Environmental Science Advances

CRITICAL REVIEW

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Cite this: *Environ. Sci.: Adv.*, 2026, **5**, 941

Satellite remote sensing and artificial intelligence for livestock greenhouse gas benchmarking: measurement, attribution, and verification challenges

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Received 18th November 2025
Accepted 4th February 2026

DOI: 10.1039/d5va00425j

rsc.li/esadvances

Livestock agriculture contributes 14.5% of global anthropogenic greenhouse gas (GHG) emissions, yet current monitoring approaches carry 30–50% uncertainty, limiting credible mitigation assessment and carbon-market verification. This review synthesizes recent advances in satellite remote sensing and artificial intelligence (AI) for benchmarking methane (CH_4), carbon dioxide (CO_2), and nitrous oxide (N_2O) emissions from livestock systems. Drawing on an 80-study PRISMA synthesis (2019–2025), we evaluate detection capabilities, retrieval uncertainties, and algorithmic limitations that constrain operational deployment. Medium-resolution sensors such as TROPOMI enable regional CH_4 verification but cannot resolve individual farms, while high-resolution systems like GHGSat detect only the largest emitters. AI models achieve strong accuracy for well-characterized systems but degrade substantially when applied to novel practices or sparse datasets. N_2O remains effectively undetectable from space, creating persistent blind spots for 20–40% of livestock GHG footprints. We propose a hybrid multi-scale framework integrating top-down satellite observations, bottom-up process models, and AI-driven fusion to bridge facility-level management zones, satellite footprint scales, and national inventories. This integrated approach could reduce monitoring uncertainties to approximately 15–25%, enabling farm-level benchmarking and independent verification of mitigation actions. Using Canada as a case study, we outline measurement-monitoring-verification requirements necessary for transparent, policy-relevant pathways toward net-zero agriculture by 2050.

Environmental significance

Accurate livestock emission monitoring remains a critical bottleneck for agricultural climate policy. This review demonstrates how integrating satellite observations with AI algorithms can reduce inventory uncertainties from 30–50% to 15–25%, enabling farm-level benchmarking and independent verification of mitigation interventions. By identifying fundamental attribution challenges and validation gaps, we establish research priorities for transitioning from proof-of-concept demonstrations to operational measurement, monitoring, and verification systems essential for net-zero agriculture pathways.

1 Introduction

Global agriculture faces a dual imperative: reducing greenhouse gas (GHG) emissions while expanding production to meet projected 50% demand growth by 2050.[1,2] Livestock systems contribute 10–12% of anthropogenic emissions globally,[3,4] yet fundamental uncertainties in quantification constrain evidence-based mitigation. Current estimation methodologies, primarily IPCC Tier 1 and Tier 2 approaches rely on generalized emission factors applied to livestock populations, yielding uncertainties of 30–50% for enteric fermentation and 50–100% for manure management.[5,6] Such margins substantially exceed the 10–15% accuracy required for credible verification of mitigation interventions, carbon market participation, or farm-level performance benchmarking.[7,8]

Advances in satellite-based remote sensing capabilities offer potential pathways to reduce these uncertainties through independent verification of bottom-up inventory estimates. Medium-resolution instruments such as TROPOMI aboard Sentinel-5P provide daily global coverage at 5.5 km resolution, enabling regional-scale inverse modelling of atmospheric methane concentrations.[9,10] High-resolution systems including GHGSat detect individual facility emissions with spatial resolution of 25 m and sensitivity to sources exceeding 300–500 kg

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CH_4 per h.[11,12] Concurrently, artificial intelligence (AI) and machine learning (ML) methodologies demonstrate capacity to identify complex, nonlinear relationships between emission drivers and outcomes, integrating heterogeneous data streams including satellite retrievals, meteorological parameters, and farm management records.[13–15]

However, enthusiasm surrounding these innovations must be balanced by rigorous scrutiny of their detection thresholds, potential systematic biases, attribution complexities, and extrapolation uncertainties that collectively constrain their operational reliability. Three fundamental tensions underpin these limitations: (1) scale mismatches between facility (10^2–10^4 m^2), satellite (10^3–10^7 m^2), and regional (10^6–10^9 m^2) assessments;[16,17] (2) temporal sampling biases from cloud cover, solar angles, and tasking gaps that miss short-term emissions;[18,19] and (3) limited algorithmic transparency, where AI models lack mechanistic interpretability, undermining trust and regulatory confidence.[20,21] Table 1 summarizes the principal methodological weaknesses across inventory, satellite, and AI-based emission monitoring approaches.

Existing emission estimation methodologies further reinforce structural weaknesses that propagate through policy frameworks. IPCC Tier 1 approaches employ default global emission factors, yielding uncertainties exceeding 50–100% for key sources.[22] Tier 2 methods incorporate country-specific factors but assume that research station conditions represent commercial farm diversity, an assumption demonstrably violated by heterogeneity in genetics, nutrition, and management.[5,25] Tier 3 process models such as Holos enable scenario analysis but exhibit performance degradation of 30–50% when extrapolating beyond calibration conditions, particularly for novel mitigation technologies such as feed additives or precision feeding systems.[23,26]

Satellite remote sensing can complement these approaches but introduces new challenges. Atmospheric concentration enhancements observed by sensors reflect convolutions of emission spatial distributions, atmospheric transport processes, and instrument characteristics operating at fundamentally different scales. Inverse modelling approaches used to infer emissions from concentrations exhibit uncertainties of 30–60% even for well-characterized large point sources, driven by imperfect knowledge of vertical wind profiles, sub grid-scale turbulence, and boundary layer dynamics.[17,27] Furthermore, retrieval success rates of 20–40% over agricultural regions introduce temporal sampling biases, as observations disproportionately represent clear-sky, mid-day conditions during summer months.[18,19]

Artificial intelligence methodologies promise integration of heterogeneous data streams but face fundamental extrapolation limitations. Random forest and gradient boosting methods achieve $R^2 = 0.65$–0.80 for emissions from well-characterized systems but degrade to $R^2 = 0.40$–0.60 when applied to spatially or temporally independent test sets.[13,24] Deep neural networks require training datasets of 10^4–10^6 examples to achieve robust performance, yet agricultural emission measurements number only 10^2–10^3 well-characterized cases globally.[15] This data scarcity necessitates transfer learning, synthetic data augmentation, or physics-informed constraints, each introducing new uncertainties.

This critical review addresses five interconnected objectives that collectively advance understanding of agricultural emission monitoring systems:

(1) Evaluate satellite remote sensing capabilities, detection thresholds, and operational constraints across current and emerging platforms, synthesizing validation campaign insights and identifying scale-dependent biases.

(2) Assess artificial intelligence architectures for emission prediction, examining trade-offs between accuracy, interpretability, data requirements, and extrapolation capacity.

(3) Synthesize atmospheric inversion methodologies for top-down emission quantification, evaluating transport model uncertainties, prior specification sensitivities, and validation strategies against independent measurements.

(4) Identify critical bottlenecks in source attribution, spatial scaling, and uncertainty propagation that constrain integration of satellite observations with bottom-up inventory methods.

(5) Propose hybrid multi-scale benchmarking frameworks aligned with international measurement, monitoring, and verification (MMV) standards (ISO 14064, the GHG Protocol), using Canada as a representative case study while emphasizing global generalizability.

This synthesis advances the literature through three key contributions beyond existing reviews. First, it presents the first

Table 1 Methodological limitations in livestock GHG quantification

Component	Primary limitation	Manifestation	Implication
Tier 1 emission factors	Global defaults	Do not reflect regional genetics, diets, or management	Uncertainty >50–100% for key sources[22]
Tier 2 country-specific factors	Research station bias	Limited representation of commercial variability	Systematic estimation bias[5]
Tier 3 process models	Domain-specific calibration	30–50% performance degradation outside calibration conditions	Poor novel mitigation applicability[23]
Satellite remote sensing	Scale convolution and transport uncertainty	Complex inverse modeling required	30–60% uncertainty for large emitters[17]
Temporal sampling	Cloud cover, solar geometry, and tasking	Underrepresentation of episodic emissions	Incomplete temporal profiles[19]
AI/ML models	Data scarcity and poor generalization	R^2 degradation on test sets	Reduced regulatory robustness[24]
Algorithmic transparency	Black-box predictions	Limited mechanistic interpretability	Low stakeholder trust[21]

comprehensive integration of satellite remote sensing, artificial intelligence, and emission benchmarking explicitly tailored to livestock agriculture; while prior studies have examined these components in isolation,[9,14] none have assessed their combined potential for farm-level and regional-scale monitoring aligned with policy implementation. Second, it proposes a hybrid monitoring framework that directly addresses scale mismatch by combining high-resolution targeted observations, moderate-resolution regional verification, and AI-driven spatial downscaling. Third, it identifies critical research frontiers, including the establishment of permanent ground-based validation networks, the development of causal inference approaches for evaluating novel management practices, and robust uncertainty quantification frameworks that account for correlated errors, all of which are essential for transitioning from proof-of-concept studies to operational systems.

Beyond technical advances, the framework recognizes that emission monitoring raises significant ethical and societal considerations. Data accuracy and transparency have direct implications for farmers' economic outcomes, regulatory compliance, and market access, particularly for smallholder and disadvantaged producers. By integrating technical rigor with ethical responsibility, this approach emphasizes equitable, transparent monitoring systems that reward sustainable practices rather than disproportionately penalizing producers.

2 Review methodology

We conducted a systematic literature review following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines adapted for interdisciplinary technology assessment.[28] Literature searches were conducted across four complementary databases selected for disciplinary coverage: Web of Science Core Collection (multidisciplinary science and engineering), Scopus (broader coverage including conference proceedings), ScienceDirect, IEEE Xplore, and SpringerLink (full-text access to peer-reviewed journals), and Google Scholar (grey literature, technical reports and preprints). The core search strings were designed to capture three interconnected domains: satellite remote sensing technologies, artificial intelligence methodologies, and agricultural emission quantification:

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("satellite remote sensing" OR "TROPOMI" OR "GHGSat" OR "OCO-2" OR "OCO-3" OR "GOSAT" OR "Sentinel-5P" OR "atmospheric inversion") AND ("greenhouse gas" OR "methane" OR "CH4" OR "nitrous oxide" OR "N2O" OR "carbon dioxide" OR "CO2" OR "emissions") AND ("livestock" OR "dairy" OR "cattle" OR "poultry" OR "agriculture" OR "manure" OR "enteric fermentation") AND ("artificial intelligence" OR "machine learning" OR "neural network" OR "random forest" OR "deep learning" OR "prediction model")
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Additional targeted searches focused on specific platforms ('Carbon Mapper', 'MethaneSAT', and 'PRISMA imaging spectrometer'), AI architectures ('physics-informed neural networks', 'transformer models', and 'Gaussian processes'), and validation methodologies ('eddy covariance', 'aircraft campaigns', and 'controlled release experiments'). Searches were restricted to English-language publications and with no geographic limitations to capture global methodological advances.

Database search yielded 312 initial records (Fig. 1), ensuring thorough coverage of satellite remote sensing, AI/ML, and agricultural emission literature. After deduplication, 250 unique records underwent screening against six inclusion criteria: (1) publications from 2019–2025; (2) satellite remote sensing of agricultural GHGs; (3) AI/ML methodologies; (4) validation studies; (5) atmospheric inversion methods; and (6) livestock applications. Five exclusion criteria removed non-agricultural studies, theoretical proposals without validation, unrelated AI applications, pre-2019 publications (unless seminal), and unavailable full texts. Title/abstract screening excluded 128 records; full-text assessment excluded 23 additional studies (8 lacked agricultural specificity, 7 had insufficient methodological detail, 5 were superseded, and 3 were inaccessible).

The synthesis drew on 105 sources reflecting diverse evidence for satellite-based emission monitoring. Peer-reviewed articles (52, 49.5%) provided empirical foundations, including methodology, validation, and AI comparisons. Space agency reports (12, 11.4%) detailed instruments, algorithms, and orbital data. Government documents (10, 9.5%) linked findings to policies and IPCC/UNFCCC standards. Monographs (6, 5.7%) offered theoretical context on machine learning and remote sensing. Dissertations and preprints (15, 14.3%) captured emerging research. International organization reports (10, 9.5%) synthesized global emission data, while stakeholder reports (5, 4.8%) highlighted practical and farmer-centred insights. Classification as high rigor (4–5 criteria), moderate rigor (2–3 criteria), or low rigor (0–1 criteria) informed evidence weighing in synthesis (Table 2).

The quality-weighted synthesis emphasized validated concordance between satellite and ground-based emission estimates while the 2019–2025 timeframe captures transformative advances in satellite GHG monitoring capabilities. Sentinel-5P's TROPOMI began daily global methane mapping (<7 km) in 2019.[29] GHGSat's expanding constellation (2020–2024) achieved 25 m methane detection.[11] OCO-3 on the ISS complemented OCO-2's global coverage,[30] while GOSAT-2 reached full operational precision for CO_2 and CH_4 by 2019.[31] Simultaneously, AI evolved with transformers for time series (2020),[32] physics-informed neural networks for Earth systems (2021),[33,34] and foundation models for environmental monitoring (2023–2025).[35] This period marks the convergence of satellite capabilities and AI innovations critical to operational agricultural emission monitoring.

3 Global drivers and policy context for agricultural emission monitoring

International climate commitments under the Paris Agreement require Nationally Determined Contributions (NDCs) with

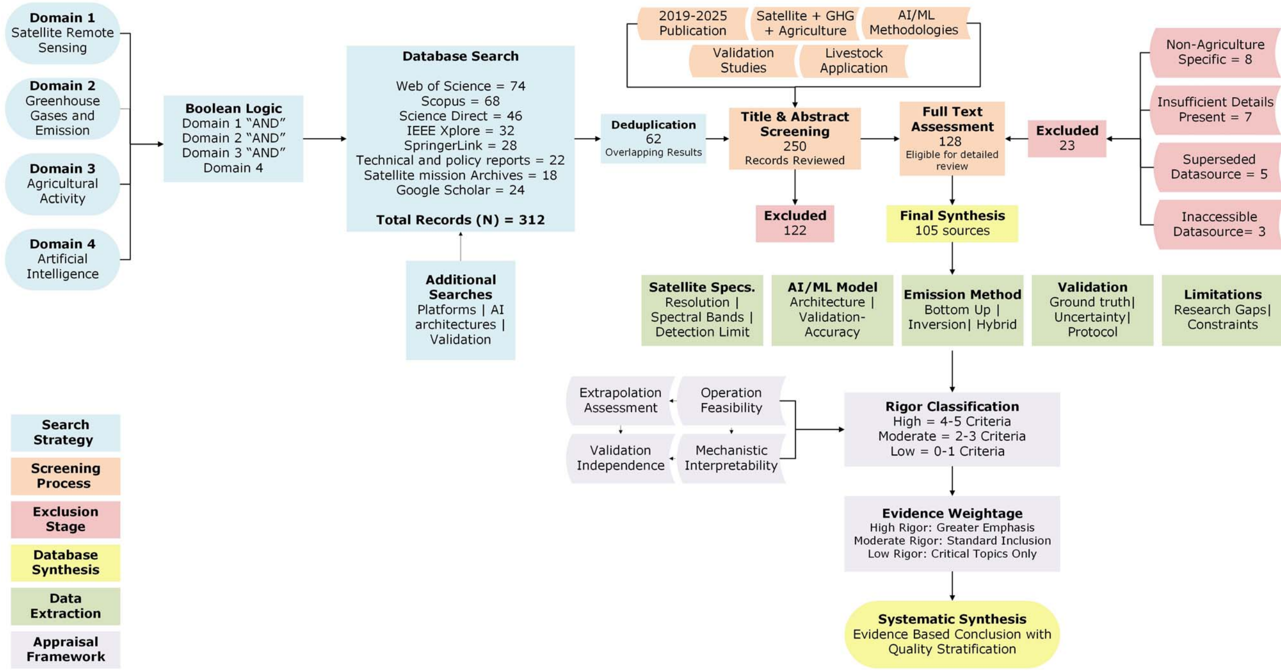

Fig. 1 Systematic review workflow: search strategy, screening criteria, and critical appraisal framework for AI-enhanced satellite remote sensing studies.

Table 2 Classification of included studies by the rigor level in the PRISMA-based systematic review

Rigor level	Criteria	No. of studies (*n*)	Percentage (%)
High rigor	Met 4–5 rigor dimensions; demonstrated strong validation, reproducibility, and transparent uncertainty treatment	72	68.6%
Moderate rigor	Met 2–3 dimensions; partial validation or limited transparency but relevant to synthesis	25	23.8%
Low rigor	Met 0–1 dimensions; exploratory or conceptual studies lacking empirical support	8	7.6%

transparent, accurate, and complete emission inventories.[36] Agriculture-specific emission reduction targets increasingly feature in updated NDCs as 119 countries included agricultural mitigation in their 2021–2023 NDC revisions, representing a 47% increase from initial submissions.[36] However, translating national commitments into verifiable farm-level actions requires monitoring systems operating at spatial scales (10^2–10^4 m^2) orders of magnitude finer than conventional inventory approaches (10^6–10^9 m^2). Fig. 2 synthesizes these interconnected policies, technical gaps, and market drivers, illustrating the timeline of regulatory developments, the spatial scale verification gap, and the growth of agricultural carbon markets.

The Global Methane Pledge, launched at COP26 (2021) and endorsed by 150+ countries, commits signatories to reducing methane emissions by 30% below 2020 levels by 2030.[37] Agricultural methane represents approximately 40% of anthropogenic methane budgets globally, with livestock systems contributing 32% directly through enteric fermentation and manure management.[38] Meeting pledge targets requires not only mitigation technology deployment but also verification systems capable of detecting emission changes at scales relevant to interventions. Current IPCC inventory methodologies cannot reliably detect changes less than 20–30% due to inherent uncertainties, creating a verification gap that undermines confidence in reported progress.[7]

3.1 Carbon markets and MRV requirements

Voluntary carbon markets have expanded rapidly, with agricultural carbon credits comprising 15–20% of total market volume in 2024, valued at approximately USD 400–600 million annually.[39] However, credibility concerns around additionality, permanence, and leakage have constrained market growth and reduced credit prices.[40,41] High-integrity carbon markets require measurement, reporting, and verification (MRV) systems achieving uncertainties less than 15% for individual projects, which is substantially beyond current capabilities for livestock emissions. The Science-Based Targets initiative (SBTi) for agriculture, launched in 2023, establishes verification protocols requiring independent third-party validation of emission reductions, creating demand for scalable monitoring

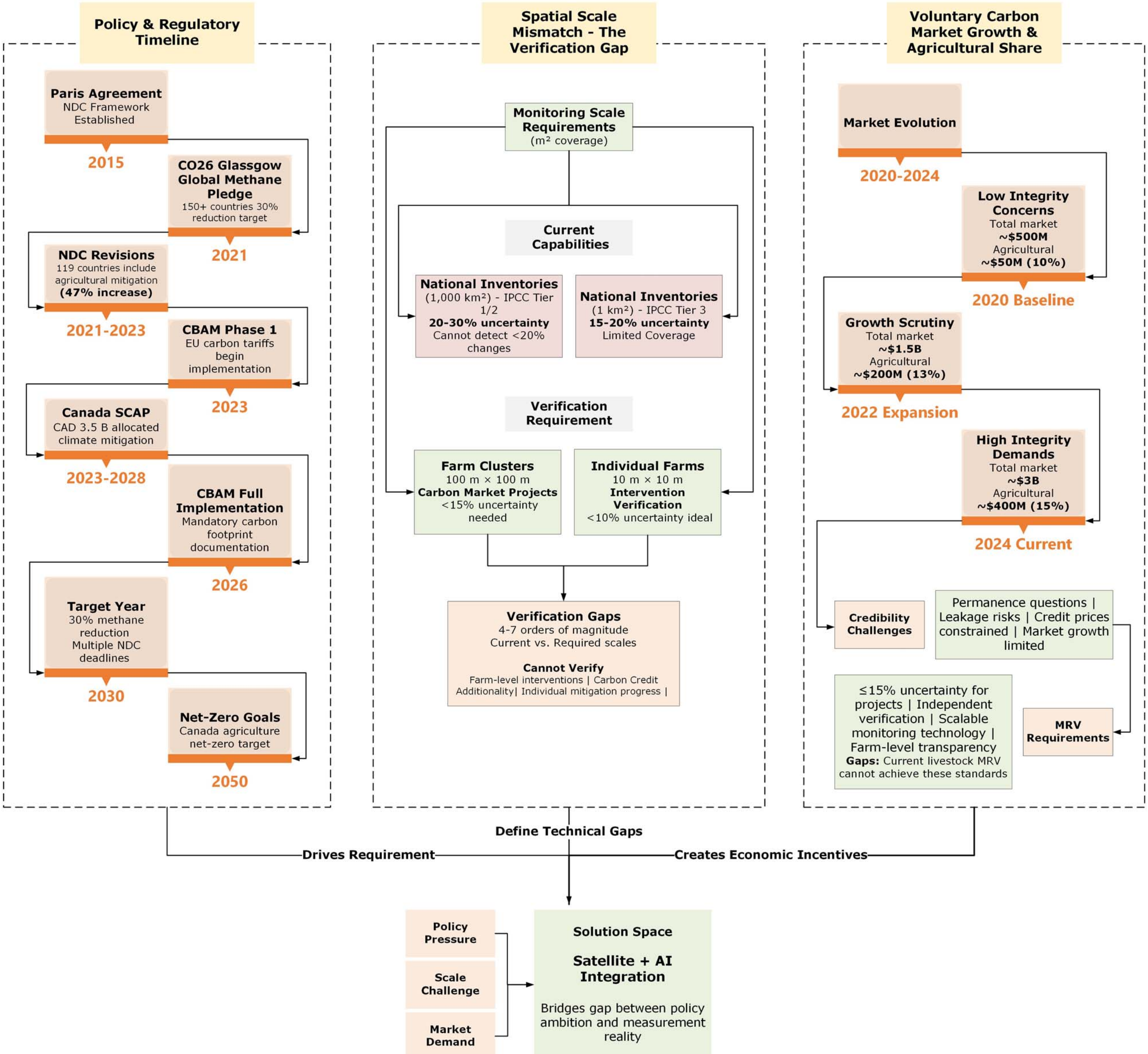

Fig. 2 Evolution of agricultural emission monitoring drivers: policy commitments, spatial scale requirements, and carbon market growth.

technologies that existing ground-based measurement approaches cannot economically provide at the farm-level.[42]

Regulatory frameworks increasingly mandate emission transparency. The European Union's Carbon Border Adjustment Mechanism (CBAM) phased implementation 2023–2026, imposes carbon tariffs on imported goods including agricultural products, with levy calculations based on embedded emissions.[43] Exporters face requirements to document product carbon footprints using methodologies compatible with EU standards, creating compliance burdens that disproportionately affect smaller producers and developing economies lacking sophisticated monitoring infrastructure. Similar mechanisms under development in Canada, the United Kingdom, and California establish a convergent regulatory environment where emission verification becomes a prerequisite for market access.[44]

3.2 Canadian context: a representative case study

Canada's agricultural sector committed to net-zero emissions by 2050 under the Sustainable Canadian Agricultural Partnership (2023–2028), allocating CAD 3.5 billion for climate mitigation and adaptation.[45] The sector currently emits approximately 73 Mt CO_2-equivalent annually, with dairy contributing 3.7% and poultry 1.2% of total agricultural emissions.[46] Canada's geographic concentration of livestock production with 66% of dairy in the Ontario-Quebec corridor and 35% of broilers in the Fraser Valley, British Columbia, creates favourable conditions for satellite-based monitoring where emission signals exceed detection thresholds through spatial aggregation.[47,48]

This production system structure is representative of moderate-intensity, spatially concentrated livestock agriculture found globally.[3] Similar production geographies and detection challenges exist in northern Europe (Denmark and the Netherlands), Argentina's pampas regions, parts of China, and India, supporting the generalizability of monitoring framework design principles across diverse agricultural contexts. While region-specific calibration remains essential, such spatial clustering creates favourable conditions for satellite-based detection, as aggregated emission signals are more likely to exceed instrument sensitivity thresholds.[9]

Yet Canada also exemplifies monitoring challenges facing moderate-intensity livestock systems globally. The average dairy herd size of 94 cows per farm falls below reliable individual detection thresholds for most satellite platforms. Climate extremes including winter temperatures reaching up to −40 °C and summer recording +35 °C introduce pronounced seasonal emission variability poorly captured by episodic satellite observations. Supply-managed production systems create regulatory environments favouring stability over rapid technological adoption, potentially slowing mitigation progress. Reconciling these realities with net-zero aspirations requires monitoring frameworks that acknowledge operational constraints while progressively tightening performance standards, a balance relevant to agricultural systems worldwide.[26]

4 Satellite remote sensing for greenhouse gas emissions in livestock systems

Satellite-based greenhouse gas observations have transitioned from research demonstrations to operational capabilities over the past decade, yet fundamental constraints limit direct applicability to agricultural emission monitoring. Multiple satellite platforms (Table 3) now provide complementary capabilities for monitoring methane (CH_4) and carbon dioxide (CO_2) concentrations, with emerging systems specifically designed for agricultural and point-source monitoring applications. This section critically evaluates platform capabilities across spatial scales, identifying detection thresholds, temporal coverage gaps, and retrieval uncertainties that shape integration strategies with bottom-up emission models.

4.1 Methane monitoring: TROPOMI and high-resolution systems

TROPOMI (TROPOspheric Monitoring Instrument) aboard Sentinel-5P represents the current benchmark for moderate-resolution methane monitoring, providing daily global coverage at 5.5 × 5.5 km native resolution (7 × 7 km pre-2019 upgrade) with a column-averaged dry-air mole fraction (XCH_4) precision of 0.6% (approximately 10–12 ppb).[19,57] This capability enables detection of regional emission enhancements from spatially aggregated sources exceeding approximately 5–10 tonnes CH_4 per day under favourable atmospheric conditions. Applied to livestock-dense regions, TROPOMI successfully identifies methane signals from clusters of large dairy operations, feedlots, and concentrated poultry production zones.[58] However, atmospheric transport rapidly dilutes point-source emissions across multiple TROPOMI pixels within 30–60 minutes, confounding source attribution and introducing systematic uncertainties in emission rate quantification through inverse modeling.[17]

Critical evaluation of TROPOMI agricultural applications reveals retrieval success rates of only 20–40% over mid-latitude regions due to cloud cover, aerosol interference, and unfavourable surface albedo.[18,59] This temporal sampling introduces systematic biases where observations disproportionately represent clear-sky, low-aerosol conditions that may correlate with meteorological factors such as temperature, humidity, and boundary layer dynamics, thereby affecting emissions. Validation against aircraft campaigns demonstrates a TROPOMI accuracy of 15–25% for regional emission totals but substantially larger errors (30–60%) when attributing emissions to specific source categories within heterogeneous agricultural landscapes.[60] Furthermore, TROPOMI cannot distinguish biogenic agricultural methane from fossil fuel or wetland sources without additional constraints from isotopic measurements or integrated emission inventory models.[58]

GHGSat's constellation with 25 m spatial resolution and detection threshold ∼300–500 kg CH_4 per h, enables individual facility methane monitoring for large livestock operations.[11,49] Validation studies using controlled release experiments demonstrate quantification uncertainties of 30–50% for emissions exceeding 500 kg CH_4 per h, improving to 20–30% for very large sources (>2000 kg CH_4 per h).[11] However, three fundamental constraints limit comprehensive agricultural coverage. First, tasking-based operations provide revisit intervals of weeks to months for individual facilities, precluding continuous monitoring or detection of transient emission events associated with manure agitation, spreading, or episodic storage releases. Second, detection thresholds exclude most small and medium-scale operations; for instance, a representative 100-cow Canadian dairy farm emits 50–100 kg CH_4 per h on average, which is below reliable detection limits.[58] Third, commercial data access costs per targeted observation constrain comprehensive monitoring to high-priority facilities, regulatory enforcement cases, or well-funded research campaigns.[49]

4.2 Carbon dioxide monitoring: challenges and context

Atmospheric carbon dioxide (CO_2) observations from OCO-2, OCO-3, and GOSAT-2 achieve a column-averaged precision of 0.5–1.0 ppm, theoretically sufficient for anthropogenic source detection given atmospheric backgrounds of ∼420 ppm.[30,31,50] However, the substantial biospheric carbon fluxes, comprising gross primary productivity and ecosystem respiration and typically ranging between 4 and 12 g C per m^2 per day across agricultural landscapes, exceed point-source anthropogenic emissions by one to two orders of magnitude, thereby obscuring direct facility-scale detection during the growing season.[61,62] Livestock-associated CO_2 emissions, which are primarily from energy use in housing, feed production, and manure treatment represent only 10–30% of total farm-gate carbon footprints, with the remainder attributed to biogenic sources and upstream supply chain emissions already captured through established accounting methodologies.[63]

Table 3 Satellite platform specifications and agricultural emission monitoring capabilities

Satellite platform	Spatial resolution	Revisit frequency	GHG detection threshold	Agricultural applications	Key limitations
TROPOMI (Sentinel-5P)	5.5 × 5.5 km	Daily global	~300–500 kg CH_4 per h (strong sources)	Regional aggregation; validation of provincial inventories	Cannot resolve individual farms; 20–40% retrieval success[9,19]
GHGSat constellation	25 × 25 m	On-demand tasking (days–weeks)	<500 kg CH_4 per h	Large facility monitoring;[11,49] manure lagoon detection	Commercial costs; exclusion of small-medium operations; episodic coverage
OCO-2	1.3 × 2.25 km footprint	16-day revisit	High precision CO_2 (~0.25 ppm)	Regional carbon cycle context; limited direct livestock application	Biospheric flux dominance[50,51] precludes facility detection
OCO-3 (ISS-mounted)	Variable (depends on mode)	Variable targeting	High precision CO_2	Targeted snapshot observations[30,51]	Limited systematic coverage
GOSAT-2	~10.5 km footprint	3-day revisit	Regional scale CH_4 and CO_2	Regional trend monitoring;[31] inventory validation[52]	Too coarse for farm-scale attribution
Sentinel-2	10 m (most bands)	5-day (constellation)	N/A	Farm infrastructure mapping; management practice indicators	Cloud interference; indirect emission proxies only[53,54]
RADARSAT constellation	1–100 m (mode-dependent)	Variable (daily capable with 3 satellites)	N/A	All-weather monitoring; soil moisture; manure application detection[55]	Complex interpretation; no direct GHG measurement
Carbon mapper tanager	~30 m	Weekly (planned regional)	Point source CH_4 and CO_2 detection	Bridging facility-regional scales; systematic coverage[56]	Not yet operational

Despite these limitations, satellite CO_2 observations provide valuable context for agricultural emission monitoring through two pathways. First, seasonal CO_2 flux dynamics impose significant constraints on biospheric carbon cycle models that are used to estimate agricultural soil carbon sequestration and crop residue decomposition rates, both of which are critical components of net greenhouse gas footprint assessments.[62] Second, future missions including the Copernicus Anthropogenic Carbon Dioxide Monitoring Mission, planned for launch in 2026, will deliver co-located CO_2 and NO_2 observations, facilitating fossil fuel CO_2 attribution through $NO_2 : CO_2$ ratio analysis, which may also be applicable to intensive livestock operations that utilize natural gas for heating or anaerobic digester systems.[64] However, these applications remain indirect indicators rather than direct livestock emission measurements, maintaining primary reliance on bottom-up process models for facility-level CO_2 quantification.[56]

4.3 Nitrous oxide: the absent dimension

No currently operational satellite platform provides nitrous oxide (N_2O) observations with sensitivity adequate for agricultural source monitoring. N_2O atmospheric concentration (~335 ppb) and weak spectral features require prohibitively high signal-to-noise ratios to detect anthropogenic enhancements above background variability.[65] Proposed missions including the European Space Agency's NITROS (Nitrous Oxide Remote Sensing Mission) target an N_2O column precision of 1–2 ppb, theoretically enabling detection of large emission hotspots (>10 kg N_2O-N per ha per day) such as heavily fertilized feed crop areas or manure application events.[66] However, even these ambitious capabilities would provide only regional-scale constraints rather than facility-level attribution.

This N_2O observational gap constitutes a critical limitation for comprehensive livestock emission monitoring, as manure management and feed production N_2O collectively represent 20–40% of dairy and poultry GHG footprints in CO_2-equivalent terms (applying a 100-year global warming potential of 273).[65] Current monitoring frameworks must therefore rely exclusively on process-based models or direct ground-based measurements for N_2O quantification, approaches exhibiting even larger uncertainties (50–100%) than methane methodologies due to pronounced spatiotemporal variability and poorly understood controlling factors.[67] Until satellite based N_2O capabilities mature, integrated monitoring systems remain fundamentally incomplete, constraining verification of mitigation interventions targeting nitrogen management optimization or manure treatment technology adoption.[68]

Bridging this observational gap requires strategic deployment of complementary measurement pathways.[8] Soil moisture retrievals from RADARSAT offer indirect N_2O constraints,[55] since post-rainfall soil saturation events reliably trigger anaerobic conditions driving pulsed N_2O emissions.[65] Machine learning models trained on fertilizer application records, weather patterns, and historical N_2O measurements can provide facility- and regional-scale estimates,[24] while the approach builds on advances in theory-guided data science that combines mechanistic process understanding with empirical pattern recognition.[34] Ground-based sensor networks strategically deployed at manure application zones, lagoon discharge points, and feed production fields capture episodic emissions where point-source sensitivity is the highest. These hybrid approaches represent near-term research opportunities that should proceed in parallel with satellite technology development.[16] Addressing this fundamental limitation requires immediate near-term research investment to enable comprehensive monitoring.

5 Detection of bottlenecks and atmospheric retrieval challenges

Beyond nominal platform specifications, operational satellite GHG monitoring confronts systematic detection challenges rooted in atmospheric physics, instrument design constraints, and retrieval algorithm assumptions. This section critically examines three fundamental bottlenecks that limit agricultural application: temporal sampling biases, spectral interference effects, and validation infrastructure deficits.

5.1 Temporal sampling and cloud contamination

Passive remote sensing systems including TROPOMI, OCO-2/3, and GOSAT-2 require cloud-free conditions and adequate solar illumination, restricting observations to daytime clear-sky scenes. Global cloud climatologies indicate 60–70% cloud cover over mid-latitude agricultural regions, reducing potential daily TROPOMI observations to 30–40% actual successful retrievals.[18,19] This sampling bias is especially pronounced at high latitudes, where livestock production in Canada and northern Europe is concentrated, as winter months (November to February) yield less than 5% successful satellite retrievals above 50°N due to low solar zenith angles, limited daylight duration, and persistent cloud cover.[58,59,69] Consequently, annual emission estimates derived from satellite observations disproportionately weight summer months, potentially missing cold-season manure storage dynamics or seasonal diet transitions affecting enteric fermentation.

Quantifying the impact of temporal sampling biases reveals substantial systematic errors in annual emission estimates.[12] Seasonal patterns in livestock emissions, including higher winter emissions from confined housing systems due to intensive feeding and stable conditions, often represent only a fraction of satellite observations due to retrieval failure rates in winter conditions.[58] Similarly, diurnal variations in manure storage emissions are only partially captured by satellite overpasses with midday-preferential observation windows.[61] These temporal sampling characteristics introduce systematic underestimation of annual emissions when satellite observations are aggregated without accounting for missed seasonal and diurnal cycles. Validation studies integrating satellite observations with continuous eddy covariance flux tower measurements confirm that these temporal biases emerge consistently across temperate agricultural regions.[67] The intermittency and variability of emission sources further complicate satellite-based quantification, as concentrated livestock operations exhibit non-uniform temporal dynamics that satellite constellation designs with fixed overpass times cannot fully capture.[60]

Systematic assessments of temporal representativeness based on continuous ground-based observations reveal a critical sampling bias. Satellite measurements consistently underrepresent wet conditions, as cloud cover prevents retrievals during and immediately following precipitation events, whereas agricultural soil N_2O emissions typically exhibit pronounced post-rainfall pulses.[65] Similarly, methane emissions from liquid manure storage systems display diurnal cycles with factor-of-two variations driven by temperature fluctuations, yet satellites observe only mid-day conditions.[70,71] Current inverse modelling frameworks implicitly assume that observed concentrations represent temporal averages, an assumption demonstrably violated when emission sources exhibit strong diurnal or episodic behaviour not randomly sampled by satellite overpass schedules.

5.2 Atmospheric transport uncertainties

Inferring surface emissions from column-averaged atmospheric concentrations requires accurate atmospheric transport modelling to relate observed enhancements to source locations and emission rates. Transport models exhibit systematic errors in boundary layer height (10–30%), vertical mixing parameterizations (15–40%), and sub-grid-scale plume dispersion (20–50%) that propagate approximately linearly into emission rate estimates.[17,72] These uncertainties are not randomly distributed but exhibit systematic biases related to topography, land surface characteristics, and weather regimes. Mountainous regions, coastal zones, and areas with heterogeneous land cover experience particularly large transport errors due to complex boundary layer dynamics inadequately captured by coarse-resolution meteorological models.[73]

Validation of transport model performance requires independent atmospheric observations at multiple vertical levels, yet such data remain sparse over agricultural regions. Aircraft campaigns provide valuable constraints but typically cover limited spatial extents (10^2–10^3 km^2) and short durations (days to weeks), potentially missing systematic biases emerging at larger scales or under different meteorological conditions.[60] Emerging networks of instrumented towers and UAV-based measurements offer improved spatial coverage but introduce new challenges in integrating observations at different scales and ensuring long-term measurement continuity necessary for establishing climatological transport error statistics.[74]

6 Spatial scaling and facility attribution challenges

Agricultural landscapes exhibit emission source heterogeneity spanning six orders of magnitude spatially, from individual animal respiration events (10^{-2} m^2) to regional livestock production zones (10^4 km^2), yet satellite footprints observe atmospheric column integrals representing convolutions across these scales. This section examines the scale mismatch problem and attribution challenges that fundamentally constrain facility-level emission quantification from space-based observations.

6.1 The scale mismatch problem

Facility-level management decisions operate at scales of 10^2–10^4 m^2 (individual barns, manure storage lagoons, and feed production fields), while satellite observations integrate atmospheric signals over 10^3–10^7 m^2 (TROPOMI at 5.5 km pixels and GHGSat at 25 m pixels). Atmospheric transport disperses point-source emissions across satellite footprints within minutes to hours, diluting concentration enhancements and confounding source attribution.[9] This dispersion process exhibits high variability depending on wind speed (factor of 5–10), atmospheric stability (factor of 3–5), and boundary layer height (factor of 2–3), introducing systematic uncertainties that current inverse modelling approaches inadequately characterize.[8]

For moderate-resolution sensors like TROPOMI, atmospheric transport typically disperses individual facility emissions across 10–50 pixels before detection, making source attribution dependent on prior knowledge of facility locations, emission factors, and temporal activity patterns.[9] This dependence creates circular logic whereby satellite observations intended to provide independent verification instead require bottom-up emission estimates as prior constraints to enable source attribution. The resulting posterior estimates blend prior assumptions with observational information in ways that obscure whether satellite data genuinely improve emission quantification or merely reproduce prior distributions with superficial modifications.[73]

6.2 Multi-source attribution in heterogeneous landscapes

Agricultural regions rarely contain isolated emission sources. Livestock facilities co-locate with intensive crop production, wetlands, wastewater treatment plants, landfills, and fossil fuel infrastructure, all contributing to observed atmospheric methane enhancements.[58] Distinguishing livestock-specific contributions from this multi-source mixture requires additional constraints beyond total column methane observations.[27] Isotopic measurements ($\delta^{13}CH_4$ and δD-CH_4) provide source discrimination capabilities, with biogenic agricultural sources exhibiting characteristic isotopic signatures distinct from thermogenic fossil fuel methane.[75] However, current satellite platforms lack isotopic measurement capability, restricting this approach to aircraft campaigns or ground-based networks. Emerging technologies including drone-mounted isotopic analyzers and portable GC-IRMS (gas chromatography-isotope ratio mass spectrometry) systems are reducing deployment costs and enabling broader geographic sampling.[75] Integrating isotopic constraints with satellite observations and machine learning models can substantially improve source apportionment accuracy, particularly in regions with mixed emission sources from agriculture, fossil fuel extraction, and natural wetlands.[33]

Current measurement capability is often restricted to aircraft campaigns or ground-based networks. Machine learning approaches offer alternative attribution strategies by learning characteristic spatial patterns, temporal cycles, and co-variates associated with different source types. Convolutional neural networks trained on high-resolution optical imagery (Sentinel-2) can identify farm infrastructure types, estimate livestock populations, and classify management practices correlated with emission patterns.[15] However, these indirect approaches introduce additional uncertainties: classification accuracies for agricultural features typically range from 70–85%, and relationships between observable proxies and emissions remain imperfectly understood, particularly for novel management practices or mitigation technologies underrepresented in training datasets.[13]

7 AI/ML approaches and algorithmic transparency

Artificial intelligence and machine learning methodologies offer capabilities for integrating heterogeneous data streams, identifying complex nonlinear relationships, and predicting emissions where direct measurements are impractical. However, critical examination reveals fundamental trade-offs between prediction accuracy, mechanistic interpretability, data requirements, and extrapolation capacity that constrain agricultural emission monitoring applications (Table 4).

7.1 Ensemble tree methods: performance and limitations

Random forests, gradient boosting machines (XGBoost and LightGBM), and related ensemble tree methods represent the most widely adopted machine learning approaches for agricultural emission prediction, achieving R^2 = 0.65–0.80 for enteric fermentation and manure emissions when trained on comprehensive datasets.[24] These algorithms offer advantages in the form of robust handling of nonlinear relationships, resistance to overfitting through ensemble averaging, minimal hyperparameter tuning requirements, and natural interpretability through feature importance metrics. However, rigorous cross-validation using spatially or temporally independent test sets where validation farms or time periods are excluded from model training consistently demonstrates performance degradation to R^2 = 0.40–0.60 and mean absolute percentage errors increasing from 10–15% (facility-to-regional aggregated predictions) to 25–40% (farm-level estimates).[21,24]

This performance degradation reflects fundamental limitations of tree-based methods in extrapolating beyond training data distributions. Decision trees partition the feature space based on observed data, inherently struggling to predict outcomes for novel combinations of input variables or values outside the training range.[82] Applied to emission monitoring, this limitation manifests critically when evaluating mitigation technologies (feed additives and manure treatment systems), emerging genetics, or management practices underrepresented in historical datasets which are precisely the scenarios where accurate predictive capability would offer the greatest value for informing adoption decisions. Feature importance analysis provides interpretability advantages but exhibits instability

Table 4 AI/ML architecture comparison for livestock emission prediction

AI architecture	Typical performance	Data requirements	Key advantages	Primary limitations	Agricultural applications
Random forest/gradient boosting	$R^2 = 0.65$–0.80 (training) $R^2 = 0.40$–0.60 (independent test)	10^2–10^3 Samples	Robust to overfitting; natural interpretability; handles nonlinear relationships	Poor extrapolation beyond the training range; performance degrades for novel practices[13,24]	Enteric CH_4 from diet composition; manure emissions from management data; inventory disaggregation
Convolutional neural networks (CNNs)	Variable by application; typically $R^2 = 0.70$–0.85 for imagery	10^4–10^6 Images	Automatic feature extraction; captures spatial patterns; end-to-end learning[15,76]	Data hunger; computational intensity; limited interpretability	Satellite imagery analysis; farm infrastructure classification; emission plume detection from TROPOMI
Recurrent/LSTM networks	$R^2 = 0.65$–0.75 for time series	10^3–10^4 Sequences	Captures temporal dependencies;[77] models seasonal cycles; handles variable-length sequences	Sequential training; vanishing gradients; requires substantial time series	Seasonal emission modeling; temporal pattern prediction integrating weather cycles
Transformer models	R^2 improvements of 5–15% over RNNs	10^5–10^6 Samples	Long-range dependencies; parallelizable; interpretable attention mechanisms[32]	Massive data requirements; computational expense; limited agricultural deployments[78]	Multi-temporal satellite integration; long-term trend analysis; emerging applications
Physics-informed neural networks	22–35% RMSE reduction *vs.* pure ML	10^2–10^3 Samples (reduced requirements)	Physically interpretable; improves extrapolation; preserves mechanistic relationships[33]	Complex design; requires domain expertise; mechanistic assumptions may introduce bias[34]	Correcting IPCC model biases; N_2O prediction with process constraints; hybrid emission modeling
Gaussian processes	$R^2 = 0.60$–0.75 for moderate datasets	10^2–10^3 Samples	Full uncertainty quantification; works with limited data; no overfitting	Kernel selection critical; challenging for large datasets ($>10^4$)[79,80]	Spatial emission interpolation; uncertainty estimation for inventories; small-dataset applications
Multi-modal deep learning	$R^2 = 0.71$–0.80 (multi-modal fusion)	10^4–10^5 Multi-modal samples	Learns optimal data integration; handles heterogeneous inputs; captures cross-modal patterns	Massive data needs; risk of mode collapse; complex architecture	Integrating TROPOMI + Sentinel-2 + weather + farm data for comprehensive emission mapping[77,81]

under different algorithm implementations, hyperparameter selections, and dataset subsampling strategies, complicating mechanistic inference.[83]

7.2 Deep learning: data hunger and interpretability deficits

Deep neural networks, particularly convolutional architectures for satellite imagery analysis and recurrent/transformer models for time series prediction, demonstrate superior performance on large-scale structured data compared to traditional methods.[14] Applications to agricultural emission monitoring include direct CH_4 prediction from TROPOMI observations, temporal pattern modelling integrating weather and management cycles, and multi-modal fusion of satellite, meteorological, and farm activity data. However, deep learning typically requires training datasets of 10^4–10^6 examples to achieve robust performance, whereas agricultural emission measurements number only 10^2–10^3 well-characterized cases globally.[20,77] This data scarcity necessitates transfer learning, synthetic data augmentation using process-based model simulations, or physics-informed constraints, each introducing new assumptions and uncertainties.

Interpretability challenges pose particularly acute problems for agricultural applications where stakeholder acceptance depends on understanding system behaviour. Farmers, advisors, and policymakers rightfully demand explanations for emission predictions that influence investment decisions, regulatory compliance, or market access.[20] While explainable AI techniques (SHAP values, attention visualization, and concept activation vectors) provide partial transparency, these generate *post-hoc* explanations of opaque models rather than inherently interpretable representations. The resulting 'explanations' may satisfy psychological needs for understanding without ensuring that predictions remain valid under novel conditions or identifying cases where model confidence is unjustified.[21]

7.3 Physics-informed machine learning: bridging data and mechanisms

Physics-informed neural networks (PINNs) and hybrid modelling approaches that combine data-driven learning with mechanistic process understanding represent a promising methodological frontier.[34,84] These frameworks constrain predictions to obey physical laws such as mass balance, thermodynamic relationships, and stoichiometric constraints, improving generalization beyond training data while reducing requirements for large datasets. Agricultural emission applications include hybrid models combining IPCC emission factor equations with neural network corrections for site-specific conditions, and constrained optimization frameworks that ensure predicted emissions satisfy energy conservation principles.[23]

However, physics-informed approaches require explicit specification of mechanistic relationships to be enforced, introducing subjectivity in determining which physical constraints merit hard enforcement *versus* soft regularization. When mechanistic models themselves exhibit systematic biases as documented for N_2O emission models under certain soil and weather conditions,[67] enforcing agreement with these models may degrade rather than improve predictions. Optimal integration of mechanistic knowledge and data-driven learning likely varies across emission sources, production systems, and geographic contexts, necessitating careful empirical evaluation rather than assuming that physics-informed approaches are uniformly superior.[84]

7.4 Transformer architectures: emerging opportunities and data requirements

Transformer architectures warrant expanded consideration in agricultural emission monitoring due to their prominence in modern machine learning and growing utility in environmental analytics.[33] Their self-attention mechanisms allow models to learn adaptive, context-dependent feature weightings, capturing nonlinear interactions among satellite observations, meteorological drivers, and facility-level characteristics without manual feature engineering.[78] In multi-temporal applications, transformers excel at integrating satellite time series, extracting seasonal dynamics, and detecting anomalous emission events from sequential TROPOMI observations.[32] Attention visualization further enhances interpretability by identifying the spectral bands, temporal lags, and landscape features most influential for predictions, supporting transparency in regulatory contexts.[21]

Transfer learning from remote-sensing foundation models offers a promising approach to mitigate the data scarcity that currently limits agricultural GHG applications.[34] However, transformers typically require 10^5–10^6 training samples, exceeding the size of most existing agricultural emission datasets.[77] As satellite constellations expand and multi-year observational archives grow, these constraints will diminish. Under such conditions, transformer-based models present a near-term opportunity to improve predictive accuracy, temporal fidelity, and interpretability relative to traditional ensemble approaches.[20]

8 Integration framework: multi-scale hybrid benchmarking

The preceding analysis converges toward a critical insight: no single technology or approach provides comprehensive monitoring across heterogeneous spatial scales, temporal dynamics, and production system diversity characterizing global livestock agriculture. This section synthesizes disconnected elements into an integrated hybrid framework (Fig. 3) that strategically combines complementary strengths while explicitly addressing limitations, uncertainties, and operational constraints.

8.1 Conceptual architecture

The proposed hybrid benchmarking system integrates three complementary data streams operating at different scales: (1) bottom-up farm activity modelling providing facility-level estimates with monthly temporal resolution; (2) satellite remote sensing enabling regional verification with weekly-to-monthly cadence and targeted facility monitoring; and (3) artificial

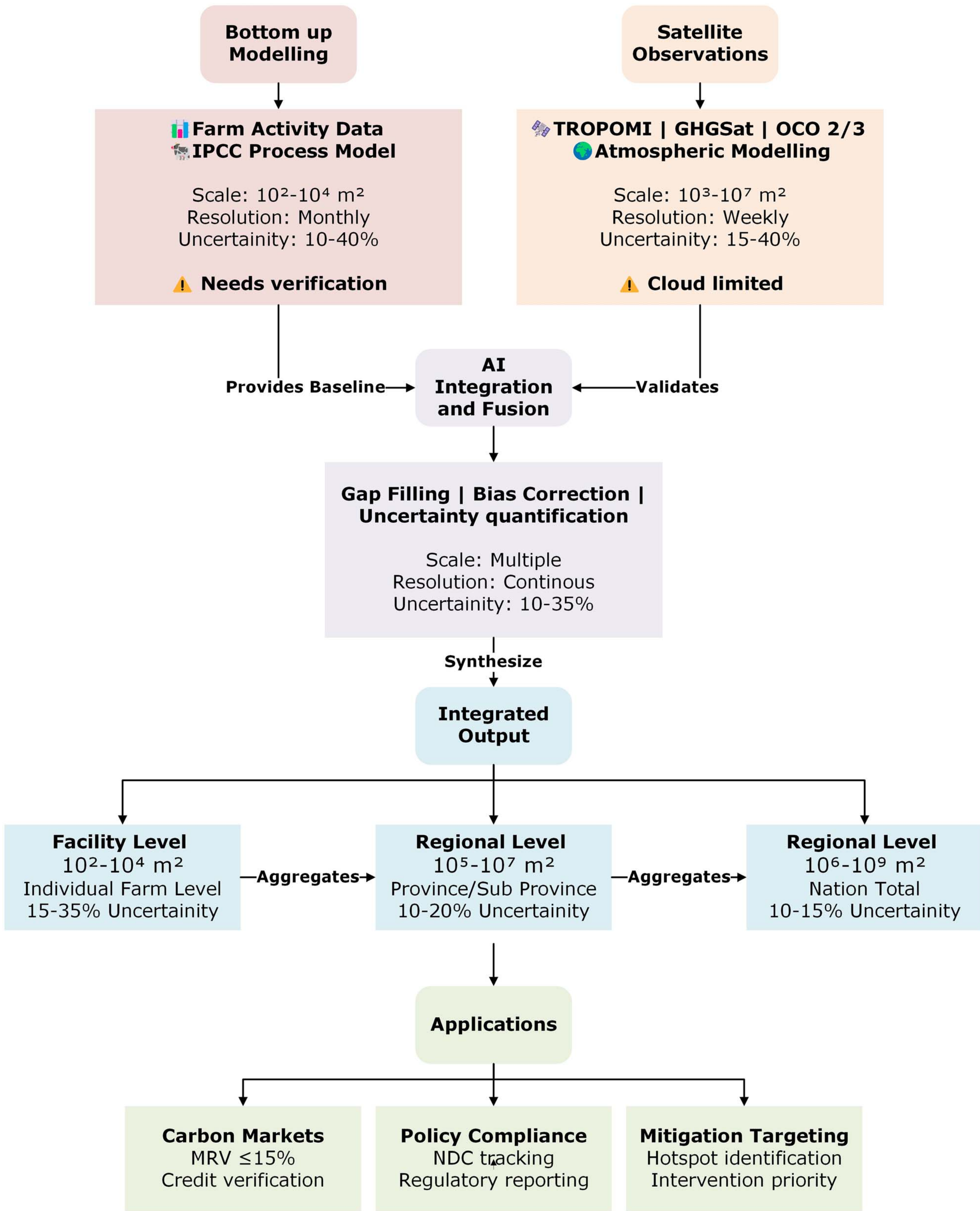

Fig. 3 Hybrid multi-scale monitoring framework integrating bottom-up models, satellite observations, and AI to verify agricultural GHG emissions with reduced uncertainty across scales.

intelligence-driven fusion synthesizing heterogeneous observations into coherent emission estimates with quantified uncertainties. This multi-scale architecture explicitly addresses the scale mismatch problem by bridging facility management decisions (10^2–10^4 m^2), satellite observations (10^3–10^7 m^2), and regional inventory estimates (10^6–10^9 m^2).[16,17,76]

Bottom-up emission modelling employs IPCC Tier 2/3 approaches using farm activity data (livestock populations, feed composition, and manure management characteristics) combined with region-specific emission factors. For participating farms providing detailed records, the system implements farm-specific modelling analogous to existing tools (Holos). For non-participating operations, regional emission factors derived from agricultural census data and representative farm surveys provide baseline estimates. This stratified approach balances data availability constraints against accuracy requirements: detailed modelling where possible and defensible approximations where necessary.[26]

Satellite remote sensing components prioritize observational resources where they provide the greatest marginal value. High-resolution targeted monitoring (GHGSat and Carbon Mapper) focuses on large facilities exceeding detection thresholds and where bottom-up uncertainties are the highest including operations with anaerobic lagoons, rapidly changing management practices, or incomplete activity data. Moderate-resolution TROPOMI observations enable regional emission aggregation at province or sub-province scales, providing independent verification of inventory totals and identifying systematic biases in emission factors or spatial allocation. Complementary optical/radar observations (Sentinel-2 and RADARSAT) characterize farm infrastructure, management practices, and environmental conditions relevant to process-based modelling.

8.2 AI fusion and architectural selection

Artificial intelligence and machine learning methodologies offer capabilities for integrating heterogeneous data streams, identifying complex nonlinear relationships and predicting emissions where direct measurements are impractical.[13–15] However, no single algorithm or architecture provides comprehensive monitoring across all agricultural systems and operational contexts. Rather than selecting a single best approach, the proposed hybrid framework strategically deploys distinct AI architectures to mitigate the individual limitations identified in Table 4, leveraging complementary strengths while explicitly addressing weaknesses through contextual selection and integration. The fundamental trade-offs between prediction accuracy, mechanistic interpretability, data requirements, and extrapolation capacity necessitate a multi-architecture approach where each method's deployment is matched to the problem context where its strengths dominate its weaknesses.

Ensemble tree methods (Random Forest, XGBoost, and LightGBM) serve as baseline predictors for farms with moderate-quality activity data and established operational records. Although tree-based approaches achieve $R^2 = 0.65$–0.80 on training data, they degrade to $R^2 = 0.40$–0.60 under spatial and temporal extrapolation (Section 7.1), reflecting fundamental limitations in predicting outcomes for novel combinations of input variables or values outside training ranges.[24,82] Within the hybrid framework, this limitation is mitigated through two mechanisms: (1) strategic deployment only for facilities within training data distributions where robust nonlinear pattern recognition and interpretability advantages outweigh extrapolation deficits; and (2) ensemble variance estimation from multiple tree-based implementations enables uncertainty flagging, automatically triggering higher-complexity models when predictions diverge substantially. This stratified approach concentrates ensemble methods where their strengths (computational speed, transparency, minimal hyperparameter tuning, and natural feature importance metrics) provide the maximum value while avoiding deployment contexts where extrapolation deficits would compromise accuracy.

Physics-informed neural networks (PINNs) and mechanistic constraint-enforced approaches directly address the extrapolation limitation through explicit incorporation of physical laws.[34,84] For novel mitigation technologies or management practices that are underrepresented in training data, which are precisely the scenarios where accurate predictive capability is most valuable for adoption decisions, PINNs enforce mass balance, stoichiometric, and thermodynamic relationships, thereby enabling reliable prediction beyond the training data distribution where standard deep learning models often fail catastrophically. However, since mechanistic models themselves exhibit systematic biases (particularly for N_2O emission dynamics under certain soil and weather conditions), PINNs are deployed selectively for scenarios where physical laws provide hard constraints (enteric methane bioconversion efficiency and energy conservation in housing systems) while using soft regularization where processes remain mechanistically uncertain (soil N_2O release dynamics and emission pulses from complex organic matter decomposition). This conditional deployment strategy exploits PINN advantages in constraining predictions while preventing degradation from over-constrained mechanistic assumptions that may themselves be imperfect.

Deep learning architectures (convolutional networks for spatial pattern extraction from satellite imagery and recurrent and transformer models for temporal sequence analysis) are reserved for scenarios where large training datasets and nonlinear complexity justify their substantial data requirements.[32,33,78] Rather than attempting to train monolithic deep models on limited agricultural emission datasets, the framework employs transfer learning from remote-sensing foundation models trained on millions of satellite images and temporal sequences, reducing data requirements from 10^5–10^6 to 10^2–10^3 samples. Temporal transformer models integrate multi-year satellite observation sequences, meteorological drivers, farm activity patterns, and facility-level characteristics to capture complex seasonal dynamics and detect anomalous emission events, which are tasks where sequence models demonstrably outperform traditional ensemble approaches. Critically, this architecture is applied exclusively to the subset of facilities with continuous multi-year satellite observations and complete temporal coverage, where deep learning's data hunger is satisfied rather than forcing deployment where datasets remain sparse or fragmented.

Bayesian hierarchical models serve as the integrative framework connecting these diverse methodologies through probabilistic synthesis. Rather than relying on any single architecture's posterior estimates, the framework treats tree-based, PINN, and deep learning predictions as alternative data sources with heterogeneous precision and systematic biases. Hierarchical priors systematically adjust facility-specific emission estimates based on: (1) systematic discrepancies between satellite-derived and process-model-based estimates revealed through regional aggregation, indicating potential biases in either data stream; (2) agreement patterns among independent AI architectures where high concordance indicates robust estimation and substantial divergence signals unresolved uncertainty; and (3) facility metadata (production intensity, management sophistication, and technology adoption) indicating relative trustworthiness of different estimation methods for specific facility types. This probabilistic framework propagates information from well-characterized facilities with multiple data streams to under-characterized operations lacking detailed activity records, enabling posterior refinement across the entire farm population.

Ensemble uncertainty quantification and transformer-based diagnostic analysis serve as the orchestrating mechanism. Rather than selecting a single best architecture, the framework maintains ensemble predictions across all applicable methodologies for each facility, generating distributional estimates from which comprehensive uncertainty metrics are derived. High divergence among tree-based, PINN, deep learning, and satellite-based estimates indicates unresolved uncertainty, automatically triggering targeted investigation. Transformer-based attention mechanisms characterize which specific features, spectral bands, temporal patterns, or facility characteristics drive prediction divergence; if predictions diverge primarily when satellite information conflicts with activity-based models, this indicates problems in activity data quality or spatial allocation; if uncertainty emerges specifically under a particular weather condition, this reveals mechanistic knowledge gaps requiring process-based research. This diagnostic capacity transforms ensemble disagreement from a liability into actionable information for system improvement and prioritization of future research efforts.

The resulting hybrid architecture overcomes the false dichotomy between interpretability and accuracy. Ensemble tree methods provide transparent baselines with clear decision logic; PINNs inject mechanistic knowledge grounded in physical theory; deep learning extracts complex nonlinear patterns from high-dimensional satellite and temporal data; and Bayesian integration provides coherent probabilistic synthesis accounting for correlated uncertainties. Each architecture's deployment is strategically matched to the problem context where its strengths dominate its weaknesses, enabling the framework to operate as an adaptable, context-aware system rather than assuming any single approach suits all monitoring scenarios.

8.3 Architectural selection and stakeholder trust

The design of the proposed hybrid architecture reflects a deliberate commitment to transparency and stakeholder engagement, rather than a narrow focus on technical optimization. Each system component *viz.*, ensemble tree models, physics-informed neural networks, satellite-based constraints, and Bayesian synthesis, is selected not only for analytical performance but also for its ability to explain decisions and justify emission estimates to affected stakeholders.

Ensemble methods provide clear feature-importance rankings that reveal which farm-level characteristics most strongly influence emission estimates.[24,85,86] Physics-informed models make underlying mechanistic assumptions explicit and auditable, while satellite observations are grounded in independent atmospheric measurements rather than proprietary algorithms.[34,69,91] Bayesian synthesis further enhances transparency by explicitly quantifying uncertainty, enabling stakeholders to understand confidence levels and model limitations.[17] This transparency-by-design approach recognizes that monitoring systems affecting livelihoods, regulatory compliance, and market access must be socially and institutionally defensible and not solely statistically robust.

While accuracy-optimized black-box models may yield marginal performance gains,[14,88] their opacity can undermine system legitimacy and stakeholder trust.[20] Accordingly, the framework balances predictive accuracy, mechanistic interpretability, and stakeholder transparency.[22] Interpretability is prioritized for facility-level decisions affecting individual producers while less transparent deep learning approaches may be used for regional or temporal pattern detection where accountability concerns are reduced. This balanced approach ensures monitoring systems are credible and accessible to farmers, regulators, and the public, with governance and participation mechanisms detailed in Section 10.

8.4 Quantitative uncertainty analysis and error propagation

The hybrid framework reduces facility-level emission monitoring uncertainties from the current 30–50% (inventory-based approaches)[7,16] to 15–25% through complementary mechanisms. Current inventory approaches combine independent error sources: activity data (5–20%),[7,16] emission factors (10–30%),[24] process models (10–30%),[60] and spatial allocation (10–30%).[62] Standard error propagation yields an analytical uncertainty of approximately 35% for a typical facility; however, empirical validation against satellite observations and direct measurements confirms that realistic baseline uncertainties are 30–50% due to correlated errors among components. When these independent error sources are combined through standard error propagation (assuming independence), analytical uncertainty calculations yield:

$$\sigma^2(E\_\text{total}) = \sigma^2(\text{activity}) + \sigma^2(\text{factor}) + \sigma^2(\text{process}) + \sigma^2(\text{spatial})$$

The framework reduces uncertainty through four complementary mechanisms. First, machine learning refines activity data from facilities with weak records by learning patterns from well-characterized operations. For operations with ≥50% activity data completeness, this approach reduces σ(activity) from 12% to 5%,[33] enabling pattern transfer rather than reliance on sparse direct measurements. Second, satellite observations (TROPOMI: ±15%, GHGSat: ±10%)[65,66] provide independent atmospheric emission constraints. Bayesian integration of satellite and bottom-up estimates is formulated as follows:

$$E\_\text{posterior} = (E\_\text{prior}/\sigma^2\_\text{prior} + E\_\text{sat}/\sigma^2\_\text{sat})/(1/\sigma^2\_\text{prior} + 1/\sigma^2\_\text{sat})$$

and

$$\sigma^2\_\text{posterior} = 1/(1/\sigma^2\_\text{prior} + 1/\sigma^2\_\text{sat})$$

For a bottom-up prior with σ_prior = 0.35E and satellite measurement with σ_sat = 0.15E, the posterior uncertainty becomes σ_posterior = 0.133E (13% relative standard deviation), representing a 2.6× improvement. This substantial reduction reveals that satellite observations provide independent constraints where bottom-up approaches are the weakest (activity data gaps and process model biases), while bottom-up methods provide facility-specific detail where satellite observations aggregate regionally.[64,67]

Third, physics-informed neural networks constrain the process model structure for mechanistically well-understood processes.[34,69] For enteric methane, enforcement of stoichiometric relationships (substrate carbon and hydrogen content determine maximum bioconversion products) reduces σ(process) from 15% (deep learning) to 8% (PINN-constrained), a ∼50% reduction.[60] This constraint-based approach is particularly effective for processes with strong underlying mechanistic understanding but limited training data. Fourth, ensemble averaging synthesizes multiple independent estimates (bottom-up with alternative factors, satellite-based, machine learning, and mechanistic models) into coherent posterior distributions. For five independent estimation approaches each with σ_i ≈ 0.20E, ensemble mean uncertainty is $\sigma(\text{ensemble}) = \sqrt{(\Sigma\sigma^2\_i)}/N \approx 0.089E$ (9%). Accounting for partial correlation among approaches ($\rho \approx 0.3$) yields $\sigma(\text{ensemble}) \approx 0.14E$ (14%), demonstrating substantial variance reduction even with imperfect independence.[60] Combining these four mechanisms sequentially yields a compound uncertainty reduction of 15–25% for well-characterized operations.

The 15–25% uncertainty target applies under specific conditions. The framework achieves the maximum benefit for (1) well-established operations with ≥2 years of operational history enabling pattern learning;[70] (2) facility-level scales (0.1–10 km^2) where satellite observations provide meaningful constraints;[65] (3) temporal averaging over ≥6-month periods where seasonal dynamics are adequately sampled;[62] (4) mechanistically well-characterized emission processes with sufficient data for PINN training; and (5) activity data completeness ≥50%, enabling meaningful machine learning pattern transfer. Conversely, larger uncertainties (25–35%) persist for emerging agricultural operations, smallholder and subsistence farms with minimal record-keeping,[72] tropical and subtropical systems where process models are calibrated primarily on temperate data,[73] temporal scales less than 3 months where satellite revisit frequency is insufficient, and extreme events (drought and disease outbreaks)[71] where historical patterns cannot predict rapidly changing conditions. Systematic biases in either satellite retrievals or activity data reporting cannot be reduced through statistical methods and require direct measurement validation.[64,68]

Validation of these uncertainty projections requires comparison to independent ground-truth measurements. Essential validation approaches include (1) eddy covariance or chamber sampling at 20–30 representative facilities spanning the diversity of production systems, providing direct emission measurements with typical uncertainty ±15–20%;[74,75] (2) regression analysis of framework estimates against independent measurements, quantifying bias and residual scatter as a function of facility characteristics; and (3) regional aggregation validation at county or sub-state scales where 50–100 facilities enable robust statistical comparison against bottom-up inventories and independent atmospheric inversions. Such validation work is beyond the scope of the current manuscript but is essential for regulatory acceptance.[7,77] Full publication of comprehensive validation results should accompany any operational deployment of the framework.

8.5 Economic feasibility and implementation costs

To assess the practical implementation of the proposed hybrid monitoring framework, systematic economic evaluation is essential. Table 5 compares the per-farm monitoring costs across three distinct approaches *viz.*, satellite-only, hybrid satellite-model integration, and ground-based validation, contextualized against typical farm revenues and carbon credit values. This analysis enables stakeholders to identify economically viable pathways stratified by production system scale and monitoring objectives.

Economic viability must be contextualized against farm level economics and regulatory requirements. For a representative 100-cow dairy operation in Canada generating \$300 000–500 000 annual revenue, satellite-only monitoring (\$500–2000 annually) represents 0.3–0.7% of gross revenue, which is economically feasible for voluntary carbon market participation.[85,86] Hybrid approaches (\$100–300 annually) offer superior cost-effectiveness for regional regulatory compliance, requiring minimal additional infrastructure.[87] Ground-based validation networks (\$10 000–30 000 annually per site) are justified only when amortized across multiple facilities or integrated into multi-purpose environmental monitoring programs.[85] As carbon credit prices increase (current voluntary market range: CAD \$15–50 per tonne CO_2e), hybrid approaches become increasingly attractive relative to direct emission reductions.

Policy frameworks should stratify monitoring requirements by farm size and production intensity. Small and medium enterprises (<50 head of cattle) should be eligible for subsidized hybrid monitoring or cooperative pooled satellite observations, analogous to extension service models.[88] Large, concentrated operations (>500 head) with demonstrable emissions >500 kg CH_4 per h should bear costs for targeted satellite monitoring or on-site validation as a compliance condition, reflecting producer-pay principles embedded in regulatory frameworks.[89]

Table 5 Economic feasibility of livestock emission monitoring approaches

Monitoring approach	Capital cost	Annual operating cost	Cost per farm-year	Data temporal resolution	Spatial scale	Applicability
Satellite-only (GHGSat targeted observations)	None	\$5000–15 000 per observation	\$500–2000	Weekly to monthly	Facility-level (25 m)	Large operations only (>500 kg CH_4 per h)
Hybrid satellite-model (TROPOMI + bottom-up IPCC Tier 2/3)	Minimal (~\$10 000 for model setup)	\$5000–15 000 annually	\$100–300	Daily (satellite)/farm activity data	Regional aggregates	Medium to large operations; requires activity data
Ground-based validation (eddy covariance flux tower)	\$50 000–200 000 capital per site	\$10 000–30 000 annually	Per-site costs; multi-farm amortization possible	Continuous (30-min intervals)	0.5–1 km footprint	Research priority; enables other validation
Physics-informed hybrid (PINN + satellite + limited ground data)	\$20 000–50 000 setup	\$8000–20 000 annually	\$150–400 (amortized across regional network)	Daily to hourly (hybrid)	Facility to landscape	Emerging; suitable for research consortia

This tiered approach balances environmental rigor with economic feasibility across diverse production systems characteristic of Canadian and international livestock agriculture.

9 Validation networks and uncertainty quantification

Transitioning from proof-of-concept demonstrations to operational emission monitoring systems requires rigorous uncertainty quantification and comprehensive validation against independent measurements (Table 6). This section examines validation infrastructure deficits, uncertainty propagation frameworks, and quality assurance protocols necessary for regulatory acceptance and stakeholder confidence.

Current satellite validation relies primarily on discrete aircraft campaigns and limited tower-based measurements, constraining comprehensive assessment of retrieval accuracy under diverse atmospheric conditions, land surface characteristics, and emission source types.[60] Aircraft campaigns provide valuable cross-validation but typically cover limited spatial extents (10^2–10^3 km^2) and short durations (days to weeks), potentially missing systematic biases emerging at larger scales or under different meteorological conditions. Furthermore, most validation efforts concentrate in oil/gas production regions or research facilities rather than agricultural landscapes, limiting direct applicability of reported accuracy metrics to livestock emission monitoring contexts.[85]

Establishment of permanent ground-based flux tower networks at representative dairy and poultry facilities, analogous to existing networks for carbon cycle research (FLUXNET and ICOS), would enable continuous validation data collection supporting detection of systematic biases, seasonal accuracy patterns, and impacts of meteorological conditions on retrieval performance.[86] Such infrastructure requires multi-year operational commitments and sustained funding beyond typical research grant cycles, yet provides an essential foundation for operational monitoring system credibility. Complementary mobile measurement platforms (vehicle-based systems, UAVs, portable emission quantification equipment) enable targeted validation campaigns at facilities where permanent infrastructure is impractical.[74]

Integration of satellite observations into official greenhouse gas inventory reporting requires quality assurance frameworks ensuring consistency with UNFCCC reporting guidelines and IPCC methodological standards. The Global Stocktake process under the Paris Agreement increasingly emphasizes independent verification of national inventory estimates through satellite observations, yet formal protocols for incorporating top-down constraints remain underdeveloped.[4] Key challenges include (1) reconciling satellite-derived emission estimates with bottom-up inventory methodologies designed for different spatial scales and temporal aggregation periods; (2) establishing uncertainty quantification frameworks compatible with inventory uncertainty assessment approaches; and (3) developing transparent procedures for resolving discrepancies

Table 6 Comparison of greenhouse gas validation platforms

Validation platform	Approximate cost	Temporal resolution	Estimated uncertainty	Scalability
Satellite retrieval	Low-medium (per unit)	Continuous/regular (hour-to-daily)	High (∼30%+)	Very high geographic coverage; agriculture-specific adaptation required[9,19]
Aircraft campaigns	Medium-high (campaign)	Episodic (days-to-weeks)	Moderate (∼20%)	Moderate; logistical constraints limit repeated coverage[60,90]
Permanent flux towers (farm-scale)	Medium (capital + ops)	Continuous (sub-hour to hourly)	Low (∼10% or better)	Low to moderate; cost and site representativeness limit network size[52,91]
Mobile platforms (UAV/vehicle)	Low-medium (setup & ops)	Targeted but episodic	Moderate (∼15%)	Moderate; flexible deployment but not continuous large-scale coverage[74,92]

between satellite observations and inventory estimates that avoid undermining confidence in either approach.[7]

10 Ethical, societal, and data governance considerations

10.1 Privacy, surveillance, and commercial sensitivity

Spatial explicit emission monitoring of agricultural operations introduces complex sociotechnical challenges involving privacy, data ownership, regulatory compliance, and equitable access to verification technologies. These dimensions are frequently overlooked in technical evaluations, yet are essential for operational deployment and stakeholder acceptance. High-resolution imagery combined with AI-driven inference can approximate livestock numbers, management patterns, and facility infrastructure, generating legitimate privacy concerns.[93] Although atmospheric methane measurements fall within the public domain, facility-specific emission estimates and derived management characteristics represent commercially sensitive information that producers reasonably expect to control. Balancing transparency required for credible climate policy verification with confidentiality necessary for producer participation remains a persistent tension.

10.2 Equity and fairness in verification access

Emerging satellite and AI monitoring systems risk creating asymmetric verification burdens and opportunities if implementation fails to address farm size heterogeneity. Operationalizing equitable access requires specific mechanisms stratified by producer scale and financial capacity. Small- and medium-scale operations lacking high-resolution detection capability should access verification through the following pathways:

(1) Tiered verification pathways where farms below individual detection thresholds (typically <500 kg CH_4 per hour) meet verification requirements through facility-level activity data documentation rather than satellite-independent confirmation.[94]

(2) Pooled monitoring consortia enabling cooperative aggregation, where small producers combine emissions accounting to achieve detection threshold scales.[95]

(3) Public subsidy programs analogous to agricultural extension services that offset monitoring infrastructure costs for farmers with limited profit margins.[96]

(4) Performance-based crediting structures that reward efficiency improvements and mitigation adoption regardless of absolute emissions,[97] enabling smaller producers to participate in carbon markets based on relative performance rather than absolute emission reductions.

These tiered approaches must be coupled with technical assistance, capacity building programs, and transparent governance structures ensuring producer voice in system design.

10.3 Data ownership and governance structures

Effective data governance frameworks must therefore establish clear ownership rights for satellite-derived emission data, define acceptable use conditions that prevent punitive enforcement, restrict exploitation by competitors or financial institutions, and incorporate meaningful farmer consent mechanisms, despite the reality that atmospheric observations occur independently of landowner approval. Addressing these intersections requires sustained engagement with producer associations, privacy advocates, legal scholars, and environmental regulators. Equity concerns emerge when benchmarking systems detect primarily large livestock facilities, potentially excluding small- and medium-scale operations that constitute 60–70% of farm numbers in many regions.[36] Such asymmetry risks reduced eligibility for carbon market participation and increased regulatory burden for producers with limited profit margins and technical capacity.

10.4 Environmental justice and spatial disparities

Environmental justice considerations are particularly acute where intensive livestock production concentrates in proximity to vulnerable communities. In North Carolina, hog CAFOs are disproportionately located in the Black Belt region, where residents face elevated exposure to ammonia, hydrogen sulphide, and odor-related health impacts including respiratory illness, gastrointestinal disease, and elevated blood pressure.[98,99] Concurrent expansion of poultry operations in Duplin and Sampson counties compounds these cumulative pollution burdens, with 93% of poultry facilities located within three miles of existing swine operations in communities where over 50% of residents are people of colour.[100]

Geographic concentration of intensive livestock production in specific regions such as southern Alberta, the Fraser Valley, and southwestern Ontario in Canada further amplifies spatial disparities, producing benefits or penalties based on location rather than management quality.[58] Mitigating these inequities requires alternative verification pathways such as cooperative aggregation, representative sampling, or performance-based proxies coupled with technical assistance programs and incentive structures rewarding efficiency improvements.[48] Environmental justice considerations are necessary where production intensification intersects with already burdened communities.[89]

11 Future research priorities

Despite substantial advances in satellite remote sensing, artificial intelligence, and emission modelling, significant research gaps constrain accuracy, operational scalability, and stakeholder confidence. This section identifies five priority research frontiers requiring sustained investment to enable the transition from proof-of-concept demonstrations to routine operational deployment.

11.1 Permanent ground-based validation networks

Optimal network design requires 15–25 core sites strategically distributed across major livestock production regions, agro-climatic zones, and facility types, complemented by mobile measurement campaigns. Site selection must explicitly represent livestock production system diversity and geographic variation in climate and soil properties.[101] Infrastructure specifications include capital establishment costs of CAD $2–5 million across all sites, with individual tall tower installations ranging from CAD $150 000–300 000 each.[102] Annual operational costs are estimated at CAD $0.5–1 million per site for data management, sensor calibration, and site maintenance, costs that reflect the complexity of long-term flux measurement systems.[103] Governance structures should be modelled on established international networks such as ICOS and FLUXNET, combining university research institutions, government environmental agencies, and commodity organization partnerships.[104] This distributed governance model, with formal legal status and sustained funding mechanisms, ensures continuity beyond typical research grant cycles. Phased deployment should establish core sites over 5 years with long-term operations sustained over 10+ years to capture inter-annual climate variability and extremes. Such multi-year operational commitments and sustained infrastructure provide an essential foundation for operational monitoring system credibility and continuous algorithm improvement.

11.2 Scale-bridging and attribution methodologies

Developing rigorous frameworks that explicitly represent multi-scale emission processes from facility emissions (10^2–10^4 m^2) through atmospheric transport (10^4–10^6 m^2) to satellite observations (10^3–10^7 m^2) rather than applying ad hoc corrections represents a critical methodological frontier. Promising approaches include hierarchical Bayesian models that constrain fine-scale emissions based on coarse-scale observations while respecting physical relationships across scales, and super-resolution techniques (computational methods that enhance the combination of satellite observations with high-resolution contextual data) to infer facility-level emission patterns.[17] Advanced source apportionment techniques integrating prior knowledge, atmospheric dispersion modelling, and statistical inference are needed to attribute observed concentration enhancements to specific sources within heterogeneous agricultural landscapes.[72]

11.3 Causal inference for novel management practices

Most machine learning applications employ correlation-based prediction rather than causal inference, limiting their capacity to accurately predict outcomes under novel conditions or evaluate counterfactual scenarios. Developing causal frameworks requires carefully designed observational studies or natural experiments where specific management changes can be isolated from confounding factors, combined with mechanistic process understanding that constrains plausible causal pathways.[105] This causal inference challenge becomes particularly acute when evaluating emerging mitigation technologies (feed additives, alternative manure treatment systems, and precision feeding) where historical data are limited. Physics-informed machine learning approaches that constrain predictions using mechanistic relationships offer partial solutions, yet require explicit specification of relevant mechanisms that may themselves be poorly understood for transformative interventions.[84]

11.4 Integration with broader sustainability metrics

Exclusive focus on greenhouse gas emissions risks optimizing single metrics while potentially degrading other sustainability dimensions (nutrient management, biodiversity, water quality, animal welfare, and socioeconomic outcomes). Integrated assessment frameworks that simultaneously evaluate multiple sustainability indicators provide more comprehensive performance characterization, yet introduce methodological challenges in metric weighting, trade-off quantification, and communication of multi-dimensional outcomes.[2] Developing such frameworks necessitates interdisciplinary collaboration that spans the agronomic, environmental, economic, and social sciences, each characterized by distinct analytical traditions, data availability constraints, and stakeholder engagement approaches. Practical deployment may necessitate phased approaches beginning with a GHG focus, but establishing data infrastructure and governance frameworks enabling future expansion to additional indicators.

12 Bridging research to practice: global implementation, pathways, and constraints

12.1 Global production system diversity and technology suitability

The review emphasizes centralized production systems in North America and Europe; however, 70% of global cattle populations are in developing countries with fundamentally different production structures. India's 85 million smallholder dairy farmers operate 1–2 hectare farms with 2–5 animals; Brazil relies on dispersed rangelands; China maintains heterogeneous production from intensive peri-urban facilities to extensive rangelands. These dispersed systems, representing the majority of global livestock, require different monitoring technologies from CAFOs.

Monitoring technology suitability is production-system dependent. High-resolution satellites (GHGSat, 25 m resolution) detect concentrated facilities exceeding 300–500 kg CH_4 per h but cannot detect individual smallholder farms with lower emissions.[11,12] Conventional sensors ($50 000–200 000 per facility) are economically justified for developed-country operations spreading costs across thousands of animals, but are cost-prohibitive for smallholdings where annual per-animal profit margins ($100–500 USD) fall below per-animal monitoring costs ($50–250 USD). Complex AI models ($R^2 = 0.85–0.95$) for centralized systems degrade substantially ($R^2 = 0.4–0.6$) when applied to smallholder farms with heterogeneous practices and sparse records.[13,24]

For dispersed systems, alternative technologies include appropriate medium-resolution satellites (TROPOMI/MODIS, 5–100 km resolution),[9,10] simplified IPCC Tier 2 process models, and community-level monitoring through cooperatives. This integrated approach achieves 15–25% uncertainty at regional scales comparable to centralized system performance while remaining economically feasible.[5] India's 84 000 plus dairy cooperatives, already collecting daily milk production data, could implement monitoring protocols at negligible additional cost.[36]

12.2 Cost solutions and policy-specific framework configuration

Commercial satellite data costs ($1000–5000 USD per scene) make national-scale deployment infeasible for most developing countries. However, free public satellite data (TROPOMI daily global coverage; Landsat/Sentinel-2 at 10–30 m; MODIS at 250 m) enable regional verification and multi-farm aggregation at zero cost.[9,10] International mechanisms (Earth Engine, Copernicus, Green Climate Fund, and ESA programs) provide free or subsidized access for developing countries. Regional cooperation through South–South data sharing and CGIAR support enables cost-sharing.[1]

A staged implementation approach aligns deployment with available resources. Stage 1: establish baselines using free MODIS/TROPOMI and census data while building capacity through international partnerships. Stage 2: deploy medium-resolution Landsat/Sentinel-2 monitoring and community-level data collection. Stage 3: integrate commercial data if climate finance becomes available.

Framework implementation must be explicitly tailored to policy requirements. Voluntary carbon markets (±15–25% uncertainty, annual verification) cost $1000–3000 USD per project. Corporate Scope 3 disclosure (±20–30%, supply chain scale) costs $2000–5000 USD per 100 farms. UNFCCC inventory reporting (±30–50%, national scale, 5-year cycles) costs $1 000 000–3 000 000 USD per cycle.[7] CBAM trade mechanisms (±10–15%, facility scale) require commercial satellite verification at $50 000–200 000 USD annually per large facility.[2,94] Each regime requires different configurations; the framework remains sound when appropriately tailored.

12.3 N_2O monitoring – realistic assessment of alternatives

Direct N_2O monitoring at the farm scale with carbon market precision (±15–25%) is currently infeasible. RADARSAT/Sentinel-1 soil moisture inversion correlates N_2O with soil moisture ($r = 0.7–0.8$ in experiments)[65] but achieves only ±50–70% uncertainty at the farm scale which is suitable for directional trends, not facility-level estimation.[66,67] Machine learning models achieve $R^2 = 0.60–0.75$ in data-rich regions but degrade to $R^2 = 0.35–0.50$ in developing countries with limited field measurements (typically 10–100 observations).[70] Mechanistic models (DNDC and DayCent) reach ±30–45% uncertainty at research stations but ±50–70% in developing-country contexts, lacking detailed soil characterization.[67,68]

A realistic N_2O monitoring strategy employs three application-specific pathways: (1) national inventories: apply IPCC Tier 3 mechanistic models accepting ±40–50% uncertainty appropriate for 5-year cycles.[5] (2) Regional monitoring: combine satellite soil moisture with empirical models for directional indicators (±50–70%), assessing whether management changes cause systematic N_2O shifts (*e.g.*, continuous to rotational grazing).[65] (3) Carbon markets: adopt management practice-based methodologies using IPCC default factors modified by practice category, eliminating the need for farm-level precision.[94]

13 Conclusions

Advances in satellite remote sensing and artificial intelligence offer a credible pathway to transform agricultural greenhouse gas monitoring from periodic inventory exercises into continuous, decision-support systems. When supported by permanent validation networks, transparent and interpretable algorithms, equitable access mechanisms, and long-term institutional commitment, these technologies can enable real-time benchmarking of farm-level performance, rapid assessment of mitigation effectiveness, and transparent verification of climate commitments. This transformation illustrates how technological innovation, when coupled with inclusive governance and sustained stakeholder engagement, can simultaneously advance climate action and reinforce food security, a defining challenge for twenty-first-century agricultural sustainability. This review has assessed the convergence of high-resolution methane detection, regional atmospheric monitoring, and AI-enabled data fusion for livestock agriculture, highlighting both the substantial gains and the remaining constraints that shape operational deployment. GeoAI systems have the potential to reduce emission-estimate uncertainties from current levels of 30–50% to approximately 15–25% in well-characterized production regions, thereby strengthening verification of mitigation outcomes and enabling credible participation in carbon markets. Yet persistent trade-offs between accuracy, spatial and temporal coverage, and economic feasibility cannot be resolved through technological advances alone. A hybrid, multi-scale benchmarking framework combining farm-level activity modelling for broad coverage, satellite observations for independent verification above detection thresholds, and machine-learning approaches for fusion of heterogeneous datasets offers a pragmatic path forward. Achieving these goals will require sustained interdisciplinary collaboration spanning atmospheric science, agricultural engineering, machine learning, economics, and policy. With strong research infrastructure, domestic satellite capabilities, and supportive policy frameworks, Canada is well positioned to lead in operationalizing such systems. Realizing this potential will depend on moving beyond pilot projects toward long-term deployment supported by stable funding and institutional continuity. By addressing the measurement, attribution, and verification challenges identified in this review, the agricultural sector can demonstrate how innovation can reduce emissions while preserving food security, an essential imperative for the decades ahead.

Author contributions

Padmanabhan Jagannathan Prajesh and Suresh Neethirajan: conceptualization, methodology. Padmanabhan Jagannathan Prajesh: data curation, writing – original draft preparation. Padmanabhan Jagannathan Prajesh and Suresh Neethirajan: visualization, investigation. Suresh Neethirajan and Kaliaperumal Ragunath: supervision, writing – reviewing and editing.

Conflicts of interest

There are no conflicts to declare.

Data availability

This article is a critical review and does not generate new primary datasets. All sources analyzed in the manuscript consist of previously published peer-reviewed articles, technical reports, and public-domain satellite documentation, which are fully cited within the text. No proprietary or restricted data were used. Any additional supporting information, including the list of acronyms and abbreviations, is provided in the supplementary information (SI). Supplementary information: the SI file 1 provides the details of the acronyms used in the manuscript. See DOI: https://doi.org/10.1039/d5va00425j.

Acknowledgements

This work was kindly sponsored by the Natural Sciences and Engineering Research Council of Canada (RGPIN 2024-04450), the Net Zero Atlantic Canada Agency (300700018), Mitacs Canada (IT36514), and the Department of New Brunswick Agriculture, Aquaculture and Fisheries (NB2425-0025).

References

1 Food and Agriculture Organization, *The Future of Food and Agriculture – Alternative Pathways to 2050*, Food and Agriculture Organization of the United Nations, Rome, 2018.

2 T. D. Searchinger, S. Wirsenius, T. Beringer and P. Dumas, Assessing the efficiency of changes in land use for mitigating climate change, *Nature*, 2018, **564**, 249–253.

3 P. J. Gerber, H. Steinfeld, B. Henderson, A. Mottet, C. Opio, J. Dijkman, A. Falcucci and G. Tempio, *Tackling Climate Change through Livestock: a Global Assessment of Emissions and Mitigation Opportunities*, Food and Agriculture Organization, Italy, 2013.

4 Intergovernmental Panel on Climate Change (IPCC), *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*, Geneva, Switzerland, 2019.

5 A. N. Hristov, M. Harper, R. Meinen, R. Day, J. Lopes, T. Ott, A. Venkatesh and C. A. Randles, Discrepancies and Uncertainties in Bottom-up Gridded Inventories of Livestock Methane Emissions for the Contiguous United States, *Environ. Sci. Technol.*, 2017, **51**, 13668–13677.

6 A. Uwizeye, I. J. M. De Boer, C. I. Opio, R. P. O. Schulte, A. Falcucci, G. Tempio, F. Teillard, F. Casu, M. Rulli, J. N. Galloway, A. Leip, J. W. Erisman, T. P. Robinson, H. Steinfeld and P. J. Gerber, Nitrogen emissions along global livestock supply chains, *Nat. Food*, 2020, **1**, 437–446.

7 S. M. Ogle, G. Domke, W. A. Kurz, M. T. Rocha, T. Huffman, A. Swan, J. E. Smith, C. Woodall and T. Krug, Delineating managed land for reporting national greenhouse gas emissions and removals to the United Nations framework convention on climate change, *Carbon Balance Manage.*, 2018, **13**, 9.

8 M. Harmsen, C. Tabak, L. Höglund-Isaksson, F. Humpenöder, P. Purohit and D. Van Vuuren, Uncertainty in non-CO2 greenhouse gas mitigation contributes to ambiguity in global climate policy feasibility, *Nat. Commun.*, 2023, **14**, 2949.

9 D. J. Jacob, D. J. Varon, D. H. Cusworth, P. E. Dennison, C. Frankenberg, R. Gautam, L. Guanter, J. Kelley, J. McKeever, L. E. Ott, B. Poulter, Z. Qu, A. K. Thorpe, J. R. Worden and R. M. Duren, Quantifying methane emissions from the global scale down to point sources using satellite observations of atmospheric methane, *Atmos. Chem. Phys.*, 2022, **22**, 9617–9646.

10 D. J. Varon, D. Jervis, J. McKeever, I. Spence, D. Gains and D. J. Jacob, High-frequency monitoring of anomalous methane point sources with multispectral Sentinel-2 satellite observations, *Atmos. Meas. Tech.*, 2021, **14**, 2771–2785.

11 D. J. Varon, D. J. Jacob, D. Jervis and J. McKeever, Quantifying Time-Averaged Methane Emissions from Individual Coal Mine Vents with GHGSat-D Satellite Observations, *Environ. Sci. Technol.*, 2020, **54**, 10246–10253.

12 S. Pandey, J. B. Miller, S. Basu, J. Liu, B. Weir, B. Byrne, F. Chevallier, K. W. Bowman, Z. Liu, F. Deng, C. W. O'Dell

and A. Chatterjee, Toward Low-Latency Estimation of Atmospheric CO_2 Growth Rates Using Satellite Observations: Evaluating Sampling Errors of Satellite and In Situ Observing Approaches, *AGU Adv.*, 2024, **5**, e2023AV001145.
13 D. A. Thumba, S. Lazarova-Molnar and P. Niloofar, in *2020 7th International Conference on Internet of Things: Systems, Management and Security (IOTSMS)*, IEEE, Paris, France, 2020, pp. 1–8.
14 K. Hu, Q. Zhang, S. Gong, F. Zhang, L. Weng, S. Jiang and M. Xia, A Review of Anthropogenic Ground-Level Carbon Emissions Based on Satellite Data, *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, 2024, **17**, 8339–8357.
15 A. Dakir, F. Barramou and O. B. Alami, in *Geospatial Intelligence*, ed F. Barramou, E. H. El Brirchi, K. Mansouri and Y. Dehbi, Springer International Publishing, Cham, 2022, pp. 107–117.
16 R. M. Duren and C. E. Miller, Measuring the carbon emissions of megacities, *Nat. Clim. Change*, 2012, **2**, 560–562.
17 A. J. Turner, C. Frankenberg and E. A. Kort, Interpreting contemporary trends in atmospheric methane, *Proc. Natl. Acad. Sci. U. S. A.*, 2019, **116**, 2805–2813.
18 O. Schneising, M. Buchwitz, M. Reuter, S. Vanselow, H. Bovensmann and J. P. Burrows, Remote sensing of methane leakage from natural gas and petroleum systems revisited, *Atmos. Chem. Phys.*, 2020, **20**, 9169–9182.
19 A. Lorente, T. Borsdorff, A. Butz, O. Hasekamp, J. Aan De Brugh, A. Schneider, L. Wu, F. Hase, R. Kivi, D. Wunch, D. F. Pollard, K. Shiomi, N. M. Deutscher, V. A. Velazco, C. M. Roehl, P. O. Wennberg, T. Warneke and J. Landgraf, Methane retrieved from TROPOMI: improvement of the data product and validation of the first 2 years of measurements, *Atmos. Meas. Tech.*, 2021, **14**, 665–684.
20 K. Liakos, P. Busato, D. Moshou, S. Pearson and D. Bochtis, Machine Learning in Agriculture: A Review, *Sensors*, 2018, **18**, 2674.
21 W. J. Murdoch, C. Singh, K. Kumbier, R. Abbasi-Asl and B. Yu, Definitions, methods, and applications in interpretable machine learning, *Proc. Natl. Acad. Sci. U. S. A.*, 2019, **116**, 22071–22080.
22 H. S. Eggleston, L. Buendia, K. Miwa, T. Ngara and K. Tanabe, *2006 IPCC Guidelines for National Greenhouse Gas Inventories, IPCC National Greenhouse Gas Inventories Programme*, Intergovernmental Panel on Climate Change IPCC, c/o Institute for Global Environmental Strategies IGES, 2108 - 11, Kamiyamaguchi, Hayama, Kanagawa (Japan), Japan, 2006.
23 E. Alexandropoulos, V. Anestis, F. Dragoni, A. Hansen, S. Cummins, D. O'Brien, B. Amon and T. Bartzanas, Decision Support Systems Based on Gaseous Emissions and Their Impact on the Sustainability Assessment at the Livestock Farm Level: An Evaluation from the User's Side, *Sustainability*, 2023, **15**, 13041.
24 A. Hamrani, A. Akbarzadeh and C. A. Madramootoo, Machine learning for predicting greenhouse gas emissions from agricultural soils, *Sci. Total Environ.*, 2020, **741**, 140338.
25 M. Niu, E. Kebreab, A. N. Hristov, J. Oh, C. Arndt, A. Bannink, A. R. Bayat, A. F. Brito, T. Boland, D. Casper, L. A. Crompton, J. Dijkstra, M. A. Eugène, P. C. Garnsworthy, M. N. Haque, A. L. F. Hellwing, P. Huhtanen, M. Kreuzer, B. Kuhla, P. Lund, J. Madsen, C. Martin, S. C. McClelland, M. McGee, P. J. Moate, S. Muetzel, C. Muñoz, P. O'Kiely, N. Peiren, C. K. Reynolds, A. Schwarm, K. J. Shingfield, T. M. Storlien, M. R. Weisbjerg, D. R. Yáñez-Ruiz and Z. Yu, Prediction of enteric methane production, yield, and intensity in dairy cattle using an intercontinental database, *Glob. Change Biol.*, 2018, **24**, 3368–3389.
26 S. Jayasundara, D. Worden, A. Weersink, T. Wright, A. VanderZaag, R. Gordon and C. Wagner-Riddle, Improving farm profitability also reduces the carbon footprint of milk production in intensive dairy production systems, *J. Clean. Prod.*, 2019, **229**, 1018–1028.
27 J. D. Maasakkers, D. J. Jacob, M. P. Sulprizio, T. R. Scarpelli, H. Nesser, J. Sheng, Y. Zhang, X. Lu, A. A. Bloom, K. W. Bowman, J. R. Worden and R. J. Parker, 2010–2015 North American methane emissions, sectoral contributions, and trends: a high-resolution inversion of GOSAT observations of atmospheric methane, *Atmos. Chem. Phys.*, 2021, **21**, 4339–4356.
28 M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M. M. Lalu, T. Li, E. W. Loder, E. Mayo-Wilson, S. McDonald, L. A. McGuinness, L. A. Stewart, J. Thomas, A. C. Tricco, V. A. Welch, P. Whiting and D. Moher, The PRISMA 2020 statement: an updated guideline for reporting systematic reviews, *BMJ*, 2021, **n71**, 1–9.
29 D. J. Varon, D. J. Jacob, J. McKeever, D. Jervis, B. O. A. Durak, Y. Xia and Y. Huang, Quantifying methane point sources from fine-scale satellite observations of atmospheric methane plumes, *Atmos. Meas. Tech.*, 2018, **11**, 5673–5686.
30 A. Eldering, T. E. Taylor, C. W. O'Dell and R. Pavlick, The OCO-3 mission: measurement objectives and expected performance based on 1 year of simulated data, *Atmos. Meas. Tech.*, 2019, **12**, 2341–2370.
31 Y. Someya, Y. Yoshida, H. Ohyama, S. Nomura, A. Kamei, I. Morino, H. Mukai, T. Matsunaga, J. L. Laughner, V. A. Velazco, B. Herkommer, Y. Té, M. K. Sha, R. Kivi, M. Zhou, Y. S. Oh, N. M. Deutscher and D. W. T. Griffith, Update on the GOSAT TANSO–FTS SWIR Level 2 retrieval algorithm, *Atmos. Meas. Tech.*, 2023, **16**, 1477–1501.
32 H. Zhou, S. Zhang, J. Peng, S. Zhang, J. Li, H. Xiong and W. Zhang, Informer: Beyond Efficient Transformer for Long Sequence Time-Series Forecasting, *AAAI*, 2021, **35**, 11106–11115.
33 M. Reichstein, G. Camps-Valls, B. Stevens, M. Jung, J. Denzler, N. Carvalhais and Prabhat, Deep learning and

process understanding for data-driven Earth system science, *Nature*, 2019, **566**, 195–204.

34 A. Karpatne, G. Atluri, J. H. Faghmous, M. Steinbach, A. Banerjee, A. Ganguly, S. Shekhar, N. Samatova and V. Kumar, Theory-Guided Data Science: A New Paradigm for Scientific Discovery from Data, *IEEE Trans. Knowl. Data Eng.*, 2017, **29**, 2318–2331.

35 R. Yu, S. Chen, Y. Xie and X. Jia, in *Data Science: Foundations and Applications*, ed X. Wu, M. Spiliopoulou, C. Wang, V. Kumar, L. Cao, X. Zhou, G. Pang and J. Gama, Springer Nature Singapore, Singapore, 2025, vol. 15875, pp. 39–57.

36 Food and Agriculture Organization, *Agrifood Systems in Nationally Determined Contributions: Global Analysis*, FAO, 2024.

37 United Nations Environment Programme and Climate and Clean Air Coalition, *Global Methane Assessment: Benefits and Costs of Mitigating Methane Emissions*, Nairobi: United Nations Environment Programme, 2021.

38 M. Saunois, A. R. Stavert, B. Poulter, P. Bousquet, J. G. Canadell, R. B. Jackson, P. A. Raymond, E. J. Dlugokencky, S. Houweling, P. K. Patra, P. Ciais, V. K. Arora, D. Bastviken, P. Bergamaschi, D. R. Blake, G. Brailsford, L. Bruhwiler, K. M. Carlson, M. Carrol, S. Castaldi, N. Chandra, C. Crevoisier, P. M. Crill, K. Covey, C. L. Curry, G. Etiope, C. Frankenberg, N. Gedney, M. I. Hegglin, L. Höglund-Isaksson, G. Hugelius, M. Ishizawa, A. Ito, G. Janssens-Maenhout, K. M. Jensen, F. Joos, T. Kleinen, P. B. Krummel, R. L. Langenfelds, G. G. Laruelle, L. Liu, T. Machida, S. Maksyutov, K. C. McDonald, J. McNorton, P. A. Miller, J. R. Melton, I. Morino, J. Müller, F. Murguia-Flores, V. Naik, Y. Niwa, S. Noce, S. O'Doherty, R. J. Parker, C. Peng, S. Peng, G. P. Peters, C. Prigent, R. Prinn, M. Ramonet, P. Regnier, W. J. Riley, J. A. Rosentreter, A. Segers, I. J. Simpson, H. Shi, S. J. Smith, L. P. Steele, B. F. Thornton, H. Tian, Y. Tohjima, F. N. Tubiello, A. Tsuruta, N. Viovy, A. Voulgarakis, T. S. Weber, M. Van Weele, G. R. Van Der Werf, R. F. Weiss, D. Worthy, D. Wunch, Y. Yin, Y. Yoshida, W. Zhang, Z. Zhang, Y. Zhao, B. Zheng, Q. Zhu, Q. Zhu and Q. Zhuang, The Global Methane Budget 2000–2017, *Earth Syst. Sci. Data*, 2020, **12**, 1561–1623.

39 N. Kreibich, Toward global net zero: The voluntary carbon market on its quest to find its place in the post-Paris climate regime, *WIREs Clim. Change*, 2024, **15**, e892.

40 G. Badgley, J. Freeman, J. J. Hamman, B. Haya, A. T. Trugman, W. R. L. Anderegg and D. Cullenward, Systematic over-crediting in California's forest carbon offsets program, *Glob. Change Biol.*, 2022, **28**, 1433–1445.

41 B. Haya, D. Cullenward, A. L. Strong, E. Grubert, R. Heilmayr, D. A. Sivas and M. Wara, Managing uncertainty in carbon offsets: insights from California's standardized approach, *Clim. Policy*, 2020, **20**, 1112–1126.

42 I. Andersen, N. Ishii, T. Brooks, C. Cummis, G. Fonseca, A. Hillers, N. Macfarlane, N. Nakicenovic, K. Moss, J. Rockström, A. Steer, D. Waughray and C. Zimm, Defining 'science-based targets', *Natl. Sci. Rev.*, 2021, **8**, nwaa186.

43 C. Bellora and L. Fontagné, EU in search of a Carbon Border Adjustment Mechanism, *Energy Econ.*, 2023, **123**, 106673.

44 Government of Canada, *2030 Emissions Reduction Plan: Canada's Next Steps for Clean Air and a Strong Economy*, Environment and Climate Change Canada, Quebec, Canada, 2022.

45 Agriculture and Agri-Food Canada, *What We Heard Report: Sustainable Agriculture Strategy*, 2023.

46 Environment and Climate Change Canada, *National Inventory Report 1990–2023: Greenhouse Gas Sources and Sinks in Canada*, Environment and Climate Change Canada, Ottawa, Canada, 2025.

47 Statistics Canada, *Canada's 2021 Census of Agriculture: A Story about the Transformation of the Agriculture Industry and Adaptiveness of Canadian Farmers*, 2022.

48 S. Neethirajan, Innovative Strategies for Sustainable Dairy Farming in Canada amidst Climate Change, *Sustainability*, 2023, **16**, 265.

49 D. Jervis, J. McKeever, B. O. A. Durak, J. J. Sloan, D. Gains, D. J. Varon, A. Ramier, M. Strupler and E. Tarrant, The GHGSat-D imaging spectrometer, *Atmos. Meas. Tech.*, 2021, **14**, 2127–2140.

50 A. Eldering, P. O. Wennberg, D. Crisp, D. S. Schimel, M. R. Gunson, A. Chatterjee, J. Liu, F. M. Schwandner, Y. Sun, C. W. O'Dell, C. Frankenberg, T. Taylor, B. Fisher, G. B. Osterman, D. Wunch, J. Hakkarainen, J. Tamminen and B. Weir, The Orbiting Carbon Observatory-2 early science investigations of regional carbon dioxide fluxes, *Science*, 2017, **358**, eaam5745.

51 T. E. Taylor, C. W. O'Dell, D. Baker, C. Bruegge, A. Chang, L. Chapsky, A. Chatterjee, C. Cheng, F. Chevallier, D. Crisp, L. Dang, B. Drouin, A. Eldering, L. Feng, B. Fisher, D. Fu, M. Gunson, V. Haemmerle, G. R. Keller, M. Kiel, L. Kuai, T. Kurosu, A. Lambert, J. Laughner, R. Lee, J. Liu, L. Mandrake, Y. Marchetti, G. McGarragh, A. Merrelli, R. R. Nelson, G. Osterman, F. Oyafuso, P. I. Palmer, V. H. Payne, R. Rosenberg, P. Somkuti, G. Spiers, C. To, B. Weir, P. O. Wennberg, S. Yu and J. Zong, Evaluating the consistency between OCO-2 and OCO-3 XCO_2 estimates derived from the NASA ACOS version 10 retrieval algorithm, *Atmos. Meas. Tech.*, 2023, **16**, 3173–3209.

52 T. Matsunaga, M. Saito, T. Saeki, H. Takagi, K. Murakami, S. Maksyutov, Y. Niwa, H. Tanimoto, H. Yashiro and Y. Yamashita, in *Sensors, Systems, and Next-Generation Satellites XXVII*, ed T. Kimura, S. R. Babu and A. Hélière, SPIE, Amsterdam, Netherlands, 2023, p. 14.

53 M. Drusch, U. Del Bello, S. Carlier, O. Colin, V. Fernandez, F. Gascon, B. Hoersch, C. Isola, P. Laberinti, P. Martimort, A. Meygret, F. Spoto, O. Sy, F. Marchese and P. Bargellini, Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services, *Rem. Sens. Environ.*, 2012, **120**, 25–36.

54 D. Phiri, M. Simwanda, S. Salekin, V. Nyirenda, Y. Murayama and M. Ranagalage, Sentinel-2 Data for

Land Cover/Use Mapping: A Review, *Remote Sens.*, 2020, **12**, 2291.

55 A. A. Thompson, Overview of the RADARSAT Constellation Mission, *Can. J. Rem. Sens.*, 2015, **41**, 401–407.

56 R. Duren, D. Cusworth, A. Ayasse, K. Howell, A. Diamond, T. Scarpelli, J. Kim, K. O'neill, J. Lai-Norling, A. Thorpe, S. R. Zandbergen, L. Shaw, M. Keremedjiev, J. Guido, P. Giuliano, M. Goldstein, R. Nallapu, G. Barentsen, D. R. Thompson, K. Roth, D. Jensen, M. Eastwood, F. Reuland, T. Adams, A. Brandt, E. A. Kort, J. Mason and R. O. Green, The Carbon Mapper emissions monitoring system, *Gases/Remote Sensing/Instruments and Platforms*, 2025, preprint, DOI: 10.5194/egusphere-2025-2275.

57 S. Li, C. Wang, P. Gao, B. Zhao, C. Jin, L. Zhao, B. He and Y. Xue, High-Spatial-Resolution Methane Emissions Calculation Using TROPOMI Data by a Divergence Method, *Atmosphere*, 2023, **14**, 388.

58 P. J. Prajesh, K. Ragunath, M. Gordon and S. Neethirajan, Satellite-Based Seasonal Fingerprinting of Methane Emissions from Canadian Dairy Farms Using Sentinel-5P, *Climate*, 2025, **13**, 135.

59 H. Lindqvist, E. Kivimäki, T. Häkkilä, A. Tsuruta, O. Schneising, M. Buchwitz, A. Lorente, M. Martinez Velarte, T. Borsdorff, C. Alberti, L. Backman, M. Buschmann, H. Chen, D. Dubravica, F. Hase, P. Heikkinen, T. Karppinen, R. Kivi, E. McGee, J. Notholt, K. Rautiainen, S. Roche, W. Simpson, K. Strong, Q. Tu, D. Wunch, T. Aalto and J. Tamminen, Evaluation of Sentinel-5P TROPOMI Methane Observations at Northern High Latitudes, *Remote Sens.*, 2024, **16**, 2979.

60 D. H. Cusworth, R. M. Duren, A. K. Thorpe, W. Olson-Duvall, J. Heckler, J. W. Chapman, M. L. Eastwood, M. C. Helmlinger, R. O. Green, G. P. Asner, P. E. Dennison and C. E. Miller, Intermittency of Large Methane Emitters in the Permian Basin, *Environ. Sci. Technol. Lett.*, 2021, **8**, 567–573.

61 A. J. Turner, P. Köhler, T. S. Magney, C. Frankenberg, I. Fung and R. C. Cohen, A double peak in the seasonality of California's photosynthesis as observed from space, *Biogeosciences*, 2020, **17**, 405–422.

62 H. Peiro, S. Crowell, A. Schuh, D. F. Baker, C. O'Dell, A. R. Jacobson, F. Chevallier, J. Liu, A. Eldering, D. Crisp, F. Deng, B. Weir, S. Basu, M. S. Johnson, S. Philip and I. Baker, Four years of global carbon cycle observed from the Orbiting Carbon Observatory 2 (OCO-2) version 9 and in situ data and comparison to OCO-2 version 7, *Atmos. Chem. Phys.*, 2022, **22**, 1097–1130.

63 M. De Vries and I. J. M. De Boer, Comparing environmental impacts for livestock products: A review of life cycle assessments, *Livest. Sci.*, 2010, **128**, 1–11.

64 European Space Agency, *Copernicus CO_2 Monitoring Mission Requirements Document*, 2020.

65 H. Tian, R. Xu, J. G. Canadell, R. L. Thompson, W. Winiwarter, P. Suntharalingam, E. A. Davidson, P. Ciais, R. B. Jackson, G. Janssens-Maenhout, M. J. Prather, P. Regnier, N. Pan, S. Pan, G. P. Peters, H. Shi, F. N. Tubiello, S. Zaehle, F. Zhou, A. Arneth, G. Battaglia, S. Berthet, L. Bopp, A. F. Bouwman, E. T. Buitenhuis, J. Chang, M. P. Chipperfield, S. R. S. Dangal, E. Dlugokencky, J. W. Elkins, B. D. Eyre, B. Fu, B. Hall, A. Ito, F. Joos, P. B. Krummel, A. Landolfi, G. G. Laruelle, R. Lauerwald, W. Li, S. Lienert, T. Maavara, M. MacLeod, D. B. Millet, S. Olin, P. K. Patra, R. G. Prinn, P. A. Raymond, D. J. Ruiz, G. R. Van Der Werf, N. Vuichard, J. Wang, R. F. Weiss, K. C. Wells, C. Wilson, J. Yang and Y. Yao, A comprehensive quantification of global nitrous oxide sources and sinks, *Nature*, 2020, **586**, 248–256.

66 P. Ricaud, J.-L. Attié, R. Chalinel, F. Pasternak, J. Léonard, I. Pison, E. Pattey, R. L. Thompson, Z. Zelinger, J. Lelieveld, J. Sciare, N. Saitoh, J. Warner, A. Fortems-Cheiney, H. Reynal, J. Vidot, L. Brooker, L. Berdeu, O. Saint-Pé, P. K. Patra, M. Dostál, J. Suchánek, V. Nevrlý and C. G. Zwaaftink, The Monitoring Nitrous Oxide Sources (MIN2OS) satellite project, *Rem. Sens. Environ.*, 2021, **266**, 112688.

67 S. Delgrosso, A. Mosier, W. Parton and D. Ojima, DAYCENT model analysis of past and contemporary soil NO and net greenhouse gas flux for major crops in the USA, *Soil Tillage Res.*, 2005, **83**, 9–24.

68 P. Smith, K. Calvin, J. Nkem, D. Campbell, F. Cherubini, G. Grassi, V. Korotkov, A. Le Hoang, S. Lwasa, P. McElwee, E. Nkonya, N. Saigusa, J. Soussana, M. A. Taboada, F. C. Manning, D. Nampanzira, C. Arias-Navarro, M. Vizzarri, J. House, S. Roe, A. Cowie, M. Rounsevell and A. Arneth, Which practices co-deliver food security, climate change mitigation and adaptation, and combat land degradation and desertification?, *Glob. Change Biol.*, 2020, **26**, 1532–1575.

69 E. Dowd, C. Wilson, M. P. Chipperfield, E. Gloor, A. Manning and R. Doherty, Decreasing seasonal cycle amplitude of methane in the northern high latitudes being driven by lower-latitude changes in emissions and transport, *Atmos. Chem. Phys.*, 2023, **23**, 7363–7382.

70 R. A. Genedy and J. A. Ogejo, Using machine learning techniques to predict liquid dairy manure temperature during storage, *Comput. Electron. Agric.*, 2021, **187**, 106234.

71 A. C. VanderZaag, J. D. MacDonald, L. Evans, X. P. C. Vergé and R. L. Desjardins, Towards an inventory of methane emissions from manure management that is responsive to changes on Canadian farms, *Environ. Res. Lett.*, 2013, **8**, 035008.

72 J. D. Maasakkers, D. J. Jacob, M. P. Sulprizio, T. R. Scarpelli, H. Nesser, J.-X. Sheng, Y. Zhang, M. Hersher, A. A. Bloom, K. W. Bowman, J. R. Worden, G. Janssens-Maenhout and R. J. Parker, Global distribution of methane emissions, emission trends, and OH concentrations and trends inferred from an inversion of GOSAT satellite data for 2010–2015, *Atmos. Chem. Phys.*, 2019, **19**, 7859–7881.

73 Y. Zhang, R. Gautam, S. Pandey, M. Omara, J. D. Maasakkers, P. Sadavarte, D. Lyon, H. Nesser, M. P. Sulprizio, D. J. Varon, R. Zhang, S. Houweling, D. Zavala-Araiza, R. A. Alvarez, A. Lorente, S. P. Hamburg, I. Aben and D. J. Jacob, Quantifying methane emissions

from the largest oil-producing basin in the United States from space, *Sci. Adv.*, 2020, **6**, eaaz5120.

74 T. Xia, J. Catalan, C. Hu and S. Batterman, Development of a mobile platform for monitoring gaseous, particulate, and greenhouse gas (GHG) pollutants, *Environ. Monit. Assess.*, 2021, **193**, 7.

75 S. Schwietzke, O. A. Sherwood, L. M. P. Bruhwiler, J. B. Miller, G. Etiope, E. J. Dlugokencky, S. E. Michel, V. A. Arling, B. H. Vaughn, J. W. C. White and P. P. Tans, Upward revision of global fossil fuel methane emissions based on isotope database, *Nature*, 2016, **538**, 88–91.

76 F. Mustafa, L. Bu, Q. Wang, N. Yao, M. Shahzaman, M. Bilal, R. W. Aslam and R. Iqbal, Neural-network-based estimation of regional-scale anthropogenic CO_2 emissions using an Orbiting Carbon Observatory-2 (OCO-2) dataset over East and West Asia, *Atmos. Meas. Tech.*, 2021, **14**, 7277–7290.

77 E. Harsányi, M. Mirzaei, S. Arshad, F. Alsilibe, A. Vad, A. Nagy, T. Ratonyi, M. Gorji, M. Al-Dalahme and S. Mohammed, Assessment of Advanced Machine and Deep Learning Approaches for Predicting CO2 Emissions from Agricultural Lands: Insights Across Diverse Agroclimatic Zones, *Earth Syst. Environ.*, 2024, **8**, 1109–1125.

78 A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser and I. Polosukhin, Attention Is All You Need, *arXiv*, 2017, preprint, arXiv:1706.03762, DOI: 10.48550/ARXIV.1706.03762.

79 C. E. Rasmussen, in *Advanced Lectures on Machine Learning*, ed O. Bousquet, U. Von Luxburg and G. Rätsch, Springer Berlin Heidelberg, Berlin, Heidelberg, 2004, vol. 3176, pp. 63–71.

80 Z. Zhen, S. Chen, T. Yin and J.-P. Gastellu-Etchegorry, Globally quantitative analysis of the impact of atmosphere and spectral response function on 2-band enhanced vegetation index (EVI2) over Sentinel-2 and Landsat-8, *ISPRS J. Photogrammetry Remote Sens.*, 2023, **205**, 206–226.

81 R. Sapkota, R. Qureshi, M. Usman Hadi, S. Zohaib Hassan, F. Sadak, M. Shoman, M. Sajjad, F. Ali Dharejo, A. Paudel, J. Li, Z. Meng, J. Shutske and M. Karkee, Multi-Modal LLMs in Agriculture: A Comprehensive Review, *IEEE Trans. Autom. Sci. Eng.*, 2025, **22**, 22510–22540.

82 L. Breiman, Random Forests, *Mach. Learn.*, 2001, **45**, 5–32.

83 C. Strobl, A.-L. Boulesteix, T. Kneib, T. Augustin and A. Zeileis, Conditional variable importance for random forests, *BMC Bioinf.*, 2008, **9**, 307.

84 G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang and L. Yang, Physics-informed machine learning, *Nat. Rev. Phys.*, 2021, **3**, 422–440.

85 Smart Prosperity Institute, Agricultural carbon markets: A comprehensive guide for Canadian farmers, 2023, available at: https://institute.smartprosperity.ca/AgriculturalCarbonMarkets.

86 Dairy Farmers of Canada, Navigating carbon markets: A toolkit for Canadian dairy farmers, 2024, available at: https://dairyfarmersofcanada.ca/en/farmer-resources/tools/navigating-carbon-markets.

87 Agriculture and Agri-Food Canada, Financial impacts of carbon pricing on Canadian farms, 2018, available at: https://agriculture.canada.ca/en/sector/data-reports/climate-change-policy-financial-impacts-carbon-pricing.

88 J. K. O'Hara, US climate-smart agricultural and forestry incentives: from offsets to clean energy credits, *Agric. Resour. Econ. Rev.*, 2024, **53**, 371–386.

89 U.S. Environmental Protection Agency, Laws and regulations that apply to your agricultural operation by farm activity, 2015, available at: https://epa.gov/agriculture/laws-and-regulations-apply-your-agricultural-operation-farm-activity.

90 S. Conley, I. Faloona, S. Mehrotra, M. Suard, D. H. Lenschow, C. Sweeney, S. Herndon, S. Schwietzke, G. Pétron, J. Pifer, E. A. Kort and R. Schnell, Application of Gauss's theorem to quantify localized surface emissions from airborne measurements of wind and trace gases, *Atmos. Meas. Tech.*, 2017, **10**, 3345–3358.

91 D. D. Baldocchi, How eddy covariance flux measurements have contributed to our understanding of Global Change Biology, *Glob. Change Biol.*, 2020, **26**, 242–260.

92 A. Bolek, M. Heimann and M. Göckede, UAV-based in situ measurements of CO_2 and CH_4 fluxes over complex natural ecosystems, *Atmos. Meas. Tech.*, 2024, **17**, 5619–5636.

93 J. Lynch, M. Cain, R. Pierrehumbert and M. Allen, Demonstrating GWP: a means of reporting warming-equivalent emissions that captures the contrasting impacts of short- and long-lived climate pollutants, *Environ. Res. Lett.*, 2020, **15**, 044023.

94 S. Everhart, Growing carbon credits: Strengthening the agricultural sector's participation in voluntary carbon markets through law and policy, *NYU Environ. Law J.*, 2023, **31**, 65.

95 R. Lema, L. B. Vargas, A. D. Gonzalez, J. Lachman, A. Maes-Anastasi, P. Kumar *et al.*, *Smallholder Farmers and the Voluntary Carbon Market: A Balancing Act: Navigating Pricing, Co-benefits, and Challenges*, 2025.

96 U.S. Department of Agriculture, A general assessment of the role of agriculture and forestry in the U.S. carbon markets, Office of the Chief Economist, 2023, available at: https://usda.gov/media/press-releases/2023/10/23/usda-releases-assessment-agriculture-and-forestry-carbon-markets.

97 N. Raina, M. Zavalloni and D. Viaggi, Incentive mechanisms of carbon farming contracts: A systematic mapping study, *J. Environ. Manage.*, 2024, **352**, 120126.

98 W. Nicole, *CAFOs and Environmental Justice: the Case of North Carolina*, 2013.

99 E. Pohl and S. R. Lee, Local and global public health and emissions from concentrated animal feeding operations in the USA: A scoping review, *Int. J. Environ. Res. Publ. Health*, 2024, **21**(7), 916.

100 J. Y. Son, B. M. Lewis and M. L. Bell, Disparities in exposure to concentrated animal feeding operations (CAFOs) and other animal feeding operations across multiple states in USA, *J. Expo. Sci. Environ. Epidemiol.*, 2025, 1–8.

101 P. Levy, R. Clement, N. Cowan, B. Keane, V. Myrgiotis, M. van Oijen, *et al.*, Challenges in scaling up greenhouse gas fluxes: Experience from the UK greenhouse gas emissions and feedbacks program, *J. Geophys. Res.: Biogeosci.*, 2022, **127**(5), e2021JG006743.

102 E. Daly, D. Burton, G. K. MacDonald, K. Dunfield, T. Li, A. Weersink, *et al.*, CANN$_2$ONET – A Canadian nitrous oxide collaboration network to meet greenhouse gas emission reduction targets, *Environ. Res. Lett.*, 2025, 1–11.

103 K. B. Delwiche, J. Nelson, N. Kowalska, C. E. Moore, G. Shirkey, T. Tarin, *et al.*, Charting the future of the FLUXNET network, *Bull. Am. Meteorol. Soc.*, 2024, **105**(3), E466–E473.

104 D. Papale, Ideas and perspectives: Enhancing the impact of the FLUXNET network of eddy covariance sites, *Biogeosciences*, 2020, **17**, 5587–5598.

105 J. Pearl, *Causality: Models, Reasoning, and Inference*, Cambridge University Press, Cambridge, UK, 2003, vol. 19.