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Innovative Data Integration Method for Enhancing GHG Inventory Reporting Accuracy and Reliability

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Abstract
Accurate and reliable greenhouse gas (GHG) inventory reporting is essential for tracking mitigation progress, informing climate policy, and supporting national commitments under international frameworks such as the Paris Agreement. However, traditional GHG inventory systems often struggle with fragmented datasets, inconsistent reporting standards, limited temporal resolution, and uncertainties arising from disparate measurement techniques. This study introduces an innovative data integration method designed to enhance the accuracy, completeness, and reliability of GHG inventories by harmonizing multisource data and leveraging advanced analytical techniques. The proposed framework integrates satellite observations, ground-based measurements, sectoral activity data, remote sensing products, emission factors, and real-time sensor networks through a unified architecture supported by machine-learning algorithms and geospatial analytics. The method employs robust data fusion techniques such as Bayesian inference, ensemble learning, and spatiotemporal interpolation to reconcile inconsistencies, fill data gaps, and quantify uncertainty across sources. A structured validation protocol is developed to align integrated datasets with internationally recognized reporting standards, including IPCC Tier 2 and Tier 3 methodologies, ensuring methodological transparency and cross-sector comparability. Application of the integrated system to national emission datasets demonstrates significant improvements in estimating emissions from agriculture, energy, transportation, waste, and industrial processes. Models reveal enhanced detection of emission anomalies, better estimation of fugitive emissions, and improved granularity in monitoring temporal changes, particularly in sectors with historically underreported emissions. Results show that the innovative integration method reduces uncertainty margins, increases reporting consistency, and offers higher-resolution insights into emission drivers. Sensitivity analysis confirms that incorporating satellite-derived metrics and continuous sensor data substantially strengthens the robustness of national GHG inventories. The study highlights the transformative potential of integrated data systems in supporting adaptive climate governance, enabling early identification of emission trends, and improving transparency for verification processes. Overall, this research underscores the importance of advanced data integration for next-generation GHG inventory systems, providing a scalable and interoperable framework suitable for national and subnational applications. The method supports more informed climate decision-making and enhances global efforts toward achieving emissions reduction targets.

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1. Introduction

Greenhouse gas (GHG) inventories serve as the foundation for national and global climate governance, providing the data needed to assess emissions trends, evaluate mitigation progress, and guide policy decisions under international agreements such as the Paris Agreement. By quantifying emissions across key sectors including energy, transportation, agriculture, industry, and waste GHG inventories enable countries to track their contributions to global warming and develop evidence-based strategies for reducing their climate impact. Reliable and accurate inventories are therefore essential for meeting Nationally Determined Contributions (NDCs), informing carbon pricing mechanisms, supporting climate finance, and enhancing transparency in global climate negotiations (Awe, Akpan & Adekoya, 2017, Osabuohien, 2017). However, despite their central role in climate action, current GHG inventory systems face significant challenges that compromise their accuracy and reliability.

Many national inventories suffer from data fragmentation, as emissions information is often dispersed across multiple agencies, sectors, and monitoring systems that operate independently and use inconsistent methodologies. This fragmentation makes it difficult to compile comprehensive and harmonized datasets, leading to gaps, overlaps, or contradictory information. Uncertainty also remains a persistent challenge, driven by limitations in measurement technologies, variability in emission factors, incomplete activity data, and methodological assumptions that may not reflect real-world conditions. In addition, reporting frameworks vary widely across countries and sectors, creating inconsistencies in emission estimation approaches, temporal resolution, and spatial granularity (Akpan, Awe & Idowu, 2019, Ogundipe, *et al*., 2019). Such inconsistencies undermine comparability and can obscure true emissions trends, making it difficult to verify progress or identify areas requiring targeted intervention.

These challenges highlight the urgent need for innovative data integration methods capable of harmonizing multisource datasets, reducing uncertainty, and improving inventory completeness. By leveraging advanced analytical tools, machine learning, geospatial technologies, and real-time monitoring systems, integrated data frameworks can bridge methodological gaps and provide more accurate representations of national and subnational emissions. As countries face increasing pressure to demonstrate credible climate action, enhancing the accuracy and reliability of GHG inventories has become a critical priority. An innovative data integration approach offers a pathway to strengthen transparency, improve decision-making, and ultimately support more effective global climate mitigation efforts (Akinola, *et al*., 2024, Bobie-Ansah, Olufemi & Agyekum, 2024, Ikese, *et al*., 2024, Osabuohien, 2024).

2. Methodology

The study adopts an innovative data integration–driven methodological approach to enhance the accuracy, reliability, and regulatory credibility of greenhouse gas (GHG) inventory reporting across complex, multi-source emission environments. The methodology is grounded in principles of data integrity, privacy-preserving analytics, explainable artificial intelligence, and enterprise-scale governance frameworks, drawing from advances in AI-enabled analytics, business intelligence, cybersecurity, and climate-focused decision systems. The approach begins with the identification and mapping of heterogeneous GHG data sources, including activity data from industrial operations, energy consumption logs, supply-chain emission records, IoT sensor feeds, satellite-derived climate indicators, and third-party reporting datasets. These datasets are characterized by differences in temporal resolution, spatial granularity, data quality, and ownership, necessitating a structured integration pipeline capable of resolving inconsistencies and preserving traceability.

Data ingestion is executed through scalable data pipelines designed to support real-time and batch processing, ensuring compatibility with continuous monitoring requirements and periodic national inventory submissions. To address confidentiality and cross-organizational data-sharing constraints, privacy-preserving mechanisms such as encrypted data exchange, federated analytics, and secure multi-party computation are embedded within the ingestion layer, consistent with homomorphic encryption and secure analytics frameworks. Automated validation routines are applied to incoming datasets to detect anomalies, missing values, duplication, and structural inconsistencies, leveraging explainable AI techniques to ensure transparency in error detection and correction processes. This step enhances auditability and aligns with international expectations for research data integrity and reproducibility.

Following validation, harmonization and standardization processes are implemented to align emission factors, activity units, temporal boundaries, and reporting scopes in accordance with internationally recognized GHG accounting standards. Bayesian inference and time-series modeling techniques are then applied to reconcile discrepancies between overlapping data streams, quantify uncertainty ranges, and generate statistically robust emission estimates. These models are designed to capture both deterministic operational drivers and stochastic climate variability, improving the reliability of reported emissions under changing environmental conditions. Machine learning–based anomaly detection models further support the identification of outliers and abnormal emission patterns that may indicate reporting errors, equipment failures, or unaccounted-for emission sources.

Integrated datasets are subsequently processed through an analytics and forecasting layer that supports scenario analysis, trend projection, and sensitivity assessment. This layer enables organizations to evaluate the impact of operational changes, decarbonization strategies, and policy interventions on future emission trajectories. Outputs from the analytical models are translated into decision-ready insights through business intelligence dashboards that provide real-time visualization of emission profiles, uncertainty bands, compliance status, and performance against reduction targets. These dashboards are designed following enterprise BI best practices to support transparency, executive decision-making, and regulatory engagement.

To ensure operational sustainability, the methodology incorporates governance and competency alignment mechanisms, including role-based access control, documentation protocols, model retraining schedules, and performance monitoring indicators. Project management and organizational readiness principles are embedded to support institutional adoption, continuous improvement, and cross-functional coordination. The final stage of the methodology focuses on verification and reporting, where integrated outputs are aligned with national and international reporting frameworks, subjected to internal audit checks, and prepared for third-party verification. This end-to-end approach ensures that GHG inventories produced through the integrated method are not only more accurate and reliable but also defensible, scalable, and aligned with emerging digital climate governance standards.

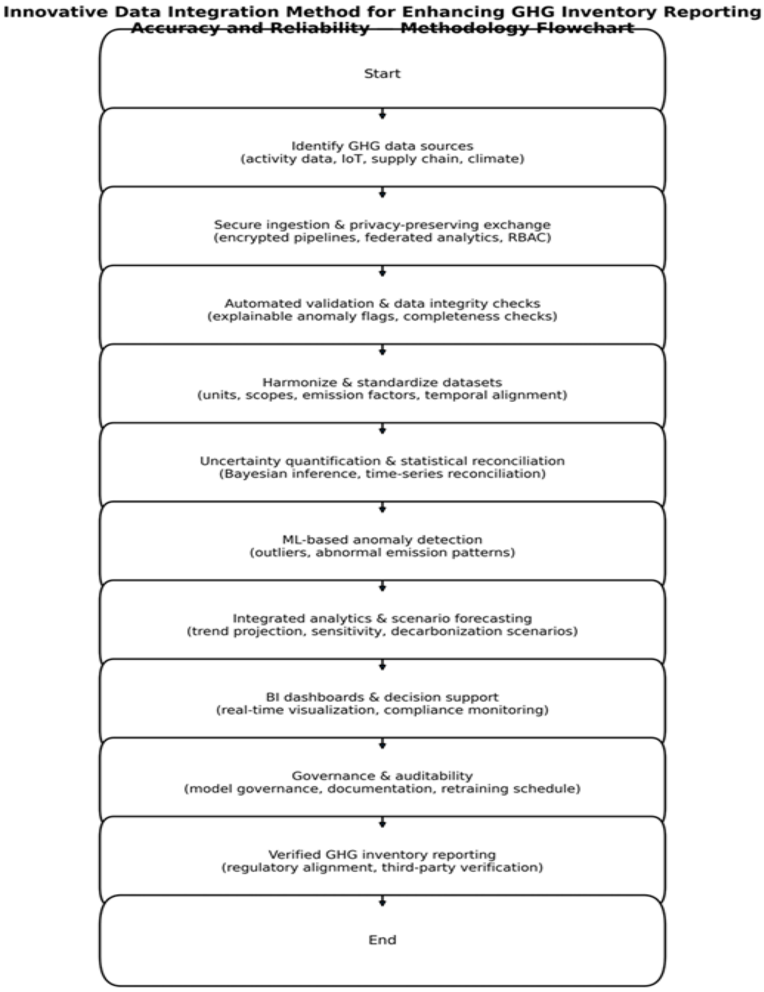

Fig 1: Flowchart of the study methodology

3. Limitations of Conventional GHG Inventory Systems

Conventional greenhouse gas (GHG) inventory systems, despite their long-established role in global climate reporting frameworks, face several limitations that hinder their ability to provide accurate, consistent, and comprehensive emission estimates. These limitations have become increasingly evident as countries strive to meet the transparency and accountability requirements of the Paris Agreement and as climate science demands higher-resolution data to support targeted mitigation strategies. Key challenges include persistent data gaps, methodological inconsistencies across sectors and regions, limited temporal and spatial resolution, and structural difficulties in integrating multisectoral and multisource emission datasets (Odezuligbo, Alade & Chukwurah, 2024, Oyeyemi, Orenuga & Adelakun, 2024, Taiwo, Akinbode and Uchenna, 2024). These constraints undermine the reliability of GHG inventories and create uncertainty in national reporting, which in turn affects global climate progress tracking and policy implementation.

One of the most pervasive limitations of traditional GHG inventory systems is the presence of data gaps across multiple sectors. Many industries lack continuous monitoring systems or structured reporting protocols, resulting in incomplete or outdated activity data. For instance, small-scale agricultural operations, informal industrial activities, and decentralized energy use often go unrecorded. In developing countries, basic emissions data such as fuel consumption, livestock populations, waste volumes, and forest cover changes may be irregularly collected or entirely missing. Even in well-established systems, fugitive emissions from oil and gas infrastructure, methane leaks from landfills, and emissions from natural disturbances such as wildfires are frequently underestimated due to limited detection capabilities (Odezuligbo, Alade & Chukwurah, 2024, Oyeyemi, Orenuga & Adelakun, 2024, Taiwo, Akinbode and Uchenna, 2024). These data gaps force inventory compilers to rely on generic emission factors or extrapolations that may not reflect real-world conditions, thereby introducing significant uncertainty into national emissions estimates.

Methodological inconsistencies represent another major challenge for conventional GHG inventory systems. The Intergovernmental Panel on Climate Change (IPCC) provides guidelines for emissions estimation, yet countries interpret and apply these guidelines differently depending on available resources, technical capacity, and national priorities. The result is a patchwork of inventory approaches, with some countries using Tier 1 default emission factors while others apply more sophisticated Tier 2 or Tier 3 methods that incorporate detailed local measurements and modeling. Sectoral differences further complicate matters; for example, agriculture and land-use sectors often rely heavily on assumptions and regional averages, whereas energy and industry sectors may use more precise data (Ayobami, *et al*., 2024, Davies, *et al*., 2024, Eyo, *et al*., 2024, Isa, 2024). These methodological discrepancies make cross-country comparisons difficult and sometimes misleading. Moreover, inconsistent reporting cycles, varying levels of transparency, and differing QA/QC (quality assurance/quality control) procedures reduce the credibility and reproducibility of emissions data.

Limited temporal and spatial resolution also constrains the effectiveness of conventional GHG inventories. Traditionally, inventories are compiled annually, using aggregated national-level data that provide only a broad snapshot of emissions. This approach fails to capture short-term fluctuations driven by seasonal activity, changes in energy demand, economic cycles, or extreme weather events. For example, methane emissions from wetlands vary significantly with temperature and rainfall patterns, while energy emissions fluctuate with heating and cooling demand. Yet annual inventories cannot reflect these variations, masking important trends and delaying policy responses. Spatial resolution is similarly limited, as national-level reporting does not provide localized insights into emission hotspots (Awe & Akpan, 2017). High-emitting industrial zones, traffic corridors, agricultural clusters, and rapidly urbanizing regions may contribute disproportionately to national emissions, but coarse spatial reporting obscures these nuances. The lack of fine-scale spatial data also restricts the development of local mitigation strategies, air quality management plans, and targeted climate adaptation efforts. Figure 2 shows CSE Research Data Integrity Concept Model presented b Condon, Simpson & Emanuel, 2022.

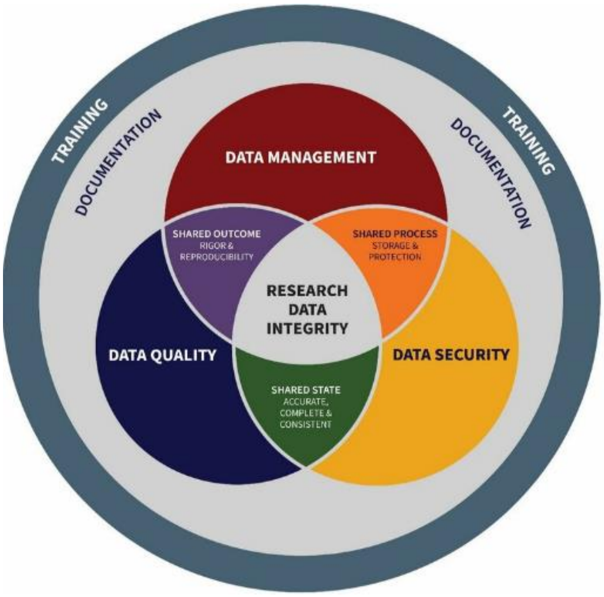

Fig 2: CSE Research Data Integrity Concept Model (Condon, Simpson & Emanuel, 2022).

Integrating multisectoral and multisource datasets presents a significant structural challenge for conventional GHG inventory systems. Emissions originate from diverse sources energy production, transportation, agriculture, industry, land use, and waste and each sector use different measurement systems, reporting formats, and temporal scales. Data from satellites, ground-based sensors, administrative records, company reports, and national surveys must be manually compiled, harmonized, and converted into standardized formats. This integration requires technical expertise and computational resources that many institutions lack (Ogunyankinnu, *et al*., 2024, Okon, *et al*., 2024, Olulaja, Afolabi & Ajayi, 2024). Moreover, the disparate nature of emission sources means that inconsistencies or inaccuracies in one sector can propagate through the entire inventory. For example, if agricultural emissions are based on outdated livestock population data while energy emissions rely on real-time monitoring, the resulting inventory will reflect an uneven level of accuracy between sectors. Integrating emissions from land-use change is especially challenging because it involves complex biophysical processes, diverse datasets, and significant uncertainty related to carbon sequestration rates, forest degradation, and soil carbon dynamics.

Another limitation of conventional GHG inventories is the reliance on emission factors that may not reflect local conditions. Many countries adopt default IPCC emission factors due to lack of national measurement data. However, emission factors for fossil fuel combustion, livestock enteric fermentation, fertilizer application, or waste decomposition vary widely depending on climate, technology, management practices, and socioeconomic context. Using generalized emission factors introduces systematic bias, which can either overestimate or underestimate true emissions. This divergence becomes particularly problematic when tracking mitigation progress, as inaccurate estimates may distort the perceived effectiveness of climate policies or misrepresent national contributions to global emissions (Akinbode, *et al*., 2024, Folorunso, *et al*., 2024, Orenuga, Oyeyemi & Olufemi John, 2024)).

Uncertainty quantification in traditional inventories is also limited. Although guidelines recommend reporting uncertainty ranges, few countries have robust systems for quantifying uncertainty across sectors. Uncertainties often stem from measurement errors, incomplete data, model assumptions, and variability in emission factors. Without transparent and comprehensive uncertainty analysis, policymakers may misinterpret emissions trends or overlook sectors with high estimation variability. This lack of clarity reduces confidence in inventory outputs and hampers international verification processes. Figure 3 shows figure of importance of artificial intelligence in reducing greenhouse gas emissions by optimizing transportation systems presented by Chen, *et al*., 2023.

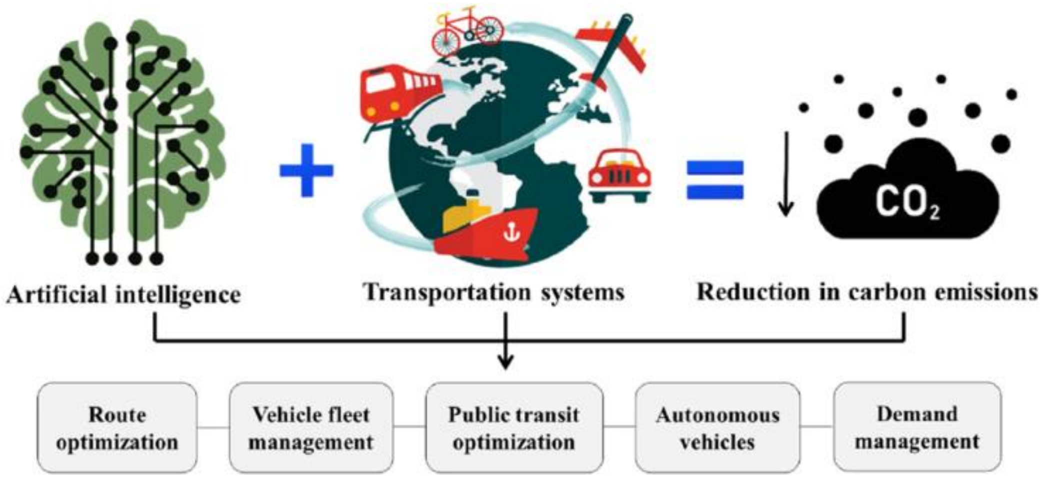

Fig 3: Importance of artificial intelligence in reducing greenhouse gas emissions by optimizing transportation systems (Chen, *et al*., 2023).

Conventional inventory systems also struggle to incorporate emerging emission sources and pollutants. As scientific understanding evolves, new categories such as black carbon, fluorinated gases, and methane emissions from unconventional oil and gas extraction become increasingly relevant. However, traditional data systems are often slow to integrate these emerging sources due to institutional inertia, limited technical capacity, or insufficient funding. This lag creates gaps between scientific knowledge and policy implementation, weakening the responsiveness of national climate strategies (Ajayi & Akanji, 2021, Ejibenam, *et al*., 2021, Osabuohien, Omotara & Watti, 2021).

Furthermore, conventional inventories typically operate on static datasets and do not support real-time or near-real-time emissions monitoring. This limitation reduces the ability of governments to rapidly adjust policies in response to unexpected emission surges or declining mitigation performance. For example, energy emissions may spike during extreme cold seasons, drought-induced power shortages, or economic recoveries, but annual inventories reflect these events only after significant delay. Without timely data, opportunities for early intervention and course correction are lost (Akanji & Ajayi, 2022, Francis Onotole, *et al*., 2022).

In conclusion, the limitations of conventional GHG inventory systems data gaps, methodological inconsistencies, limited temporal and spatial resolution, and challenges in integrating multisectoral datasets pose significant barriers to accurate and reliable emissions reporting. These constraints are increasingly untenable in a global climate governance landscape that demands precision, transparency, and accountability. As countries work toward more ambitious climate goals, innovative data integration methods, supported by advanced analytics, remote sensing, and real-time monitoring technologies, are essential for overcoming these limitations and enhancing the overall quality and reliability of GHG inventories (Awe, 2021, Halliday, 2021).

4. Data Sources Relevant to Enhanced GHG Inventory Reporting

Accurate and reliable greenhouse gas (GHG) inventory reporting depends fundamentally on the quality, diversity, and integration of data sources used to estimate emissions across sectors. As global climate commitments intensify and nations face increasing scrutiny regarding their emissions trajectories, the need for comprehensive, high-resolution, and verifiable data has never been greater. Conventional GHG inventories traditionally rely on aggregated national statistics, sectoral reports, and standardized emission factors; however, these sources are often insufficient for capturing the complexity and variability of real-world emissions. Innovative data integration methods require the incorporation of advanced and diverse data streams that provide richer insights into emission dynamics (Babalola, *et al*., 2024, Udensi, Akomolafe & Adeyemi, 2024). Among these, satellite remote sensing, ground-based monitoring networks, sectoral activity data, updated emission factors, and automated sensor technologies form the backbone of enhanced GHG assessment.

Satellite remote sensing has emerged as one of the most transformative data sources for improving GHG inventory accuracy. High-resolution satellite instruments such as TROPOMI, OCO-2, GOSAT, and Sentinel missions provide direct and indirect measurements of atmospheric concentrations of key GHGs, including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). These data capture spatially explicit emissions patterns over large geographic areas, offering insights into emission hotspots, plume dispersion, land-use changes, and biomass burning events. Satellites offer a unique advantage by enabling consistent global coverage, including regions where ground-based monitoring is limited or nonexistent (Afolabi, Ajayi & Olulaja, 2024, Ilemobayo, *et al*., 2024, Selesi-Aina, *et al*., 2024). They also support near-real-time detection of emission anomalies, such as methane leaks from oil and gas facilities or unexpected CO_2 spikes from industrial clusters. When integrated with machine-learning models and atmospheric inversion techniques, satellite data can help identify discrepancies between reported and actual emissions, thus improving the transparency and accuracy of national inventories.

Ground-based monitoring networks complement satellite observations by providing detailed, localized, and continuous measurements of atmospheric concentrations, fuel combustion efficiency, and sector-specific emissions. These networks include air quality monitoring stations, industrial emission reporting systems, meteorological stations, and specialized GHG monitoring facilities equipped with Fourier-transform infrared (FTIR) analyzers or gas chromatography instruments. Ground-based systems offer high precision and temporal continuity, which are essential for validating satellite-derived estimates and calibrating atmospheric models. Stations located in urban centers, industrial zones, agricultural regions, and remote natural areas provide a comprehensive picture of emissions across different environments (Adeshina, 2021, Isa, Johnbull & Ovenseri, 2021, Wegner, Omine & Vincent, 2021). These data help capture diurnal, seasonal, and episodic emission patterns that cannot be fully resolved through annual inventory reporting.

Sectoral activity data represents another critical data stream for enhanced GHG inventory reporting. Unlike satellite or sensor data, which measure atmospheric concentrations, sectoral activity data captures the human activities driving emissions. These data include fuel consumption statistics, vehicle kilometers traveled, industrial production outputs, livestock numbers, fertilizer application rates, waste generation volumes, and land-use change records. Activity data form the basis for bottom-up inventory approaches, where emissions are calculated by multiplying activity levels by appropriate emission factors. High-quality sectoral data enable more precise emission estimation, especially when broken down by technology type, efficiency levels, production processes, and management practices (Ajayi & Akanji, 2023, Halliday, 2023, Udensi, Akomolafe & Adeyemi, 2023). For example, detailed agricultural activity data allow inventories to capture differences in crop types, irrigation methods, and manure management practices, which significantly influence methane and nitrous oxide emissions. Similarly, granular energy-sector data help identify emission variations across power plants, industries, and transportation systems. Figure 4 shows a comparison of GHG verification guidelines between GHG Protocol and ISO 14064 presented by Liu, Wu & Chau, 2023.

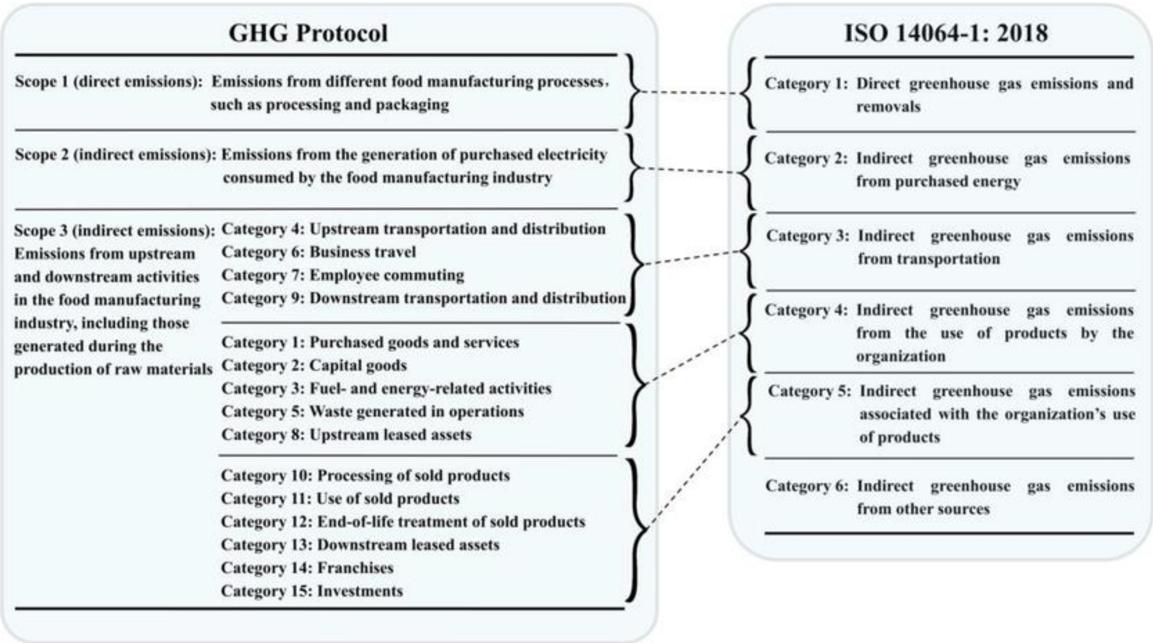

Fig 4: A comparison of GHG verification guidelines between GHG Protocol and ISO 14064 (Liu, Wu & Chau, 2023).

Emission factors remain fundamental to GHG estimation, but their accuracy depends on their relevance to local conditions. Conventional inventories often rely on IPCC default emission factors, which may not accurately represent technology-specific efficiency, fuel quality, or local environmental conditions. Enhanced GHG reporting requires updated, country-specific, and sector-specific emission factors based on direct measurements, scientific studies, and technological assessments. For instance, emissions from diesel generators in tropical regions differ significantly from those in colder climates, while methane emissions from rice cultivation vary with irrigation practices and soil types. Improved emission factors reduce systematic bias and uncertainty, especially when derived from empirical measurements and integrated with remote sensing and sensor-based observations (Akinbode, *et al*., 2023, Onibokun, *et al*., 2023, Osabuohien, *et al*., 2023). Developing dynamic emission factors that adjust based on real-time conditions such as variations in fuel quality, combustion efficiency, or agricultural practices further strengthens inventory accuracy.

Automated sensor technologies introduce another valuable dimension to GHG assessment, offering continuous, high-frequency, and site-specific emissions measurements. Sensors deployed in industrial facilities, landfills, wastewater treatment plants, agricultural barns, and oil and gas infrastructure provide real-time monitoring of methane leaks, CO_2 emissions, and other pollutants. Technologies such as optical gas imaging cameras, laser-based detectors, eddy covariance towers, and Internet of Things-enabled gas sensors allow emissions to be tracked minute-by-minute, enabling rapid detection of leaks or abnormal emission events (Asonze, *et al*., 2024, Davies, *et al*., 2024, Odezuligbo, 2024, Wegner, 2024). These systems enhance the capacity for verification and support rapid mitigation actions. Automated sensors also help quantify emissions from diffuse or fugitive sources that are traditionally underreported, such as methane seepage from aging pipelines or nitrous oxide emissions from fertilized soils. When aggregated and integrated with atmospheric data, these sensor networks contribute to more robust, data-rich inventory frameworks.

Land-use, land-use change, and forestry (LULUCF) data constitute an additional essential component of enhanced GHG reporting. Forest biomass inventories, satellite-derived canopy cover assessments, soil carbon measurements, and deforestation tracking systems help quantify carbon sequestration and emissions from land-use change. High-resolution remote sensing instruments detect forest degradation, afforestation, reforestation, and peatland disturbances with increasing precision. LULUCF-related emissions remain one of the most uncertain components of national inventories due to the complexity of biophysical processes and spatial heterogeneity. Integrating multiple data sources such as LiDAR imagery, forest plot measurements, and soil carbon sampling helps minimize uncertainty and improve the reliability of carbon stock estimates (Akande & Chukwunweike, 2023, Awe, *et al*., 2023, Ogundipe, *et al*., 2023).

Waste-sector data, including landfill gas capture rates, waste composition analyses, and methane oxidation factors, provide critical information for quantifying emissions from municipal solid waste and wastewater treatment facilities. These emissions are often subject to high uncertainty due to inconsistent measurement approaches and data collection gaps. Enhanced monitoring using landfill gas sensors, drone-based plume detection, and remote sensing technologies can provide more accurate and continuous data (Ajayi & Akanji, 2022, John & Oyeyemi, 2022, Osabuohien, 2022).

Energy-system data generated from smart meters, grid monitoring systems, and industrial process controls offer real-time insights into fuel consumption patterns, combustion efficiency, and energy demand fluctuations. These data streams support improved emission estimation by linking energy use directly to operational conditions rather than relying solely on annual consumption reports. Smart-grid and digital energy systems facilitate sector-specific emission tracking at unprecedented granularity.

Integrating these diverse data sources requires advanced data management systems, interoperability standards, and analytical frameworks. Machine-learning algorithms, data fusion techniques, and geospatial information systems enable the harmonization of multisectoral datasets, filling gaps, correcting inconsistencies, and generating comprehensive emissions profiles. Data integration transforms disparate information into coherent, actionable inventories that enhance accuracy, transparency, and international comparability (Adeshina, 2023, Onyedikachi, *et al*., 2023, Wegner & Ayansiji, 2023).

In conclusion, enhanced GHG inventory reporting relies on a multifaceted data ecosystem built on satellite observations, ground-based monitoring, sectoral activity data, accurate emission factors, automated sensor technologies, and land-use assessments. Together, these data streams enable more precise, timely, and verifiable emissions estimates that support informed policymaking, robust climate strategies, and credible participation in global climate governance frameworks (Akpan, *et al*., 2017, Oni, *et al*., 2018).

5. Innovative Data Integration Framework

An innovative data integration framework designed to enhance greenhouse gas (GHG) inventory reporting accuracy and reliability must overcome longstanding challenges associated with fragmented datasets, inconsistent methodologies, and limited observation coverage across sectors. As countries strive to meet more stringent reporting and transparency requirements under global climate agreements, there is an increasing need for a unified architecture capable of harmonizing heterogeneous data sources into coherent and verifiable emissions estimates. The proposed integration framework achieves this by combining advanced data fusion methods, machine-learning analytics, and geospatial tools within a structured, interoperable architecture. This framework not only improves the precision of emissions reporting but also serves as the foundation for dynamic, scalable, and future-ready GHG inventory systems (Adeleke & Ajayi, 2023, Adeshina, Owolabi & Olasupo, 2023, Oyeyemi, 2023).

At its core, the innovative data integration framework is designed to aggregate and harmonize multiple streams of emissions-relevant information, including satellite remote sensing data, ground-based monitoring networks, sectoral activity records, updated emission factors, automated sensor outputs, and land-use datasets. These inputs often differ in format, resolution, accuracy, and temporal coverage. The architecture begins with a multi-layered data ingestion system capable of acquiring data from diverse sources in both real-time and batch modes. Standardized interfaces and interoperability protocols ensure that datasets generated by different agencies, sectors, or technological systems can be integrated seamlessly. For example, satellite data may arrive in raster formats with hourly or daily temporal resolution, while sectoral activity data may come from statistical databases recorded monthly or annually (Ajayi & Akanji, 2022, Leonard & Emmanuel, 2022). The ingestion layer harmonizes metadata, spatial referencing, and temporal units to create a unified foundation for subsequent processing.

Once data is ingested, the framework employs advanced data fusion techniques to reconcile discrepancies, fill gaps, and merge overlapping datasets. Data fusion in this context involves synthesizing information from multiple observational sources to generate more accurate and representative estimates of emissions or emission drivers. For instance, methane concentration data from satellites can be fused with ground-based sensor measurements to correct atmospheric retrieval biases and improve spatial resolution. Similarly, bottom-up emissions estimates derived from activity data and emission factors can be cross-referenced with top-down atmospheric inversion models to validate emissions or detect underreported sources (Adeleke & Olajide, 2024, Awe, *et al*., 2024, Davies, *et al*., 2024). Data fusion methods can range from statistical techniques such as Bayesian hierarchical modeling and Kalman filtering to more advanced machine-learning approaches that infer relationships between disparate datasets. These techniques ensure that the resulting dataset represents the most accurate and complete picture of emissions available.

Machine-learning tools play a central role in the innovative integration framework by enabling predictive modeling, anomaly detection, uncertainty reduction, and automated harmonization of emissions information. Machine-learning algorithms can learn complex patterns in emissions data driven by factors such as economic activity, temperature variations, energy consumption, vegetation changes, or industrial operations. For example, gradient boosting and random forest models can estimate missing activity data or refine emission factors by analyzing correlations among multiple variables. Neural networks can integrate satellite-derived atmospheric data with surface measurements to predict plume dispersion patterns or identify previously undetected emission hotspots (Abdulkareem, *et al*., 2023, Adeleke & Ajayi, 2023, Halliday, 2023). Machine-learning techniques are also valuable for identifying anomalies or outliers in GHG datasets such as sudden increases in CO_2 concentrations near industrial facilities or unexpected methane spikes from agricultural regions which may signal unreported emissions or data errors. By continuously learning from new data inputs, these models allow the inventory system to evolve and improve over time, increasing the reliability of reported emissions.

The integration framework also incorporates geospatial analytics, which provide spatial context and visualization capabilities essential for understanding emissions distribution and identifying regional patterns. Geographic Information System (GIS) tools and geospatial processing engines are used to map emissions, overlay relevant environmental or socio-economic layers, and model spatial interactions among emission sources. Geospatial analytics help bridge the gap between high-level national inventories and local emissions events, enabling finer resolution assessments of sectors such as transportation, agriculture, and waste management. Spatial interpolation techniques, such as kriging or spline modeling, allow the system to estimate emissions in areas lacking direct measurements (Ogunyankinnu, *et al*., 2022, Onibokun, *et al*., 2022). Furthermore, integrating digital elevation models, land-use maps, industrial facility coordinates, and transportation networks enhances the precision of spatial emission modeling. These geospatial insights support local-level mitigation planning, climate vulnerability assessment, and zoning decisions.

A critical strength of the innovative integration framework lies in its modular, scalable architecture. The framework is structured around interconnected layers including data ingestion, preprocessing, analytics, fusion, visualization, and reporting that allow new data sources, tools, or models to be added without disrupting system operations. This modularity enables continuous updates as countries adopt new technologies such as advanced methane imaging satellites, low-cost air quality sensors, drone-based monitoring, or smart-grid energy systems. It also allows for expansion into emerging sectors or pollutants, such as hydrogen production, carbon capture and storage, or black carbon emissions (Afolabi, Ajayi & Olulaja, 2024, Joeaneke, *et al*., 2024, Olulaja, Afolabi & Ajayi, 2024). Scalable cloud-based infrastructure ensures that the system can process large datasets and support computationally intensive machine-learning models, making it suitable for both national-level and city-scale inventory systems.

Another vital component of the framework is uncertainty quantification and propagation. Given that emissions estimates inherently carry uncertainty due to measurement limitations, methodological assumptions, and data gaps, the system integrates statistical tools that quantify uncertainty at each step of the inventory process. Bayesian inference methods evaluate the probability distribution of emissions estimates, while Monte Carlo simulations assess how uncertainty in input variables translates into uncertainty in final emissions outputs. Machine-learning models further refine uncertainty estimates by identifying variables with high influence on prediction variability. This transparency is essential not only for improving scientific credibility but also for fulfilling international reporting guidelines that increasingly require detailed uncertainty reporting (Akande, *et al*., 2023, Akinbode, Taiwo & Uchenna, 2023, Onotole, *et al*., 2023).

The final layer of the framework supports reporting, visualization, and decision support. User-friendly dashboards and interactive visualizations allow policymakers to explore emissions trends, compare scenarios, identify hotspots, and track progress toward climate targets. The system can automatically generate sectoral emissions summaries, temporal trend analyses, geospatial risk maps, and compliance reports aligned with IPCC guidelines. Decision-support tools integrated into the framework can run mitigation scenarios such as the impact of renewable energy expansion, methane leak repair programs, or changes in agricultural practices allowing policymakers to evaluate the outcomes of various climate strategies (Akinbode, *et al*., 2024, Isa, 2024, Olufemi, Anwansedo & Kangethe, 2024).

Collectively, the innovative data integration framework transforms GHG inventory reporting from a predominantly manual, backward-looking exercise into a dynamic, data-driven system capable of reflecting real-world emissions more accurately and in near real-time. By integrating heterogeneous datasets through data fusion methods, machine-learning analytics, and geospatial tools, the framework overcomes traditional barriers of data fragmentation, uncertainty, and inconsistency. Its modular and adaptive nature ensures that it remains relevant in an evolving technological and climatic landscape. Ultimately, this integrated architecture strengthens transparency, enhances confidence in national reporting, and empowers policymakers with actionable insights necessary for effective climate mitigation and compliance with global climate agreements (Babalola, *et al*., 2024, Udensi, Akomolafe & Adeyemi, 2024).

6. Methodological Components and Analytical Techniques

An innovative data integration method for enhancing the accuracy and reliability of greenhouse gas (GHG) inventory reporting relies on robust methodological components and advanced analytical techniques capable of reconciling fragmented datasets, resolving uncertainties, and producing coherent emissions estimates. Given the substantial variability inherent in multisource environmental data, the analytical foundation of such a system must be both flexible and rigorous. Bayesian inference, ensemble modeling, spatiotemporal interpolation, calibration procedures, uncertainty quantification, and harmonization processes together form the methodological backbone of an integrated framework, enabling the transformation of disparate data streams into scientifically defensible GHG inventories. These techniques address the critical challenges posed by inconsistent reporting practices, limited observational coverage, and the need for high-resolution emissions information (Ajayi, *et al*., 2024, Bamigbade, Adeshina & Kemisola, 2024, Taiwo and Akinbode, 2024).

Bayesian inference represents one of the most powerful analytical tools within the framework, particularly in reconciling top-down and bottom-up emissions estimates. Traditional inventory methods rely heavily on bottom-up calculations based on activity data and emission factors, which often suffer from incomplete coverage and methodological assumptions. Conversely, atmospheric measurements and satellite observations provide top-down estimates that reflect real-world emissions but may contain retrieval errors, resolution limitations, or interference from meteorological conditions. Bayesian inference integrates these independent estimates through probabilistic reasoning, treating both data sources as conditional evidence and quantifying the likelihood of different emissions scenarios (Ajayi & Akanji, 2022, Isa, 2022). This allows the system to generate posterior emissions estimates that are statistically consistent with observed atmospheric concentrations and known sectoral activities. In practice, Bayesian frameworks also enable the incorporation of expert judgment and prior knowledge, making them especially valuable for sectors with sparse measurement data or high uncertainty, such as agriculture, land use, and fugitive methane emissions.

Ensemble modeling further strengthens the reliability of GHG inventories by combining predictions or estimates from multiple models rather than relying on a single analytical approach. Different models often produce divergent outcomes due to variations in assumptions, input datasets, or methodological design. Ensemble approaches address this issue by averaging or weighting model outputs to produce a more robust combined estimate. For example, atmospheric inversion models, machine-learning regression models, and physical emissions models may each capture different aspects of emissions behavior; aggregating their outputs reduces model-specific biases and increases overall reliability (Adeleke & Ajayi, 2024, Isa, 2024, Oboh, *et al*., 2024, Olufemi, *et al*., 2024, Umukoro, *et al*., 2024). Ensemble modeling also supports scenario analysis by enabling comparisons across multiple emissions trajectories under different socioeconomic or technological assumptions. This methodological diversity ensures that the integrated system is resilient against errors or biases that might arise from any single model or dataset.

Spatiotemporal interpolation is another essential analytical technique embedded in the innovative integration method, especially in addressing data sparsity across geographic regions or time periods. Many countries lack continuous ground-based monitoring networks, resulting in significant spatial gaps in emissions measurement. Even in regions with monitoring systems, sensor data may be unevenly distributed due to logistical or financial constraints. Spatiotemporal interpolation techniques such as kriging, spline-based interpolation, inverse distance weighting, and geostatistical modeling estimate emissions or activity values for unobserved locations or times by leveraging spatial correlations and temporal patterns in available data. For instance, methane emissions from agriculture may be interpolated based on livestock densities and climatic variables, while CO_2 emissions from industrial regions may be inferred from economic output and energy consumption data (Akomea-Agyin & Asante, 2019, Awe, 2017, Osabuohien, 2019). In addition, advanced spatiotemporal models can integrate satellite observations to refine estimates in hard-to-access regions, improving the spatial granularity of national inventories.

Calibration procedures ensure that different data sources align with consistent reference standards and contribute coherently to the integrated inventory system. Calibration may involve adjusting satellite-derived emissions concentrations to match ground-based measurements, refining emission factors based on laboratory studies, or correcting sensor drift in automated monitoring systems. Calibration processes are particularly important for harmonizing emissions datasets that vary in temporal resolution, measurement techniques, or spatial scale. For instance, satellite-derived methane concentrations may require calibration using surface-based flux towers or mobile plume-detection campaigns (Adeleke & Ajayi, 2024, Babalola, *et al*., 2024, Davies, *et al*., 2024, Egbemhenghe, *et al*., 2024). Similarly, sectoral activity data may be cross-validated with independent administrative records or statistical surveys. Calibration not only improves the accuracy of individual datasets but also ensures that integrated emissions estimates remain internally coherent and scientifically defensible across all sectors.

Uncertainty quantification is a central methodological component of the integration method, providing transparency about the confidence level associated with emissions estimates. Given that GHG inventories involve multiple layers of assumptions ranging from emission factors and activity data to sensor measurements and model outputs quantifying uncertainty helps identify which components contribute most to overall inventory variability. Techniques such as Monte Carlo simulation, error propagation analysis, sensitivity analysis, and Bayesian credible interval estimation allow the system to assess the range of possible emissions values under different assumptions or measurement errors (Adeleke, Olugbogi & Abimbade, 2024, Ikese, *et al*., 2024, Ojuade, *et al*., 2024). Uncertainty quantification is particularly important for sectors with high variability, such as land-use change, methane emissions, and agricultural processes. By explicitly reporting uncertainty bounds, the integrated method aligns with international reporting guidelines and strengthens the credibility of emissions inventories in global climate negotiations.

Harmonization processes ensure that all datasets contributing to the GHG inventory adhere to compatible standards, definitions, and methodological assumptions. Harmonization involves aligning sectoral categories, emission factor units, data collection protocols, temporal resolutions, and spatial boundaries. For example, industrial emissions reported annually must be made compatible with satellite observations recorded daily or weekly. Land-use data must be categorized consistently across agencies to avoid double-counting or omission. Harmonization also applies to integrating socioeconomic and environmental datasets, such as linking energy consumption statistics with atmospheric CO_2 measurements or aligning agricultural production data with methane emission models. Through harmonization, the integration framework eliminates contradictions and ensures that emissions estimates remain coherent when aggregated across sectors (Ogunyankinnu, *et al*., 2022, Oyeyemi, 2022).

These methodological components Bayesian inference, ensemble modeling, spatiotemporal interpolation, calibration, uncertainty quantification, and harmonization work synergistically to create a comprehensive and reliable GHG inventory system. Bayesian inference integrates and balances conflicting datasets; ensemble modeling increases robustness; interpolation fills data gaps; calibration ensures measurement consistency; uncertainty analysis provides transparency; and harmonization guarantees semantic and methodological coherence. Together, they form an integrated analytical engine that transforms fragmented, multisectoral data into accurate, high-resolution, and verifiable emissions information (Ajayi & Akanji, 2022, Isa, 2022).

In conclusion, the methodological sophistication embedded within this innovative data integration approach represents a major advancement in the field of GHG inventory reporting. By addressing foundational issues in data quality, consistency, and uncertainty, these analytical techniques make it possible for countries to produce more accurate and transparent emissions estimates. This, in turn, strengthens national climate planning, supports international reporting obligations, and enhances global efforts to track and mitigate greenhouse gas emissions.

7. Application to Sector-Specific GHG Estimation

The application of an innovative data integration method to sector-specific greenhouse gas (GHG) estimation offers a transformative opportunity to improve emissions reporting accuracy across agriculture, transportation, energy, waste management, and industrial processes. Each of these sectors has unique emissions characteristics, measurement challenges, and data requirements. Traditional GHG inventories often rely on generalized emission factors or sparse activity data, which limit their ability to capture real-world variability, detect anomalies, or quantify fugitive emissions. By integrating diverse datasets ranging from satellite observations and ground-based monitoring systems to machine-learning predictions and sectoral databases the innovative framework enhances the precision, granularity, and reliability of emissions estimates across sectors. This integrated approach not only improves scientific accuracy but also strengthens transparency, regulatory oversight, and climate policy design (Akande, *et al*., 2023, Akinbode, *et al*., 2023, Chukwuemeka, Wegner & Damilola, 2023).

In agriculture, emissions arise primarily from enteric fermentation, rice cultivation, manure management, fertilizer application, and soil carbon changes. These emissions are influenced by numerous variables such as livestock type, feed quality, climate conditions, irrigation practices, and soil characteristics. Conventional inventories often use national averages or static emission factors that fail to account for spatial and temporal variability. The integrated data framework addresses this limitation by incorporating satellite-derived land-use and vegetation indices, soil moisture data, climatic information, and agricultural production statistics to generate dynamic emissions estimates. Machine-learning models trained on these variables can predict methane and nitrous oxide fluxes with substantially higher accuracy than static emission factor approaches. Sensors placed in barns or manure storage facilities can detect real-time methane fluctuations, improving fugitive emission detection. Additionally, anomalous emissions such as spikes caused by extreme rainfall events, unexpected crop burning, or changes in livestock feeding patterns can be detected more reliably using integrated top-down and bottom-up datasets. This enables agricultural policymakers to develop targeted interventions, optimize fertilizer use, and adopt climate-smart agricultural practices (Adeshina & Ndukwe, 2024, Isa, 2024, Joeaneke, *et al*., 2024, Olufemi, *et al*., 2024).

The transportation sector presents distinct challenges due to the diversity of vehicle types, fuel varieties, traffic patterns, and driving behaviors. Traditional inventories calculate emissions based on fuel sales or vehicle kilometers traveled, which overlook real-time fleet dynamics and local emissions hotspots. The integrated data method leverages telematics data, GPS-based fleet monitoring, road traffic sensors, satellite-derived nitrogen dioxide (NO_2) concentrations, and fuel quality assessments to produce high-resolution emissions estimates. Machine-learning algorithms can analyze traffic density, road conditions, and vehicle type distributions to predict emissions at a granular level. Such models also help identify anomalies such as unusual emissions peaks due to road congestion, unauthorized fuel adulteration, or malfunctioning catalytic converters in urban fleets (Ajayi & Akanji, 2023, Oyeyemi & Kabirat, 2023). Integrating satellite NO_2 measurements with ground-based air quality sensors enables cross-validation and detection of unreported or inaccurately reported transport emissions. As cities move toward low-emission zones and electrification strategies, this approach provides crucial evidence to guide transportation planning and emissions mitigation.

The energy sector, particularly electricity generation, oil and gas extraction, and fuel combustion, contributes significantly to national GHG inventories. Conventional reporting relies heavily on facility-level self-reported data, which may be incomplete, outdated, or subject to reporting bias. Integrated data systems improve accuracy by combining remote sensing data, such as nighttime lights and thermal imagery, with ground-based continuous emissions monitoring systems (CEMS). Satellite measurements of methane (CH_4) and carbon dioxide (CO_2) allow detection of fugitive emissions from pipelines, compressor stations, and extraction fields. For example, plume detection algorithms can identify methane leaks even when companies fail to report them. Machine-learning models can then estimate leak sizes, emissions duration, and potential causes (Adeleke & Baidoo, 2022, Oyeyemi, 2022). In fossil fuel power plants, integrated datasets capturing fuel quality, combustion efficiency, stack emissions, and plant operational hours enable precise estimation of CO_2 emissions. Calibration against atmospheric concentration data further enhances accuracy. The integrated method thus enhances transparency in the energy sector and supports rapid mitigation of fugitive emissions, which are often underestimated but contribute substantially to GHG totals.

Waste management is another sector where integrated data methods significantly enhance emissions estimates. Landfills and wastewater treatment plants release methane, carbon dioxide, and nitrous oxide, often through diffuse or poorly monitored pathways. Traditional inventories estimate emissions using simplified decay models and default emission factors. The innovative data integration framework incorporates landfill gas sensor networks, drone-based gas plume measurements, infrared imaging, and satellite methane observations to improve detection of fugitive emissions and quantify gas capture efficiency (Awe, Akpan & Adekoya, 2017, Osabuohien, 2017). Machine-learning models can analyze weather patterns, waste composition, moisture levels, and site operating conditions to enhance the accuracy of methane generation predictions. Spatiotemporal interpolation techniques help estimate emissions from informal waste sites, which are often unmonitored but contribute significantly to national GHG totals. Early detection of anomalous emissions helps landfill operators prevent gas buildup, improve capture systems, and enhance safety while contributing to more reliable national inventories.

Industrial processes including cement production, steel manufacturing, chemical processing, and refining emit CO_2, methane, nitrous oxide, and fluorinated gases. Emissions from these processes depend on specific technologies, input materials, process temperatures, and operational conditions. Conventional reporting often relies on plant-level declarations, which may not fully capture operational variations or unforeseen emissions events. Integrated data frameworks incorporate thermal imagery from satellites, process sensor readings, production statistics, and emissions monitoring instruments to achieve more detailed and accurate estimates. For instance, thermal anomalies detected in satellite imagery can reveal hidden emissions from industrial stacks or flare inefficiencies (Akpan, Awe & Idowu, 2019, Ogundipe, *et al*., 2019). Machine-learning models trained on historical production and emissions data can predict emissions under different operational scenarios and identify deviations from expected patterns. These deviations may indicate underreported emissions, equipment malfunctions, or unauthorized operational changes. In sectors emitting fluorinated gases, which have high global warming potential, such anomaly detection is essential to ensure regulatory compliance and accurate reporting.

Across all sectors, one of the most valuable contributions of the integrated method is its ability to improve fugitive emission estimation. Fugitive emissions unintentional releases of gases are notoriously difficult to quantify and are often excluded or underestimated in traditional inventories. Methane leaks from oil and gas infrastructure, refrigerant losses from cooling systems, and unintended emissions from industrial facilities significantly affect GHG totals. By integrating satellite observations with ground-based leak detection systems and machine-learning algorithms, the framework can detect, localize, and quantify fugitive emissions with a level of precision unattainable through traditional methods. Top-down atmospheric measurements reveal anomalies that bottom-up inventories may miss, while bottom-up activity data help explain the sources and drivers of these emissions (Akinola, *et al*., 2024, Bobie-Ansah, Olufemi & Agyekum, 2024, Ikese, *et al*., 2024, Osabuohien, 2024).

Ultimately, sector-specific applications of the innovative data integration method demonstrate how advanced analytics and multisource harmonization significantly enhance the accuracy, transparency, and utility of GHG inventories. This approach transforms GHG reporting from a static, retrospective exercise into a dynamic, data-rich system capable of identifying emerging risks, supporting regulatory enforcement, and informing targeted mitigation strategies. By providing high-resolution insights into emissions across agriculture, transportation, energy, waste, and industrial sectors, the integrated method strengthens national climate governance and contributes to global efforts to reduce greenhouse gas emissions in an increasingly complex and data-intensive world.

8. Validation, Uncertainty Reduction, and Compliance with IPCC Standards

Validation, uncertainty reduction, and compliance with IPCC standards are essential dimensions of an innovative data integration method designed to enhance greenhouse gas (GHG) inventory reporting accuracy and reliability. As countries strengthen their climate mitigation commitments and face growing scrutiny in international transparency frameworks, the credibility of national inventories depends not only on the quality of underlying data but also on the robustness of validation procedures, the clarity of uncertainty estimates, and the alignment of methodologies with globally recognized guidelines (Odezuligbo, Alade & Chukwurah, 2024, Oyeyemi, Orenuga & Adelakun, 2024, Taiwo, Akinbode and Uchenna, 2024). The integration of multisource datasets ranging from satellite monitoring and ground-based sensors to activity data, emission factors, and machine-learning outputs introduces both opportunities and complexities. A rigorous validation and uncertainty management system ensures that such integrated inventories remain scientifically defensible, policy-relevant, and internationally comparable within the IPCC's methodological hierarchy of Tier 1, Tier 2, and Tier 3 practices.

A central benefit of the integrated method is its capacity to significantly improve data accuracy through systematic cross-validation of independent data sources. Traditional inventories often rely on single-source information, such as self-reported industrial data or national statistics, which may contain biases, gaps, or temporal inconsistencies. By contrast, the integration framework brings together atmospheric measurements, remote-sensing observations, sector-specific sensor readings, and activity databases, enabling each dataset to be evaluated against others. For example, methane emissions estimated from oil and gas operations using activity data and emission factors can be validated against satellite retrievals of atmospheric methane concentration. If discrepancies arise, machine-learning models and Bayesian inference methods can help reconcile differences and refine the emission estimates (Ayobami, *et al*., 2024, Davies, *et al*., 2024, Eyo, *et al*., 2024, Isa, 2024). This triangulation across data streams improves accuracy and reduces dependence on any one dataset, ultimately producing more robust national totals.

Reduction of uncertainty ranges is another major strength of this innovative method. GHG inventories inherently involve uncertainty due to limited measurement precision, incomplete activity data, generic or outdated emission factors, and variability in physical processes. The integrated system employs several quantitative techniques such as Monte Carlo simulations, probabilistic modeling, and Bayesian credible intervals to quantify and propagate uncertainty across different stages of the estimation process. These tools reveal how uncertainties in input variables, such as fuel quality or livestock counts, influence final emission outputs. With enhanced data integration, uncertainty often decreases because the system can draw on more reliable or higher frequency measurements (Awe & Akpan, 2017). For instance, continuous methane monitoring at landfills or industrial facilities reduces uncertainty associated with fugitive emissions, which are historically among the most poorly quantified sources. Remote sensing also allows verification of land-use and forestry emissions, decreasing uncertainty associated with forest cover estimates and carbon stock assessments. The result is a narrower confidence interval for national emissions, which increases transparency and trustworthiness in international reporting.

Cross-validation procedures embedded in the integrated method further strengthen emissions estimates. Cross-validation involves dividing datasets into training and testing subsets to evaluate the predictive performance of machine-learning models or statistical estimators. For example, machine-learning tools used to estimate missing activity data or to predict emission factors are validated through k-fold cross-validation or time-series validation to ensure that they accurately generalize to new inputs (Ogunyankinnu, *et al*., 2024, Okon, *et al*., 2024, Olulaja, Afolabi & Ajayi, 2024). Atmospheric inversion models used as top-down validation tools are cross-checked against surface sensor data and historical patterns to ensure their accuracy. Spatial cross-validation uses geographic partitions to evaluate how well the model predicts emissions in areas not included during model training. These procedures prevent overfitting, enhance reliability, and identify weaknesses or biases in the integrated framework. Moreover, cross-validation helps policymakers understand which datasets contribute most strongly to accuracy improvements and which sectors may require enhanced measurement systems.

Compliance with IPCC standards specifically Tier 2 and Tier 3 methodologies is crucial to ensuring international comparability and credibility. The IPCC methodology hierarchy reflects increasing levels of sophistication and country-specific detail, with Tier 1 representing default emission factors and simple activity data, Tier 2 involving country-specific emission factors, and Tier 3 relying on advanced models, continuous monitoring systems, and high-resolution datasets. The innovative data integration method naturally supports higher-tier estimation by enabling country-specific parameterization and by incorporating rich observational data. For example, continuous emissions monitoring systems (CEMS) in power plants and industrial facilities represent Tier 3 methodologies, as do advanced livestock models calibrated through local measurements, and remote-sensing-based land-use assessments (Akinbode, *et al*., 2024, Folorunso, *et al*., 2024, Orenuga, Oyeyemi & Olufemi John, 2024)). The integration of automated sensors, atmospheric observations, and machine-learning predictions helps nations transition from Tier 1 defaults to higher precision Tier 2 and Tier 3 methods. This transition is particularly important for key categories major sources of emissions where the IPCC strongly recommends the use of more detailed and accurate methodologies.

Alignment with IPCC guidelines also ensures that the integrated method adheres to core principles of transparency, accuracy, consistency, comparability, and completeness (TACCC). Transparency is achieved through documentation of data sources, harmonization protocols, uncertainty analysis, and cross-validation procedures. Accuracy improves through data fusion and calibration. Consistency is maintained by applying uniform methodologies across inventory years, while comparability is ensured by following standard IPCC categories and reporting formats. Completeness is enhanced because the integrated system identifies and fills gaps in emissions data, particularly in sectors that have historically lacked reliable monitoring, such as fugitive methane from oil and gas infrastructure, open burning in agriculture, and emissions from informal waste sites (Ajayi & Akanji, 2021, Ejibenam, *et al*., 2021, Osabuohien, Omotara & Watti, 2021).

An essential contribution of the integrated method lies in improving the estimation of fugitive emissions, which have traditionally been a major source of uncertainty. Fugitive emissions particularly methane often escape detection in conventional inventories because they result from leaks, venting, or equipment malfunctions that are not captured by activity data. The innovative approach combines satellite observations, mobile sensor surveys, ground-based monitors, and machine-learning leak detection algorithms to quantify these emissions more accurately. This aligns with the IPCC encouragement for countries to adopt Tier 3 methods for methane emissions in key categories. Similarly, for land-use and forestry emissions, the integration of high-resolution satellite imagery, LiDAR data, soil carbon measurements, and geospatial modeling aligns with advanced Tier 3 land-use change approaches, improving national estimates of carbon stock changes and sequestration (Akanji & Ajayi, 2022, Francis Onotole, *et al*., 2022).

Another important aspect of compliance is methodological harmonization over time. The integrated system ensures temporal consistency by adjusting historical time-series using standardized recalibration techniques whenever new data sources or methodologies are introduced. This prevents artificial jumps in emissions caused by methodological updates rather than real-world changes, preserving the integrity of long-term mitigation assessments required by the IPCC.

International comparability is also strengthened through the standardized structure of the integrated method. Because many countries increasingly adopt satellite observations, automated monitoring systems, and machine-learning tools, the resulting inventories become easier to compare globally. This comparability is essential for global stocktakes under the Paris Agreement, which assess collective progress toward global climate goals (Awe, 2021, Halliday, 2021).

In conclusion, the validation, uncertainty reduction, and compliance components of the innovative data integration method collectively elevate the scientific rigor, transparency, and credibility of GHG inventories. By improving data accuracy, reducing uncertainty ranges, enabling robust cross-validation, and aligning with advanced IPCC Tier 2 and Tier 3 standards, the integrated approach addresses long-standing weaknesses in national reporting systems. It enables countries to produce inventories that better reflect real-world emissions, support evidence-based policymaking, and meet international expectations for accountability and transparency.

9. Conclusion

The innovative data integration method for enhancing GHG inventory reporting represents a transformative advancement in the way countries measure, verify, and communicate their greenhouse gas emissions. By unifying diverse data sources ranging from satellite remote sensing and ground-based monitoring to sectoral activity data, automated sensors, and advanced modeling tools the method strengthens the scientific foundation upon which national inventories are built. This integrated approach overcomes long-standing challenges associated with fragmented information, inconsistent methodologies, and limited observational coverage. As a result, it produces emissions estimates that are more accurate, transparent, and reflective of real-world conditions. Through data fusion, machine-learning analytics, geospatial techniques, and rigorous calibration, the system reconciles discrepancies between top-down and bottom-up datasets, reduces uncertainty, and identifies anomalies and fugitive emissions that might otherwise remain undetected. This greatly enhances confidence in reported emissions and supports the continuous refinement of national monitoring systems.

The significance of this innovation extends far beyond technical improvements. Accurate and reliable GHG inventories are foundational to national climate policy, as they inform mitigation strategies, guide resource allocation, and shape regulatory frameworks. When countries can trust the precision of their emissions data, they are better equipped to design targeted, cost-effective interventions that address the most impactful sources of emissions. The integration method also supports dynamic emissions tracking, enabling governments to respond more swiftly to unexpected changes, such as spikes in methane leaks, shifts in land-use patterns, or fluctuations in energy consumption. This agility is essential in an era where climate impacts are becoming increasingly variable and unpredictable.

From a global perspective, the integrated approach significantly strengthens the transparency and comparability of GHG reporting, two pillars of international climate cooperation under the Paris Agreement. By aligning inventory methodologies with advanced IPCC Tier 2 and Tier 3 practices, the method ensures that countries meet the expectations of the Enhanced Transparency Framework while generating emissions estimates that can be reliably compared across borders. This reduces disputes in international reporting, enhances trust among parties, and contributes to more effective global stocktakes aimed at evaluating collective progress toward climate goals.

Furthermore, the integrated method lays the groundwork for long-term emissions monitoring systems capable of adapting to new technologies, expanding data availability, and evolving policy needs. As countries deploy more satellites, sensors, and digital reporting systems, the framework can seamlessly incorporate these advancements, ensuring inventories remain current and scientifically rigorous. The ability to conduct continuous, high-resolution emissions monitoring also empowers nations to track the effectiveness of mitigation policies over time, measure progress toward net-zero commitments, and adjust strategies as necessary.

In essence, this innovative data integration method represents a major leap forward in the accuracy, reliability, and policy relevance of GHG inventories. It bridges gaps between observational science and national reporting practices, enhances transparency and accountability, and equips policymakers with the insights needed to make informed, impactful climate decisions. As global efforts to address climate change intensify, such integrated, data-driven approaches will be indispensable tools for ensuring that mitigation actions are grounded in evidence, adaptable to future challenges, and aligned with the urgency of reducing greenhouse gas emissions worldwide.

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