore essential for understanding true environmental impacts and informing decision making, yet this need remains insufficiently met today.

Practices that support cross-scale and cross-domain integration include:

- Combining automated and high-frequency manual chamber systems for plot- and field-scale measurements.
- Using eddy covariance and atmospheric optical/laser technologies for continuous, landscape-scale monitoring.
- Integrating remote sensing, mobile sensors, and data assimilation tools to link field observations with regional inventories and decision-support systems.
- Applying statistical and machine-learning approaches to interpolate and scale fluxes across gradients of management, soil, and climate.

Combined, these approaches support robust, verifiable, and actionable N_2O MMRV that meets scientific, regulatory, and sustainability needs.

High-Value Opportunities to Enable Cross-Scale and Cross-Domain Integration

- **Research coordination investment:** Improve community coordination around the siting and distribution of monitoring systems to enable efficient data collection and create benchmark datasets for process modeling. Research is needed to understand how to locate and design multi-scale agricultural N_2O monitoring networks most effectively.
- **Research coordination investment:** Integrate agricultural and nonagricultural monitoring networks (e.g., atmospheric inversion sites, ship-based datasets) relevant to constraining top-down modeling.
- **Targeted research investment:** Develop improved methods for interpolation and extrapolation of chamber-based data to link with tower-based measurement systems.
- **Targeted research investment:** Advance approaches that integrate process-based model knowledge with machine-learning architectures (e.g., KGML-ag) to improve interpretability, physical realism, and data efficiency.

- **Research translation/operationalization investment:** Build protocols and pipelines to move observational N_2O data into nitrogen and greenhouse gas cycle models rapidly and reliably to meet industry needs.
- **Targeted research investment:** Develop novel sensor deployment methods that can bridge scale gaps or provide more flexible placement to improve representation and coverage.
- **Research coordination investment:** Coordinate with nonagricultural N_2O monitoring communities to integrate additional datasets useful for constraining top-down modeling.

Advancing Data Infrastructure

Why do we need to advance data infrastructure?

MMRV systems, as well as modeling and decision-support tools, depend fundamentally on robust data infrastructure. By connecting field observations and information from primary literature to model projections and statistical outputs, data infrastructure forms the link between what we observe in the world and the tools we use to interpret those observations. It also has the potential to make large volumes of historical and contemporary data usable for MMRV, decision support, and basic research. However, this potential has often gone unrealized due to politically driven data siloing, the absence of shared vocabularies, and limited computational platforms to support analysis.

We live in an era of unprecedented data availability, and N_2O data are no exception. Observations used to estimate and predict N_2O emissions range from high-frequency sensors capturing short-lived emission hot moments to high-resolution satellite products tracking moisture hot spots. These remote and proximal sensors generate massive data streams (on roughly a terabyte scale), and managing such data has long been a focus of both industry and research communities. The high volume of data is not a solved problem, but it is relatively well scoped. However, agricultural N_2O estimation often requires combining these large data streams with sparse, heterogeneous observations about soil conditions and management histories when modeling, which introduces a different set of infrastructure challenges.

Diverse data require infrastructure focused on clearly naming observations, documenting methodologies, and describing relationships among observations. Even foundational terms, such as the definition of "forest", may be highly contested (Chazdon et al. 2016). To support this work, we need an N_2O ontology.

A common response to data diversity is the creation of templates or unified data models to harmonize inputs. However, such models are often too broad to be practical for specific data streams and too narrow to accommodate new observational methods. Existing systems such as the International Soil Carbon Network (ISCN3) illustrate both progress and persistent challenges.

Rather than a single data model, we need standard vocabularies, structured methodological descriptors, and formalized relationships between observable properties, captured in ontologies or knowledge graphs. Developing these semantic resources requires active partnership between ontological experts and the N_2O research community. It also requires collaboration practices that are uncommon in the N_2O field specifically and soil science generally. The required domain expertise is specialized and dynamic, meaning these resources must be maintained over time.

We therefore need both virtual and in-person venues where researchers, land managers, industry partners, and other stakeholders can work directly with knowledge engineers, facilitators, and community-development experts. Developing semantic resources in parallel with real data applications is essential to avoid misalignment between vocabularies and use cases. Ontology-building efforts in other fields show that lack of project success often stems from limited community adoption, insufficient long-term maintenance plans, or inadequate engagement. In contrast, this collective sense-making has successfully been done, or started at least, in organismal biology (Leonelli 2019), which provides an example approach.

Historically, semantic tools, such as keyword vocabularies used by repositories and journals (e.g., DataOne), have been designed to support data discovery. These tools help users locate related datasets but lack the methodological specificity needed for true data interoperability. Interoperability requires detailed information about how observations were made and clarity about their intended use, both of which determine whether data can be safely merged. **This calls for more precise, expert-driven vocabularies and hierarchical method descriptions.**

As data streams grow and diversify, they are being used to address increasingly complex questions. Process-rich models and AI are two complementary tools that must be extended into N_2O MMRV applications, and both depend on strong semantic resources.

Process-rich models require highly specific methodological descriptions, as these models encode scientific understanding of mass and energy fluxes using differential equations. Aligning model inputs with observations demands detailed knowledge of measurement methods.

AI tools benefit from structured relationships among observed properties. Knowledge graphs provide essential constraints that guide AI learning and improve interpretability. These graphs can be developed from the ontology-based semantic resources described above.

Semantic resources support not only data integration but also the connection of data to modeling and decision-support systems. However, tooling for semantic development, data access, modeling, and decision support remains challenging. Despite long-standing interest in integrated platforms for collaboration among field scientists, modelers, and decision makers, such platforms have been difficult to sustain (Arkin et al. 2018; Swetnam et al. 2024).

To advance N_2O data infrastructure, we need committed, ongoing support. Drawing on lessons from the broader research community, N_2O data workflows should distinguish among three stages: archived data, intermediate interoperable data, and fit-for-purpose data products (O'Brien et al. 2021), mirroring NASA's multi-stage data processing levels for satellite data. Each stage may use independent or integrated semantic structures, providing flexibility and future-proofing.

Data governance remains a key concern. Decisions about who can access which data, and under what conditions, are essential for trustworthy infrastructure. For N_2O MMRV, questions often involve geolocation protection and removal of personally identifiable information. Yet geolocation is frequently needed for linking field observations to satellite records. Potential solutions include data embargoes, geolocation-fuzzing algorithms, and trusted gatekeepers. Any credible infrastructure must clearly define access restrictions.

Key Takeaways

- We need semantic resources, including vocabularies, methodological definitions, and defined relationships among observable properties, to link data across sources.
- These semantic resources require new community structures for ongoing development and maintenance.
- Process-rich models require detailed methodological definitions, and AI systems benefit from structured relationships among observed properties.
- Full-stack data infrastructure, from source streams to decision tools, remains challenging, and N_2O MMRV efforts should collaborate with existing initiatives.
- Multiple established data-permission models must be incorporated into N_2O MMRV data governance.

High-Value Opportunities

- Develop robust, standardized methodological descriptions for data annotation.
- Define vocabularies tailored to specific use contexts, such as farmer-facing MMRV reports or policy-level executive summaries, and integrate them with data annotations.
- Build sustainable maintenance plans that incorporate community engagement, including research coordination, facilitation, and community management.
- Provide ongoing support for digital platforms used across the data-to-decision workflow, e.g. AgGateway, MODUS or the ADAPT-Standard.

Appendix A: High-Value Research Opportunities

Summary of High-Value Research Opportunities

This community-developed roadmap outlines 37 high-value opportunities for targeted research, research coordination, and research translation and operationalization across the agricultural N_2O MMRV and modeling domain. These opportunities reflect a consensus on where additional effort and investment are most likely to:

- advance fundamental understanding of nitrogen and N_2O dynamics in agricultural systems across local to global scales;
- build capacity to guide interventions using data-driven models; and
- provide reliable information to support policies on nitrogen management and N_2O emissions reductions.

Research Translation and Operationalization Investments

1. Further develop open-path N_2O sensors and NDIR systems optimized for low power use to support long-term deployment in remote agricultural settings.
2. Integrate self-diagnostic and wireless calibration capabilities to improve reliability and reduce labor-intensive recalibration requirements.
3. Engineer systems that combine low-power wireless protocols (e.g., LoRaWAN, mesh networking) with sensor hardware to support scalable, low-cost N_2O monitoring.

4. Develop on-sensor firmware that enables integration of N_2O measurements with machine-learning tools, environmental models, and farm management platforms, allowing data to be more immediately actionable.
5. Design chambers capable of dynamically adjusting sampling intervals on the basis of environmental triggers (e.g., rainfall, fertilizer applications) to optimize measurement cost and scientific value, especially for capturing episodic, high-magnitude N_2O emissions (Lawrence and Hall 2020).
6. Reduce the cost of tower-based data collection systems, currently a major barrier to wider agricultural N_2O monitoring. Key opportunities include lower-cost manifolds, microcontroller-based multiplexers, and low-power pumps that maintain required data quality.
7. Develop higher-precision multi-pass analyzers that exceed the performance of current closed-path commercial systems, enabling detailed quantification of small N_2O fluxes (e.g., <20 nmol m^{-2} s^{-1}) for studies of diurnal patterns and background conditions.
8. Create standardized instrument kits for eddy covariance systems to replace today's user-assembled approaches, emphasizing optimization of sample flow, pump performance, tubing length, and flow restrictions.
9. Reduce power requirements for monitoring systems to enable deployment in more remote settings and to support scaling for both eddy covariance and flux gradient approaches. Research is needed on low-power operation and remote data transfer.
10. Improve in situ airborne N_2O sensors by enhancing vibration and thermal stability; improving electrical isolation from aircraft electronics; and reducing instrument weight, complexity, and power needs, thereby strengthening performance under flight conditions.
11. Increase sensor robustness, and reduce form factors to enable easier integration into diverse airborne platforms.
12. Develop protocols and data pipelines that more rapidly incorporate observational N_2O emissions data into nitrogen and greenhouse gas models. Faster and more reliable data delivery is essential for industry-scale decision-support systems.

Research Coordination Investments

13. Develop sustainable maintenance plans for data and model infrastructures that include ongoing community engagement to update and refine semantic resources. Long-term support for coordination and community management is critical.
14. Integrate semantics and ontologies aligned with FAIR principles to address bottlenecks in data sharing and multi-model integration. Existing efforts (e.g., Crop Ontology, AgroPortal, Planteome) only partially cover N_2O process and emissions data and lack links to process-based models and field measurement methods.
15. Improve the consistency and quality of semantic information by developing robust method descriptions for data annotations and establishing vocabularies tailored to specific reporting contexts (e.g., farmer-facing MMRV reports versus policy-level summaries).
16. Strengthen integration of N_2O MMRV systems with broader greenhouse gas monitoring frameworks, including national inventories, international reporting structures, and carbon markets. Standardized interfaces and data exchange protocols would enable tighter integration across systems.
17. Enhance community coordination around the distribution and design of monitoring sites to improve data efficiency and support development of benchmark datasets for modeling.
18. Coordinate with nonagricultural N_2O monitoring efforts, including atmospheric inversion networks and ship-based measurements, to support top-down modeling applications.
19. Address shortages of trained staff capable of operating field equipment by supporting engineering research for easier-to-use systems and expanding training programs.
20. Invest in international calibration and validation networks (tower, chamber, airborne) to benchmark and enhance N_2O satellite retrievals, helping transform noisy measurements into usable agricultural data products.
21. Support model cross-validation initiatives across regions, recognizing that different models are used around the world. Ongoing model intercomparison is essential for global credibility and for benchmarking emerging models.

Targeted Research Investments

22. Develop advanced sensing materials, such as metal-oxide semiconductors, nanomaterials (e.g., carbon nanotubes, graphene), and novel polymers, to improve sensor sensitivity and selectivity, potentially enabling low-cost, low-power operation.
23. Advance research on chemi-resistive sensors and plasmonic or optical nanomaterials to develop inexpensive, robust, highly sensitive sensors suited for challenging agricultural environments, potentially reducing reliance on chamber-based methods (Milam-Guerrero et al. 2022).
24. Conduct engineering research to miniaturize N_2O sensors using MEMS and integrated components. Compact, chip-scale devices (Bandara et al. 2021) could reduce cost and power needs, supporting distributed wireless sensor networks.
25. Develop instrumentation capable of measuring multiple species (e.g., NH_3, CO_2) to support more comprehensive assessments of agricultural emissions (see MIRO).
26. Prioritize development of alternative sensing technologies such as active lidar remote sensors (Kiemle et al. 2024), which could expand airborne quantification capabilities beyond extractive sampling methods.
27. Build on early work (e.g., ARPA-E SMARTFARM program) to improve drone-based N_2O measurement systems, both for onboard instruments and remote sensing approaches. This would increase flexibility in airborne sampling.
28. Advance methods for interpreting airborne N_2O data by identifying complementary data sources that enhance interpretability, especially when field access is limited during airborne campaigns.
29. Improve satellite sensor design by enhancing high-resolution infrared spectrometers capable of distinguishing N_2O spectral features from overlapping gases and atmospheric noise.
30. Develop robust satellite retrieval algorithms that correct for atmospheric variability (e.g., humidity, temperature, aerosols) and surface reflectance to improve N_2O quantification across diverse agricultural landscapes.
31. Create low-cost, lightweight sensors suitable for deployment on small-satellite constellations (e.g., CubeSats) to enable high-frequency, regionally targeted N_2O observations.
32. Investigate proxy-based N_2O inference, identifying emissions that co-occur with N_2O and developing methodologies to derive N_2O estimates from satellite-based proxy measurements.
33. Develop improved methods for interpolating and extrapolating chamber measurements to reconcile them with tower-based observations and better understand scale relationships.
34. Conduct research on methods that integrate domain knowledge from process-based models with machine-learning architectures (e.g., KGML-ag) capable of identifying patterns in multi-scale observational datasets, enabling more interpretable and physically informed ML models.
35. Develop novel deployment methods for sensors on platforms designed to bridge current measurement scale gaps, increasing flexibility in sensor placement and improving representativity.
36. Continue advancing understanding of nitrogen cycle dynamics as agricultural practices and environmental conditions evolve, and improve their representation in process-based models through targeted research and model–measurement comparisons.
37. Design efficient tools to extract historically collected N_2O and management data from PDFs and other non-machine-readable formats, enabling reuse of legacy data.

Appendix B: Feedback from 2025 AGU Session

Sensors

What new technology is most needed to develop faster, better sensors?

L1: Reduced sensor power requirements

L2: Sensors capable of distinguishing N_2O production versus consumption in situ

L3: Lower-cost sensors

L4: Hyperspectral sensors

L5: Open-path sensors

L6: Increased cross-disciplinary collaboration

L7: Clearer articulation of use cases to engage external sensor and technology developers

L8: Higher temporal resolution

L9: Reduced deployment, setup, training, and removal time

L10: Improved wireless connectivity

L11: Sensors that can be more easily mounted on agricultural equipment

L12: Higher spatial resolution (airborne or satellite)

L13: Sensors that can also manage metadata—linking management data, soil temperature, and moisture with N_2O measurements

L14: Auto-calibrating sensors

L15: More portable/transportable sensors

L16: Sensors capable of continuous measurement to capture hot moments

Cross-Scale Calibration

What advances are most needed to improve cross-scale calibration?

L17: More stable, long-term funding sources

L18: Clearer leadership and organizational structure—potentially through a federal agency or neutral coordinating platform

L19: Increased community development via regular exchanges, networking, and workshops

L20: Better protection of intellectual property to reduce risk of scooping

L21: Stronger engagement and buy-in from farmers and landowners for measurements on working farms

L22: Improved coordination across geographies, climates, and sites

L23: Systematic coordination of sampling plans for long-term monitoring and modeling

L24: Integration of measurements across temporal and spatial scales

L25: Development of a large ground-truth management dataset

L26: Creation of a coordination network analogous to NEON

L27: Wider deployment of sensors capable of capturing long-term emissions

L28: Shared knowledge on priority locations for N_2O measurements

L29: Consensus on data standards, measurement protocols, and supporting infrastructure

L30: A robust framework for connecting measurements across scales

More Accurate Models

What advances are most needed to improve model development?

L31: Greater availability of observations and datasets—across more environmental contexts, with clearer definitions of needed data, including mechanistic data to support model development

L32: Clearer identification of data needs for present and future models, including ML-specific data requirements

L33: Better alignment of incentives for model development with academic tenure, promotion, and publication priorities

L34: Improved data standardization and quality control

L35: Increased dialogue with modelers regarding data use, including the value of small-scale measurements

L36: Greater model transparency and expanded availability of open-source code

L37: More multi-model intercomparisons and ensemble approaches to evaluate competing model structures

L38: Better alignment between model and observation scales

L39: More co-located N_2O and SOC (soil organic carbon) measurements

L40: Additional methods to quantify model uncertainty

L41: Expanded on-the-ground data collection in the Global South

L42: Ensuring that all N-transformation processes are incorporated in process-based models, including microbial pathways, diverse N_2O sources, and gas partitioning processes

L43: More models specifically designed to estimate emissions on working lands

L44: Integration of N_2O modeling with process-based models of other greenhouse gases and with atmospheric models

L45: More complete N mass balance datasets to support accurate N_2O estimates

Better Data Pipelines

What advances are most needed to improve data pipelines?

L46: Clearer articulation of what constitutes a large, useful dataset

L47: Clarification of data ownership—particularly for farmer-generated data

L48: More stable funding for data pipeline development

L49: Improved coordination

L50: More standardized and consistent data collection protocols

L51: Increased data transparency

L52: Stronger protections for data confidentiality, especially for farmers

L53: Protocols for combining datasets with differing levels of coverage

L54: Better integration of N_2O data into nationally determined contribution (NDC) estimates

L55: Increased visibility and appeal of data pipeline work to funders and the public

L56: Better alignment of data collection and modeling scales

L57: Improved usability of data for on-farm management decisions

L58: Integration of N_2O data with information on other nitrogen pollutants

L59: Expansion of an N_2O measurement network and pipeline similar to the one used in Canada

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