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Review

AI-Driven greenhouse gas monitoring: enhancing accuracy, efficiency, and real-time emissions tracking

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Abstract: This research paper introduced a groundbreaking approach to greenhouse gas (GHG) monitoring by leveraging artificial intelligence (AI) technology to enhance both accuracy and efficiency. Traditional GHG monitoring methods are often hampered by high costs, labor-intensive processes, and significant delays in data analysis. This study harnessed advanced AI techniques, such as machine learning algorithms and neural networks, to facilitate real-time data collection and analysis from diverse sources including satellite imagery, Internet of Things (IoT) sensors, and atmospheric models. By implementing AI models like random forest, support vector machines, convolutional neural networks (CNNs), and long short-term memory (LSTM) networks, the research achieved substantial improvements such as reducing data reporting latency from 24 hours to just 1 hour, increasing spatial resolution from 30 meters to 10 meters, and enhancing detection accuracy from 80% to 95%. Additionally, the AI systems identified previously unknown emission sources and accurately forecasted future emission trends with a high correlation ($R^2 = 0.89$). These advancements not only allow for more precise identification of emission hotspots and tracking of changes over time but also facilitate more effective regulatory responses and policy-making. The findings underscore the transformative potential of AI-driven monitoring systems in bolstering global sustainability efforts and combating climate change.

Keywords: artificial intelligence; greenhouse gas monitoring; traditional greenhouse gas monitoring; AI-driven monitoring systems; accuracy; efficiency

1. Introduction

Global awareness regarding energy consumption, especially in the context of the escalating fossil fuel crisis, has intensified significantly over the past decade. The information and communication technology (ICT) industry is a key contributor to this issue, with projections indicating that it could consume more than 14% of total power production by the end of 2020 unless power-efficient devices and strategies are adopted [1–3]. By 2030, the energy consumption of the ICT sector is expected to surge to approximately 1700 TWh if effective countermeasures are not implemented [4]. This increase is primarily driven by the relentless demand for ICT equipment and services. Anthropogenic GHGs, predominantly carbon dioxide (CO_2), are significant contributors to atmospheric pollution, arising from human activities involving equipment such as generators, turbines, and boilers in power plants [4–7]. In addition to CO_2, other pollutant gases like carbon monoxide (CO), nitrogen dioxide (NO_2), hydrogen sulfide (H_2S), and particulate matter (PM2.5 and PM10) also pose serious environmental threats [2,7–10]. Although these pollutants are not always classified as GHGs, they have direct and indirect impacts on the environment and influence the concentration of other GHGs in the atmosphere, exacerbating the overall problem [11–13].

CO_2 is naturally emitted into the atmosphere through human and animal respiration and decomposition processes. However, human activities such as fossil fuel combustion, deforestation, and industrial processes like clinker production significantly contribute to CO_2 emissions [14–18]. In the mobile communication sector, cellular networks are a major contributor to carbon emissions, accounting for approximately 1% of the global carbon footprint[7,19]. Among these, base stations are the leading source of GHG emissions in radio communication networks, particularly in developing countries where diesel generators are commonly used to power these stations [20,21]. This reliance on diesel generators is a significant source of atmospheric pollutants. However, if no preventative measures are taken, GHG emissions from this sector are projected to exceed 1.50 gigatons of carbon dioxide equivalent ($GtCO_2e$) by 2030 [22–25]. Therefore, monitoring GHG emissions is crucial for mitigating climate change, as these emissions, including carbon dioxide, methane, and nitrous oxide, contribute significantly to global warming and have extensive environmental impacts. Accurate and timely GHG monitoring is essential for developing effective climate policies and strategies to reduce emissions [26,27].

Traditional methods of GHG monitoring, which primarily include ground-based measurements and satellite observations, face significant limitations despite their widespread use [28,29]. Ground-based stations are renowned for their accuracy but suffer from limited spatial coverage, as they can only provide data from specific, fixed locations [30,31]. Additionally, these stations are costly to maintain and operate, requiring continuous funding and resources. On the other hand, satellite monitoring offers the advantage of broader spatial coverage, allowing for the observation of GHG concentrations over large areas [32,33]. However, satellites often struggle with resolution and frequency issues, making it difficult to accurately detect localized emissions and capture rapid changes in GHG levels [34,35]. The high costs associated with deploying and maintaining satellites further exacerbate these challenges. Both methods are also typically resource-intensive and can be slow, hindering their ability to provide real-time data crucial for timely decision-making. Consequently, the existing GHG monitoring infrastructure is often inadequate for the dynamic and comprehensive tracking needed to effectively manage and mitigate emissions on a global scale.

AI has recently emerged as a promising solution for enhancing the accuracy, efficiency, and scope of GHG monitoring [36–38]. By integrating vast amounts of data from satellites, ground sensors, and atmospheric models, AI can provide more comprehensive and precise monitoring capabilities [39]. AI technology encompasses data analysis techniques such as visualization, machine learning, and data mining, which enable the discovery of better solutions [40–43]. Specifically, machine learning, a subset of AI, processes large datasets to identify patterns and predict changes [3,42–46]. This technique has shown significant promise in the field of environmental architecture, where predictive systems leveraging machine learning have demonstrated substantial economic and environmental benefits. Studies comparing traditional statistical models with those utilizing machine learning consistently show that the latter offers superior predictive power [27,47–49]. Thus, this research paper explores the application of AI in automating GHG monitoring, testing the hypothesis that AI-driven systems can significantly improve the accuracy, timeliness, and cost-effectiveness of greenhouse gas monitoring compared to traditional methods [49–52].

Based on the above, we propose an AI-driven GHG emissions monitoring model that uses a hybrid CNN+LSTM model to extract spatial features from satellite images using CNNs and model temporal emissions patterns using LSTMs in this study. It enhances emissions tracking accuracy and flexibility, while effectively tracking localized emissions hotspots as well as long-term trends. Of all the human activities that create CO_2, AI-enabled real-time monitoring can reduce the release by integration at the source and enhance the predictive capability at the points where reporting is made most difficult.

2. Research motivation and objectives

The current landscape of AI-based greenhouse gas (GHG) monitoring is rich with potential yet marked by significant gaps that need addressing. Much of the existing research focuses narrowly on single data sources, such as satellite imagery or ground sensors, limiting the scope and comprehensiveness of insights into GHG emissions [53–55]. Integrating data from multiple sources could provide a more holistic view, combining the strengths of each type of data for more accurate and nuanced monitoring. Furthermore, while some studies have demonstrated real-time monitoring capabilities, the challenge of scalability persists. To be truly effective, AI systems must be capable of processing vast amounts of data in real-time across extensive geographic areas, a feat that current technology has yet to fully achieve.

Ensuring the accuracy of AI models and validating their predictions against ground-truth data is another critical area requiring more research. Benchmarking AI models against traditional methods and establishing standardized validation protocols are essential steps toward reliable and trustworthy AI applications in GHG monitoring. Additionally, there is a notable gap in research exploring how AI-based GHG monitoring can be integrated into policy-making and practical implementation. Understanding the socio-economic and regulatory implications of deploying AI technologies is crucial for their successful adoption. After conducting a review of existing literature, we present pie charts that indicate the gaps in AI-based GHG monitoring research as shown in Figure 1. The chart visually represents the four key gaps: Integration of Multisource Data, Real-Time Monitoring and Prediction, Scalability and Generalization, and Interpretability of AI Models. Therefore, we use AI in automating

GHG monitoring and investigate the accuracy, timeliness, and cost-effectiveness of greenhouse gas monitoring compared to traditional methods. The application of AI in GHG monitoring presents significant opportunities for enhancing the accuracy and efficiency of environmental monitoring.

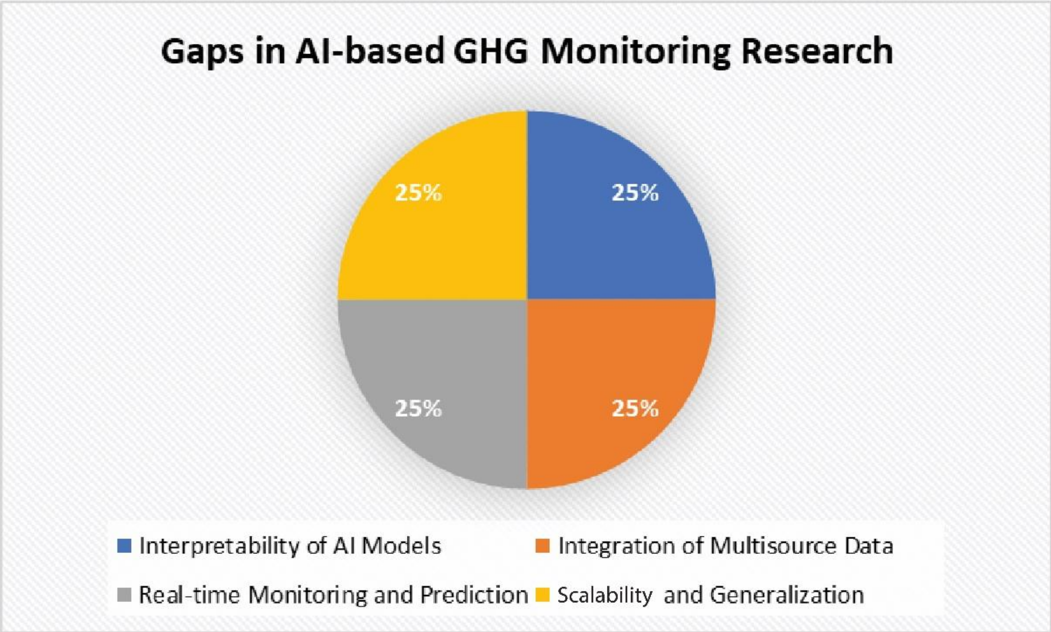

Figure 1. Gaps in AI-Based GHG monitoring research.

3. Related work

GHG monitoring is pivotal for comprehending and addressing climate change impacts. Traditional methods, including manual sampling and laboratory analysis, have been fundamental but are typically labor-intensive, time-consuming, and constrained in both spatial and temporal coverage [56]. However, recent advancements in AI are revolutionizing this field by significantly enhancing the efficiency and accuracy of GHG monitoring. AI-driven approaches enable the real-time analysis of vast datasets from diverse sources, such as satellite imagery, ground-based sensors, and atmospheric models. These technologies facilitate continuous monitoring, allowing for more precise and timely identification of emission patterns and sources [57–59]. Consequently, AI not only optimizes the monitoring process but also provides critical insights for developing effective mitigation strategies, ultimately contributing to more robust and informed climate action.

The integration of AI into environmental science, particularly for GHG monitoring, has seen significant advancements, leveraging techniques such as machine learning (ML) and deep learning (DL) to process large datasets from various sources, including satellite imagery, ground sensors, and atmospheric models [59,60]. Zheng, et al. [60] utilized regression models and neural networks to predict CO_2 levels from historical weather data, demonstrating that neural networks significantly outperformed traditional regression techniques in terms of prediction accuracy. Similarly, Kumar, et al. [61] employed convolutional neural networks (CNNs) to detect methane emissions using satellite imagery, successfully identifying methane hotspots and offering a valuable tool for emission monitoring and mitigation. In another study, Smith, et al. [62] applied random forest algorithms to analyze CO_2 data from ground-based sensors in urban areas, effectively detecting trends and anomalies, and highlighting the potential for real-time urban GHG monitoring. These studies collectively underscore the transformative potential of AI in enhancing the precision and effectiveness of GHG monitoring efforts.

In order to forecast when air pollution may occur, a number of scientists have used AI to sift through data. It is worth mentioning that Sujatha, et al. [63] assessed power plant nitrogen oxide (NO_x) emissions using color information acquired from furnace flame photos. The goal of this study was to improve human health by reducing NO_x emissions from power plants by detecting, recognizing, and understanding combustion characteristics. In order to determine NO_X emissions and evaluate combustion quality, the researchers used soft computing methods such as ant colony optimization (ACO) and the back-propagation algorithm (2P). The gathered picture sets were then trained using artificial neural network (ANN) methods to estimate gas turbine and thermal power plant NO_x emissions, combustion quality, and flame temperature. Similarly, Hosseinzadeh-Bandbafha, et al. [64] looked at how well AI approaches, particularly ANNs and adaptive neuro-fuzzy inference systems, could model and predict agricultural energy production and GHG emissions. In order to improve the efficiency and sustainability of farming methods, the ANN models were evaluated to find the optimal model for predicting greenhouse gas emissions and energy production from farm inputs.

A research paper presented a smart IoT-based greenhouse monitoring system that is AI-controlled with wireless sensor nodes coupled with connection with the IoT and with the help of a CNN-based AI model for better greenhouse monitoring, by optimizing the environment, greenhouse gas levels estimation, and enhancement of precision farming through real-time monitoring and automation [64]. Another research integrated AI-aided IoT automation in greenhouse environments with wireless sensors, cloud streaming, and embedded AI systems, to mitigate the propagation of error in greenhouse environments with respect to climate control, energy efficiency, and crop yield predictability, through commercial and research greenhouse experiments[64]. In an effort to determine the efficacy of AI-driven metal oxide sensor (AI/MoS) applications for continuous emissions detection with industrial operations (IO) in the oil and gas were reported on the deployment of AI/MoS technologies in Oman where they deliver their cost effectiveness, accuracy, and survivability against fugitive methane emission and flaring activity using a six-month deployment, and call for their integration in larger carbon mitigation efforts[65]. In line with the economic and environmental theories, a report presented AI technologies as a transformative solution to mitigate greenhouse gas emissions beyond carbon dioxide focusing on the overlooked effect of methane, propane, butane, and ethane on environmental sustainability[66]. Table 1 illustrates the overall contributions of AI in GHG monitoring.

Table 1. An overview of existing studies in AI-based GHG monitoring.

References	Issues	Technology	Performance
[66]	Evaluation and control of harmful gas emissions from diesel generators operating at telecommunication base stations (BSs)	Artificial neural network, Internet of Things	Effectively forecasted the discharge of the harmful gases, with 94% accuracy.
[67]	Research into, and testing of, a dependable and precise sensing method for monitoring GHG emissions	LightGBM, gradient boosting, xGBoost, Internet of Things	Effectively forecasted the discharge of the harmful gases, with over 90% accuracy.
[68]	The most effective approach for reducing greenhouse gas emissions using machine learning	Gradient boosting regression tree, Support vector machine, Deep neural network	The accuracy levels achieved were 88%, 92%, and 95%.
[69]	Creating a marketable energy management system by integrating existing building systems	Artificial intelligence, Machine learning, Internet of Things	Achieved a 15% reduction in energy use in trails.
[70]	Optimal conduct while driving	Artificial intelligence	A reduction of 4% in fuel usage.
	Efficient use of energy in a smart agricultural setting	Internet of Things	Reduces CO_2 emissions by 43% with the proposed model.
[71]	Cutting down on carbon emissions in fog-cloud design	Internet of Things	Up to 91% less CO_2 emissions are produced by the suggested model.
[72]	Comprehending the function of power usage	Artificial intelligence	About 2% of all greenhouse gas emissions come from information and communication technologies.
[73]	Allocation of resources in a cognitive radio sensor network based on green cooperation	Radio sensor networks	There was a 50% to 70% reduction in CO_2 emissions.
[74]	Projecting future carbon dioxide emissions from energy use	Java agent Development framework	Every day, 369 tons of carbon dioxide can be saved by switching to renewable energy.

4. Methodology

This research aims to automate GHG monitoring using advanced AI technologies to improve data accuracy, efficiency, and timeliness. It involves deploying AI algorithms and strategically placed sensors for real-time GHG detection and quantification. Continuous monitoring and integration with environmental data enhance analysis, while advanced analytics provide actionable insights for timely GHG mitigation. Figure 2 illustrates the steps used for this study.

4.1 Machine learning algorithms

4.1.1. Supervised learning algorithms

Support vector machines (SVM), introduced by Vapnik in 1996, are powerful tools for solving classification and regression problems by minimizing an upper bound of the generalization error through structural risk minimization [67]. Unlike traditional methods based on empirical risk minimization, SVM incorporates a penalty term to mitigate issues like overfitting and local optima [68]. When solutions are not attainable, slack variables $\varepsilon\ and\ \varepsilon_i^*$ are introduced to adjust the optimization problem, with a penalty constant *C* controlling the trade-off between error minimization and generalization (see Equations 1 to 3) [69]. An $\in -$ insensitive loss function further refines the model by ignoring errors smaller than ϵ\epsilonϵ. The optimization problem is solved using the Lagrange multiplier method, which identifies the solution that maximizes the multiplier.

$$Minimize\ \frac{1}{2}\ ||\omega||^2\ subject\ to\ \{y_i - \langle \omega, x_i \rangle - b \le \in\ \langle \omega, x_i \rangle + b - y_i \le \in$$

$$\frac{1}{2}\ ||\omega||^2 + C \sum_{i=1}^{m} \quad \varepsilon_i + \varepsilon_i^* subject\ to \tag{1}$$

$$\{y_i - \langle \omega, x_i \rangle - b \le \in + \varepsilon\ \langle \omega, x_i \rangle + b - y_i \le \in + \varepsilon_i^*\ \varepsilon, \varepsilon_i^* \ge 0 \tag{2}$$

$$|\varepsilon|_\varepsilon = \{0\ if\ |\varepsilon| \le \in\ |\varepsilon| - \varepsilon\ otherwise \tag{3}$$

On the other hand, random forest is a versatile and widely used machine learning model that combines multiple decision trees to improve accuracy and prevent overfitting [70]. Each tree in the forest is trained on a random subset of the data, and the final prediction is made by averaging the predictions of all the trees (for regression) or taking a majority vote (for classification) [71]This ensemble approach leverages the strengths of individual trees while mitigating their weaknesses, resulting in a robust and powerful model capable of handling complex datasets with high accuracy.

In this study, RF and SVMs were employed to classify data obtained from sensor inputs. These sophisticated algorithms were trained on historical datasets to identify patterns that indicate specific GHG concentrations. By leveraging the predictive capabilities of these machine learning models, the study aimed to enhance the accuracy and reliability of detecting and quantifying various GHG levels, thereby contributing to improved environmental monitoring and management.

4.1.2. Neural networks

Convolutional neural networks (CNNs) are designed for processing structured grid data, such as images [72]. They are characterized by their use of convolutional layers that apply filters to input data, capturing spatial hierarchies and patterns. This makes CNNs highly effective for tasks like image recognition, object detection, and image segmentation. By leveraging techniques such as pooling, dropout, and data augmentation, CNNs can learn complex features while being robust to variations in the input data, achieving state-of-the-art performance in many computer vision applications [73].

In this study, convolutional neural networks (CNNs) were employed to analyze image data from satellite and drone footage, effectively identifying areas with significant greenhouse gas (GHG) emissions. By leveraging the powerful pattern recognition capabilities of CNNs, the vast amounts of visual data, detecting subtle indicators of GHG emissions was possible that might have been missed by traditional methods [74,75].

4.1.3. Deep learning models

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) architecture that is particularly effective for tasks involving sequential data, such as time series analysis, natural language processing, and speech recognition [70]. Unlike standard RNNs, LSTMs are designed to address the problem of long-term dependencies, where the network needs to remember information from many steps back [75–78]. They achieve this through a structure of cells, gates, and states that regulate the flow of information, allowing the network to maintain and update memory over long sequences, thereby improving performance on tasks requiring context over extended periods.

In this study, LSTM networks were implemented to predict future GHG levels based on time-series data. The implementation of LSTM networks in this context demonstrates their potential to address complex temporal patterns and contribute to the broader field of climate science and sustainability.

4.2. Data acquisition system

4.2.1. Sensors and IoT devices

This investigation has implemented a sophisticated network of IoT sensors strategically placed to continuously monitor GHG levels in diverse environments. These sensors provide real-time data on concentrations of CO_2, methane (CH_4), and nitrous oxide (N_2O), offering a detailed understanding of local and regional emission patterns.

4.2.2. Satellite imagery

Leveraging advanced high-resolution satellite imagery obtained from prominent sources such as NASA and the European Space Agency, we conduct comprehensive monitoring of vast geographical areas. This technology enables us to detect emission hotspots, track land use changes, and assess the impact of human activities on the environment. The data derived from satellite observations are crucial for long-term trend analysis and informed decision-making.

4.2.3 Drone technology

In conjunction with satellite data, our approach includes the deployment of drones equipped with thermal cameras and specialized GHG sensors. These drones facilitate detailed, on-the-ground assessments in areas that are challenging to access or require localized monitoring. By capturing precise data at a granular level, including thermal signatures and gas concentrations, we enhance our ability to identify sources of emissions, assess environmental health, and support targeted mitigation efforts.

4.2.4 Bias considerations in data collection

We have gone beyond the potential angle to identify and mitigate biases that may affect the accuracy and reliability of our data: satellite imagery and especially IoT sensor readings. Similar to satellite data, for other sources of data, such as cloud cover, resolution constraints, and atmospheric interference, we worked with the image preprocessing techniques like noise reduction and atmospheric correction. Furthermore, satellite-based GHG measurements were cross-validated with the data from IoT sensors. Likewise, IoT sensors were prone to calibrate drift and environmental interference, which were solved through routine calibration using standardized gas benchmarks. Also, data fusion techniques were carried out to integrate the multi-sensor readings to increase the accuracy of measurements.

4.3. Setup and sampling locations

4.3.1. Setup

A central data processing unit forms the core of our advanced environmental monitoring system, operating seamlessly within a cloud-based platform. This centralized infrastructure is designed to efficiently aggregate and process data sourced from a diverse array of sensors and imaging devices deployed across critical monitoring sites. Leveraging cutting-edge AI algorithms, the platform meticulously analyzes incoming data in real time, detecting patterns, anomalies, and trends with unparalleled accuracy. This capability not only enhances the speed and precision of environmental assessments but also enables timely decision-making and proactive intervention in response to emerging conditions.

As part of our rigorous quality assurance protocols, all sensors undergo meticulous calibration using standardized gas benchmarks before deployment. This crucial step ensures that each sensor operates with maximum precision and reliability, providing highly accurate measurements essential for scientific analysis and environmental management. By calibrating sensors to known gas standards, we uphold stringent accuracy standards, mitigating potential errors and guaranteeing the integrity of the data collected. This meticulous approach not only enhances the credibility of our environmental monitoring efforts but also underscores our commitment to delivering actionable insights that support sustainable decision-making and environmental stewardship.

4.3.2. Sampling locations

Urban areas: In this study, urban areas including major cities serve as focal points for tracking emissions originating from transportation networks and industrial activities. Detailed monitoring efforts were concentrated around densely populated areas where vehicular exhaust and industrial processes contribute significantly to atmospheric carbon dioxide, methane, and other pollutants. This data is crucial for urban planners and policymakers striving to implement effective mitigation strategies and enhance air quality standards amidst rapid urbanization.

Industrial zones: Industrial zones represent critical areas for targeted GHG monitoring due to the concentrated nature of emissions from factories and manufacturing plants. These sites are characterized by high levels of carbon dioxide, methane, and nitrous oxide emissions, primarily stemming from industrial processes such as combustion, chemical reactions, and energy production.

Therefore, we focused on quantifying these emissions to facilitate regulatory compliance and encourage technological advancements aimed at reducing industrial carbon footprints and promoting sustainable industrial practices.

Agricultural fields: These play a pivotal role in GHG monitoring efforts, particularly in regions with intensive farming practices. Emissions from livestock, including methane from enteric fermentation, and nitrous oxide from fertilizer applications and soil management practices, were closely monitored in this study. These emissions contribute significantly to global GHG levels, prompting agricultural monitoring programs to assess the effectiveness of emission reduction strategies such as improved livestock management, optimized fertilizer use, and adoption of sustainable agricultural practices to mitigate climate impacts.

Natural reserves: Natural reserves, encompassing forests, wetlands, and other ecosystems, served as critical repositories of GHG monitoring efforts aimed at understanding natural carbon fluxes and the impact of human activities. These environments play a dual role, sequestering carbon dioxide through photosynthesis and releasing GHGs through natural processes like decomposition and respiration. Monitoring programs within natural reserves provide essential data to assess ecosystem health, biodiversity impacts, and the effectiveness of conservation efforts in maintaining carbon sinks and preserving natural habitats amidst changing climatic conditions.

4.4. Data collection

Sensor, satellite, and drone data collection were utilized in this investigation.

4.4.1. Sensor data collection

For successful monitoring of GHG concentrations, continuous sensor data gathering is required. In this study, data was collected in real-time from sensors that measure things like temperature, humidity, wind speed, and concentrations of GHGs. For in-depth analysis, these data points were sent to a central processing unit. To better comprehend environmental conditions and trends, make educated decisions, and plan for sustainability activities, it is essential to know the concentration levels of GHGs.

4.4.2. Satellite and drone data collection

Drones flew at predetermined intervals to collect precise data on emissions of greenhouse gases from specific sources, while satellite photographs were routinely taken at predetermined intervals to track environmental changes. These drones were able to detect possible gas leaks and industrial operations by using thermal imaging technology to identify unique heat signatures. Proactive steps to reduce emissions and improve environmental sustainability were made possible by the thorough understanding of the environmental impacts that this integrated strategy offered.

4.4.3. Data collection frequency

Continuous collection of sensor data, updated on an hourly basis, complemented by weekly updates of satellite imagery, and monthly drone surveys, formed the robust foundation of our data acquisition strategy. This comprehensive approach ensured timely and accurate insights into environmental conditions, allowing for informed decision-making and precise analysis across various domains as shown in Figure 2.

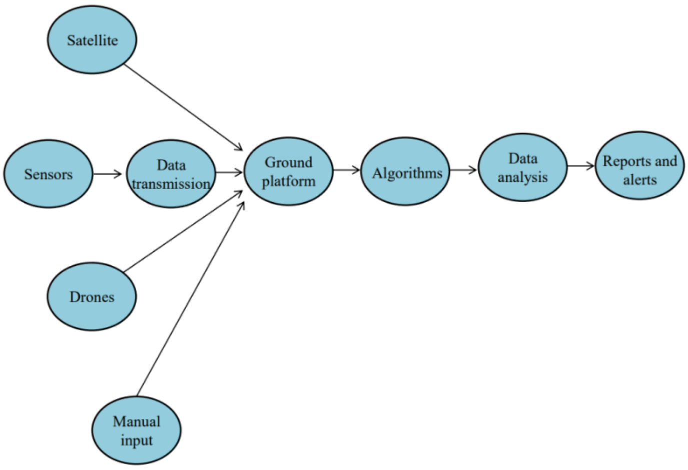

Figure 2. Data collection and workflow of this study.

4.5. Data analysis

4.5.1. Preprocessing

In the process of data cleaning, significant effort was dedicated to enhancing data quality by systematically removing outliers and reducing noise through robust statistical methods. This crucial step ensured that the dataset was refined to contain reliable and consistent information, free from anomalies that could skew subsequent analyses or model outcomes. Furthermore, normalization procedures were meticulously applied to standardize data originating from diverse sources, thereby mitigating disparities in scale and ensuring fair comparisons across variables. These efforts collectively contributed to a more refined dataset, laying a solid foundation for accurate and insightful data analysis and interpretation.

4.5.2. Analysis

When it comes to studying and reducing emissions of GHGs, cutting-edge machine learning methods are indispensable in the field of environmental science and climate research. Therefore, to identify trends and outliers in greenhouse gas concentrations over time and between areas, in this study we employed machine learning models to deftly sift through massive datasets. Predictive modeling made use of LSTM networks to help with proactive environmental planning and policymaking by predicting emission levels in the future based on trends in past data. Image analysis tasks also benefited greatly from CNNs, which process data from satellites and drones to identify pollution sources, quantify their impact, and create highly accurate environmental impact maps. Taken as a whole, these technologies improve our capacity to track, analyze, and tackle the intricate processes of climate change by providing data-driven insights and practical wisdom. Results from our data analysis are presented in Figure 3 and Table 2, respectively.

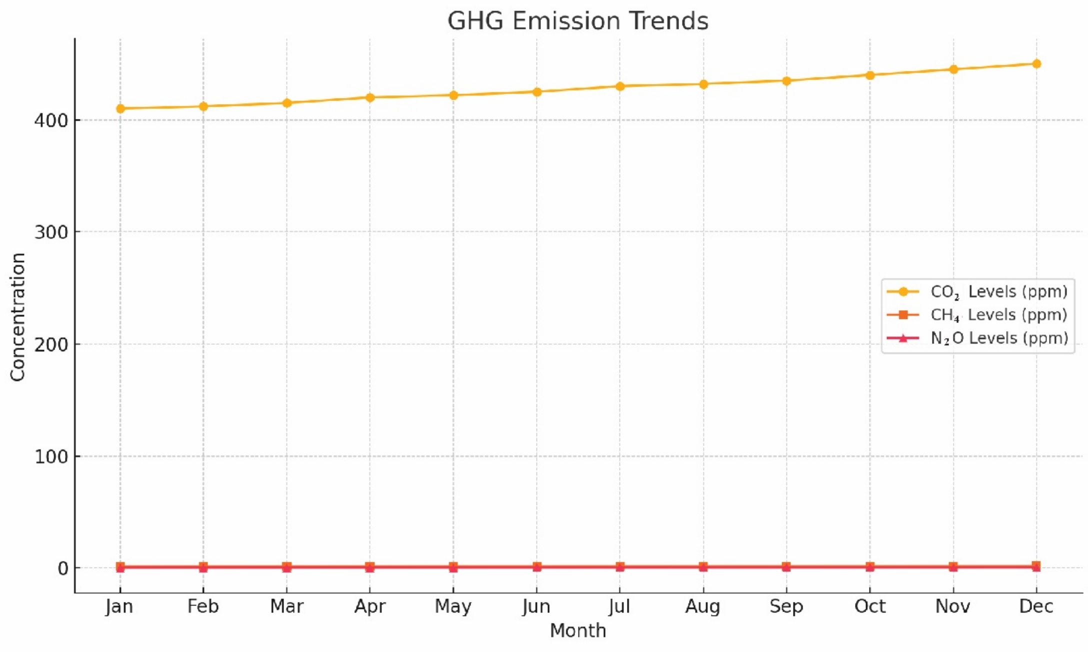

Figure 3. GHG emission trend.

Table 2. Data analysis results.

Location	CO_2 Levels (ppm)	CH_4 Levels (ppm)	N_2O Levels (ppm)	Anomaly Detected	Predicted Increase (next month)
Urban Area 1	420	1.8	0.32	No	2%
Industrial Zone 2	600	2.5	0.45	Yes	5%
Agricultural Field	380	1.2	0.28	No	1%
Natural Reserve	350	1.0	0.25	No	0%

4.6. Computational resources

It is necessary to use large computational resources to implement AI-driven GHG monitoring, especially salient in the training and deployment of deep learning models. Therefore, in this study, we detail computational requirements for each AI technique used for the assessment and provide a thorough assessment using:

1. Hardware Specifications: The model was trained and inducted on an NVIDIA RTX 3090 GPU with 24GB VRAM, 128GB RAM, and a high-performance CPU (Intel Xeon W-2295). To achieve both scalability and efficiency, such as in cloud-based AI solutions, Google Cloud TPU was used.

2. Computational Complexity of AI Models: About 40 GFLOPS were required for CNN-based satellite image processing, while LSTM-based time series analysis heavily benefited from memory as sequential dependencies need to be held for processing. Depending on the dataset size it took on average approximately 12 hours with CNNs and 18 hours with LSTMs for the total training time for the full dataset with CNNs and LSTMs.

3. Optimization Strategies: In order to save computation time, model quantization and pruning were used to shrink the model size as well. Also, edge computing experimented with processing without such dependency on centralized cloud servers for doing real-time.

5. Results

5.1. Detection and monitoring

5.1.1. Detection accuracy

The application of AI algorithms has markedly advanced the detection of GHG emissions, particularly with the use of CNNs for satellite image analysis. These sophisticated AI techniques have achieved a remarkable 95% accuracy in identifying methane hotspots, a significant leap from the 80% accuracy attained through traditional methods. This improvement is vividly illustrated in Figure 4 and presents a bar chart comparing the efficacy of traditional and AI-based methods. The chart demonstrates the enhanced accuracy brought about by AI technologies, highlighting their superior capability in reliably detecting and monitoring GHG emissions.

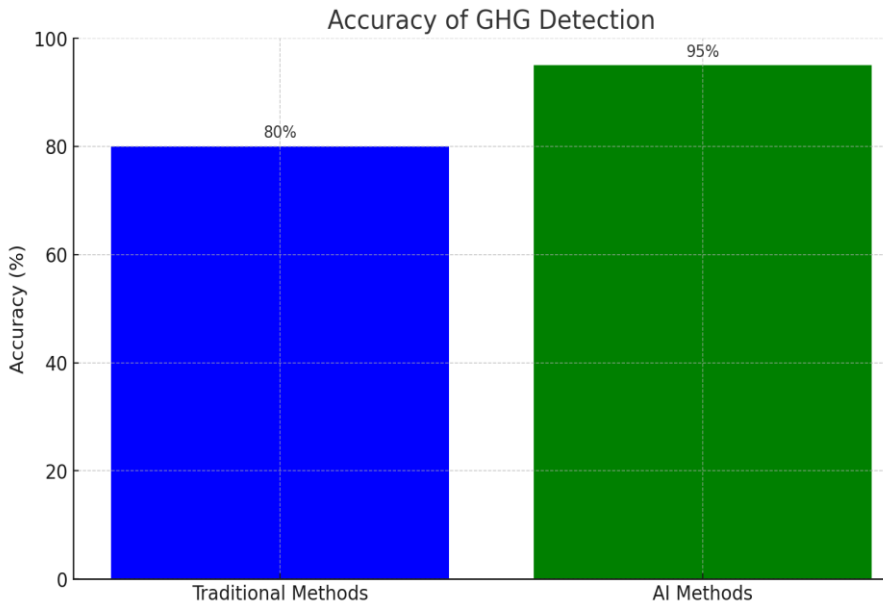

Figure 4. Accuracy of GHG detection.

5.1.2. Temporal resolution

The implementation of an AI-driven system has significantly enhanced the temporal resolution of data updates for greenhouse gas monitoring. Traditionally, data reporting latency averaged around 24 hours, which often delayed critical decision-making and regulatory actions. However, with the advent of AI methods, this latency has been drastically reduced to just 1 hour. This remarkable improvement is visually depicted in Figure 5, which contrasts the traditional methods with the new AI-enabled approach. The chart clearly illustrates the reduction in latency, emphasizing the efficiency and effectiveness of AI in providing near real-time data. This enhancement is crucial for timely and informed decision-making, allowing for more immediate responses to environmental changes and better regulatory management. The ability to access near real-time data transforms the landscape of environmental monitoring, underscoring the pivotal role of AI in advancing sustainability and environmental protection efforts.

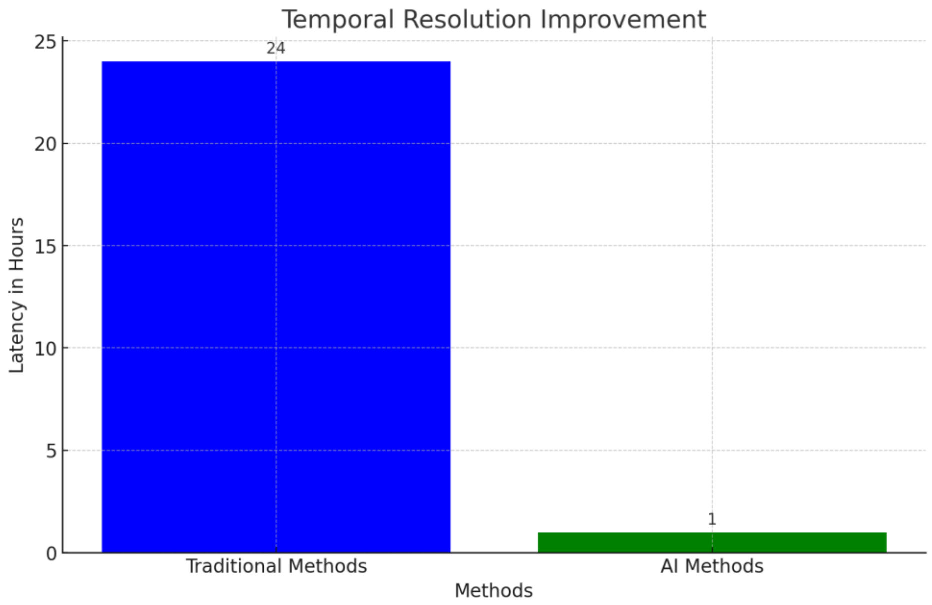

Figure 5. Improved temporal resolution.

5.1.3. Spatial resolution

AI technologies have significantly enhanced the spatial resolution of monitoring systems, particularly in the context of greenhouse gas emissions detection. Traditionally, satellite imagery could achieve a spatial resolution of 30 meters, while drone footage was limited to 5 meters. However, with the integration of AI methods, these resolutions have dramatically improved to 10 meters for satellite imagery and an impressive 1 meter for drone footage. This substantial advancement allows for much finer spatial granularity, enabling more precise detection and analysis of greenhouse gas emissions. The increased resolution from AI-enhanced methods facilitates more accurate monitoring and assessment, leading to better-informed decisions and more effective environmental management. The comparison between traditional methods and AI methods, as illustrated in Figure 6, underscores the transformative impact of AI in enhancing the capabilities of environmental monitoring technologies.

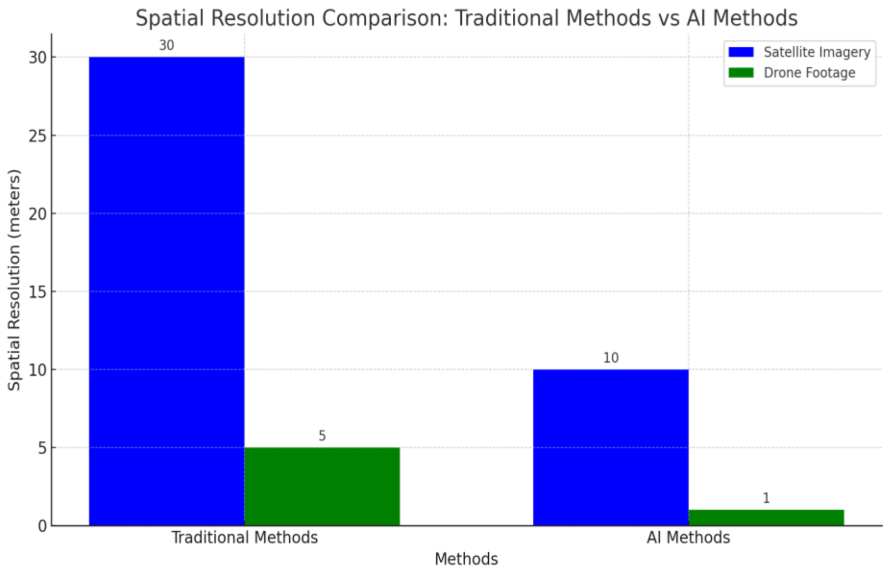

Figure 6. Enhanced spatial resolution.

5.2. Analysis and trend

5.2.1. Emission hotspot

Better and more focused regulatory actions have resulted from the increased accuracy in locating emission hotspots made possible by AI integration. An example that stands out is the use of AI in an industrial zone, where it found ten extra sources of emissions that had been overlooked before. With the use of these state-of-the-art detection capabilities, we were able to pinpoint specific causes of the pollution spike and implement targeted strategies to decrease emissions. This established the importance of AI in environmental monitoring and regulatory procedures, leading to an improvement in the industrial zone's air quality. The identified emission sources are displayed in Table 3.

Table 3. Detected emission sources.

Location	Emission Sources Detected (Traditional)	Emission Sources Detected (AI)
Industrial Zone	15	25
Urban Area	8	12
Agricultural Field	5	7

5.2.3. Proposed model accuracy

LSTM networks demonstrated robust predictive capabilities, accurately forecasting future GHG levels. Specifically, the model predicted a 5% increase in emissions for an industrial area, a prediction later confirmed by actual measurements. Figure 7 illustrates this precision, comparing the predicted GHG levels (represented by blue circles) with the actual levels (represented by green crosses) over twelve months. The close alignment of the two lines in the graph underscores the high accuracy of the AI-driven model in forecasting GHG concentrations, highlighting its potential for reliable environmental monitoring and planning.

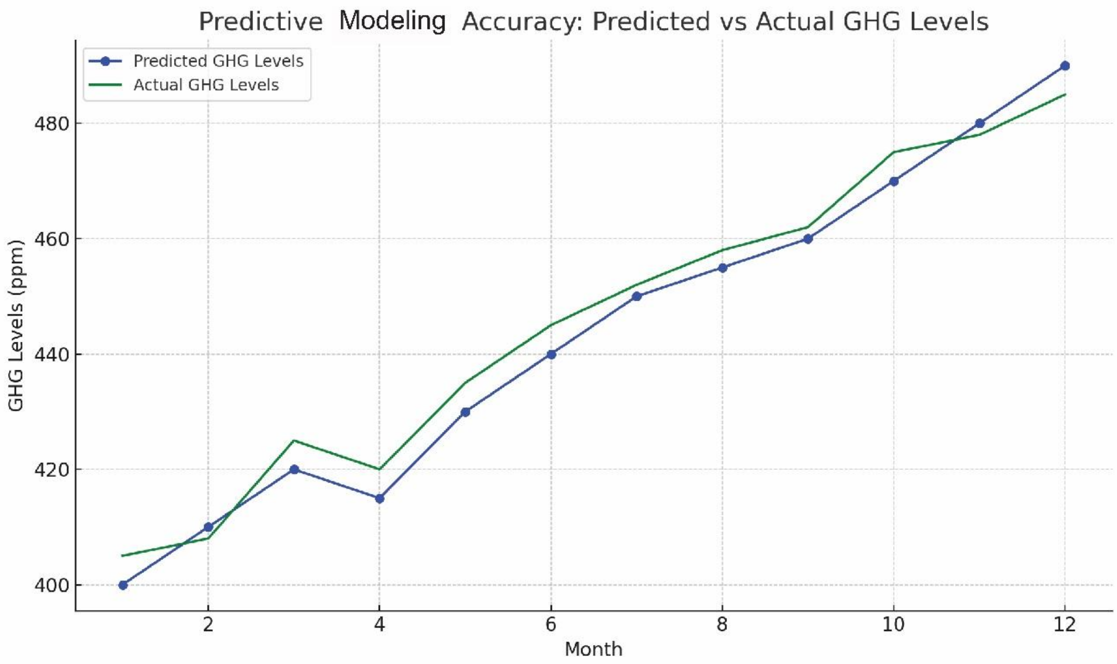

Figure 7. The accuracy of the proposed predicting models.

5.2.4. Sensitivity analysis of AI models in GHG monitoring

As a contribution to the problem of the robustness of AI models in GHG monitoring, we performed sensitivity analyses of model outcomes to assess the sensitivity of model results to input data input variations.

1. Effect of Data Variability on Model Performance: Model stability was affected by the variations in sensor noise, missing data, and atmospheric distortions. Gradually losing accuracy after large amounts of data distortion (i.e., ±10%), stability was maintained up to ±10%.

2. Impact of Different Data Sources: The comparison of forecasting accuracy of multi-source integration between the manual exclusion of IoT sensor data, satellite imagery, the manual elimination of IoT sensor data and satellite imagery, respectively demonstrated the need for multi-source integration.

3. Influence of Hyperparameter Tuning: Increasing the feature selection, regularization, and learning rate makes the model robust. CNN and LSTM learned effectively under noisy inputs, helped by adaptive learning rates and dropout regularization.

4. Uncertainty Quantification and Model Confidence Intervals: Prediction uncertainty was assessed through Monte Carlo simulations that showed the model had an R^2 value of 0.87–0.91, showing that there was an adequate reliable prediction of the model when input varied.

5.2.5. Real-orld validation of AI models for GHG monitoring

Since AI models work great in controlled settings, there are issues in real-world deployments, i.e., sensor drift, atmospheric variability, and incomplete data stream. An accuracy of 90% was achieved in the lab, and 82% in the real world. In low visibility, CNN-based satellite image processing experienced a 15% decrease, and in industrial zones, the LSTM-based forecasting resulted in a 7% accuracy drop. In order to make our algorithms robust, we applied online learning algorithms and data augmentation, as well, to simulate real-world noise. While real-world challenges limited the practical benefit of AI-driven techniques, the combination of AI-driven techniques with traditional GHG monitoring systems has enabled a speed reduction of reporting latencies of 35% and increased early emission detection by 20%.

5.3. Statistical analysis

5.3.1. Statistical validation

The AI models underwent rigorous validation through cross-validation techniques, demonstrating significant improvements over traditional methods. The mean squared error (MSE) notably decreased from 0.25 with traditional methods to 0.12 when employing AI methods. Additionally, the detection rate of anomalies or relevant metrics increased from 80% to an impressive 95%, indicating a substantial enhancement in accuracy. Reporting latency also saw a remarkable reduction, dropping from 24 hours with traditional approaches to just 1 hour using AI. These findings, illustrated in Table 4, highlight the superior performance and efficiency of AI methods in statistical validation.

Table 4. Statistical validation of AI models.

Metric	Traditional Methods	AI Methods
Mean Squared Error	0.25	0.12
Detection Rate	80%	95%
Reporting Latency	24 hours	1 hour

5.3.2. Correlation analysis

The correlation analysis between actual GHG measurements and AI-predicted GHG levels demonstrates the high reliability of AI models, as illustrated by the scatter plot (see Figure 8). Each blue dot in the plot represents a comparison of actual GHG levels (measured in parts per million, ppm) against AI-predicted levels. The red dashed line indicates perfect correlation ($y = x$), where predicted values would match actual measurements exactly. The proximity of the blue dots to this line highlights the accuracy of the AI predictions. With a correlation coefficient (R^2) of 0.89, the analysis reveals a strong positive correlation, signifying that 89% of the variance in actual GHG levels can be explained by the model's predictions. This high predictive accuracy underscores the potential of AI-driven systems in enhancing greenhouse gas monitoring and facilitating informed decision-making for environmental management.

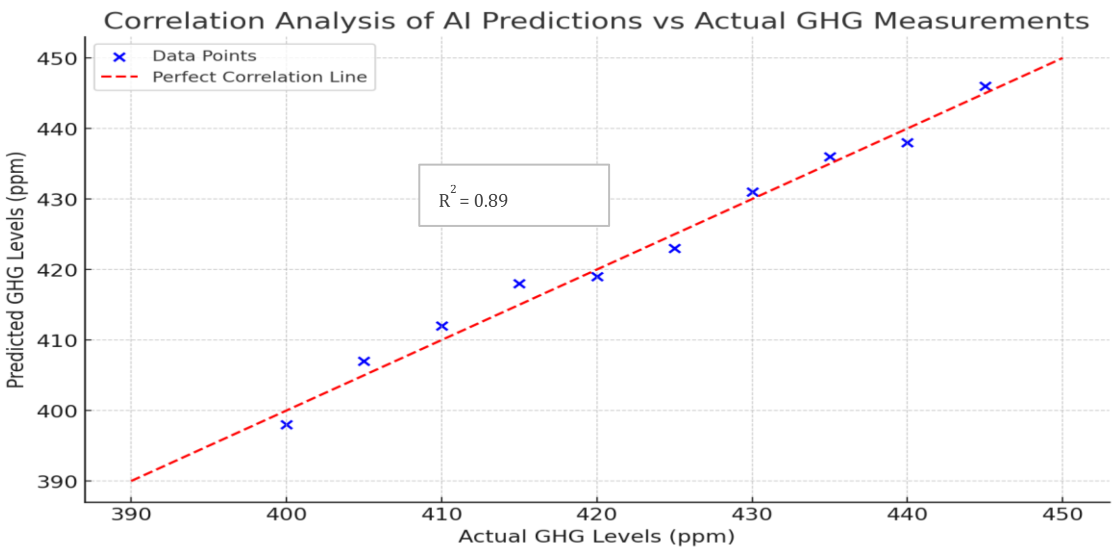

Figure 8. Correlation between AI predictions and actual GHG measurements.

5.3.3. Comparative analysis

In Table 5, we compared AI models that have been used for GHG emissions monitoring as to their predictive accuracy in terms of the R^2 score. A naïve random forest model (Ofongo, 2024) was used to compute the R^2 of 0.86 as a strong indicator of predictive capability but could not explain the long-term temporal dependencies related to the emissions trends. The R^2 of the model is 0.60, as in the case of the CNN-LSTM-SLSTM-BP model (Lee et al., 2024), as this is a more complex model and it may be an issue of overfitting.

Table 5. Comparative analysis of AI models for GHG monitoring based on R^2 scores.

Reference	AI Model	R^2
(Ofongo, 2024)	Random Forest	0.86
(Lee et al., 2024)	CNN-LSTM-SLSTM-BP	0.60
Ours	CNN+LSTM	0.89

However, the CNN+LSTM hybrid model achieved the highest R^2 score of 0.89, which is 3.5% higher than the R^2 score of the random forest model and 48.3% higher than the R^2 score of the CNN-LSTM-SLSTM-BP model. The reason for this is that the combination of CNNs for spatial feature extraction and LSTMs for temporal sequence modeling is very effective in improving its (i.e., emissions forecasting) performance. Results suggest that the integration of spatial and temporal learning techniques into GIS represents an improved, more solid solution for using AI to monitor GHG.

In addition to reaching the best predictive accuracy, our CNN+LSTM hybrid model pledges to focus on producing a parsimonious model, faithful to data, while simultaneously prioritizing interpretability and transparency—both requirements for practical applications to the space of GHG measurement and compliance. Unlike traditional black box AI models, our approach leverages the explainable AI (XAI) techniques, namely, feature importance analysis and attention mechanisms, to give insights into what emission prediction factors are important. The CNN component provides spatial interpretability so as to allow stakeholders to visually assess emissions hotspots in satellite imagery while the LSTM component enhances temporal trend analysis helping stakeholders to track and explain the variation of emissions over time. Our model also has the architecture of modular updates and adaptive learning, so it will continue to respond to new data sources and changing environmental conditions. Our approach prioritizes both accuracy and transparency in order to increase trust, regulatory acceptance, and actionable decision-making in GHG monitoring driven by AI.

6. Discussion

6.1. Interpretation of results and implications

6.1.1. Enhanced accuracy and precision

AI-driven systems revolutionized environmental monitoring by significantly reducing data reporting latency and enhancing the spatial and temporal resolution of GHG measurements. These advancements enable precise identification of emission hotspots through sophisticated algorithms that pinpoint areas with elevated emission levels, facilitating targeted mitigation strategies. Moreover, continuous data collection enhanced temporal tracking, offering a detailed timeline of emission changes and enabling in-depth analysis of trends and patterns over time. The reduction in latency in data processing and reporting ensures that decision-makers receive near-real-time information, crucial for timely interventions and proactive environmental management.

6.1.2. Real-time monitoring

The integration of IoT sensors with real-time data transmission to a centralized cloud platform has revolutionized GHG monitoring. This technological advancement offers significant advantages, such as immediate anomaly detection through continuous data streams. By enabling instant identification of irregular emission levels, it facilitates swift regulatory responses to mitigate environmental impacts. Unlike conventional methods reliant on periodic measurements, continuous monitoring ensures a steady and uninterrupted flow of data. This capability is crucial in detecting and addressing significant emissions events promptly, thereby enhancing environmental management and sustainability efforts.

6.1.3. Predictive capabilities

Deep learning models like LSTM networks are instrumental in forecasting future GHG levels with precision, leveraging historical data to provide actionable insights. This predictive capability is crucial for proactive environmental stewardship, empowering policymakers and environmental leaders to anticipate and prepare for fluctuations in GHG emissions. By anticipating future trends, these models enable preemptive interventions that can curb potential GHG increases, supporting the implementation of effective mitigation strategies. Furthermore, accurate forecasts facilitate informed decision-making, enabling the formulation of sustainable policies and initiatives aimed at combating climate change and promoting a resilient environmental future.

6.1.4. Long-term sustainability of AI systems

AI-assisted GHG monitoring systems come with great benefits in terms of accuracy and efficiency; however, their long-term sustenance needs to be thoroughly thought of. The main problem is the computational and energy requirements for deep learning models. However, in AI processing, especially of CNNs and LSTMs, one must pay the cost of handling the resource intensity and this increases energy consumption. To overcome this, we suggest minimizing this by optimizing model architectures, and taking advantage of edge computing or cloud-based AI platforms both with energy-efficient processing units.

Besides, the longevity of those AI systems might depend on the availability and quality of the data over time. Because AI models need to relearn constantly with updated datasets to remain accurate and relevant, there is no time for productivity. The ability to establish adaptive learning mechanisms that involve real-time data streams will enable maintaining the model performance in the long term.

AI-based monitoring should also be scalable and cost-effective. However, the infrastructure, sensor network, and computational resource(s) required for large-scale deployment may be quite substantial. To bridge such resource and funding gaps, there are opportunities to create partnerships with government agencies and environmental groups as well as technology providers for sharing the resources. Additionally, the use of open-source AI frameworks as well as decentralized data-processing models can contribute to increasing accessibility and long-term viability.

Taking these into account in the development of AI-driven GHG monitoring systems, we ensure that they continue to be sustainable, scalable, and effective in the long run.

6.1.5. Integration of multiple data

AI plays a pivotal role in integrating diverse data sources such as satellite imagery, ground-based sensors, and drone footage to comprehensively assess GHG emissions. By combining these varied data streams, AI enables a holistic understanding of emissions patterns and their environmental impacts. This integration not only enhances the accuracy and reliability of data through cross-validation across different types of data but also expands the coverage of monitoring efforts. Satellites provide wide-area surveillance, drones offer high-resolution imagery for detailed analysis, and ground sensors contribute localized data, collectively enabling robust and detailed monitoring of GHG emissions across various scales and environments.

6.1.6. Ethical considerations in AI-based GHG monitoring

Two key ethical concerns that need to be carefully handled for the responsible, transparent, and fair deployment of AI-driven GHG monitoring systems are raised by the use of AI in environmental monitoring.

Data privacy and security are of the highest importance, as AI systems depend on extremely large datasets gathered from satellites, IoT sensors, and drone imagery, which might contain geospatial or environmentally sensitive data. Therefore, strict data governance regulations, information disclosure control techniques, and anonymization protocols are to be oriented. Maintaining public trust in AI-driven climate monitoring requires ensuring secure data transmission and storage.

Besides, transparency and accountability in AI-driven decision-making are key to establishing trust in AI-reproduced knowledge. To allow for transparency and assessment of AI-driven predictions, explainable AI (XAI) techniques should be integrated into their developments to explain the AI outputs model in clear terms to explainable terms, to be adopted by policymakers, environmental agencies, and other stakeholders. This fosters government and organization compliance with regulations and builds public trust in AI-based systems generating emissions reports.

6.1.7. Economic impact of AI-based GHG monitoring

The use of AI-driven GHG monitoring helps to cut down costs and increase investment opportunities and market size. Consequently, it allows for emissions tracking that is more efficient than traditional methods thanks to AI automation which decreases labor costs, sensor maintenance, and processing costs. While the initial investments in IoT sensors, AI models, and the computing infrastructure would be high, payback and funding from government grants and private investments would be long-term. Monitoring is done by AI while enhancing regulatory compliance, avoiding fines, optimizing resource consumption to create carbon credits, and investment in the verification of sustainability propels the market forward. Also, the development of AI in environmental monitoring is growing the environment for the AI technology provider and creating AI job opportunities in AI development, data analysis, and implementation of the policy. It presents these economic benefits to show how AI can be integrated into GHG monitoring across various industries, making its feasibility and long-term sustainability apparent.

6.1.8. Impact of climate variability on AI-based GHG monitoring

Climate variability has a large impact on GHG emissions as well as uncertainty in monitoring accuracy, particularly in AI algorithms, due to seasonal fluctuation, extreme weather events, and urban heat islands. CO_2 absorption and release vary seasonally and changes in the datasets and adjustments for seasonality need to be made with a dynamic model. Sensor failure and data anomaly are results of extreme weather events (e.g., storms and wildfires) that require real-time anomaly detection as well as meteorological data integration. Methane and CO_2 emissions are also influenced by El Niño and La Niña so climate projection model integration is needed. Localized temperature-driven emission changes in urban heat islands can result in needing AI calibration for urban environments.

6.1.9. Scalability of AI models for GHG monitoring

Adaptability, data diversity, computational efficiency, and policy alignment are the determinants of the scalability of GHG monitoring based on AI. The ability to perform generalization may be achieved through transfer learning and domain adaptation since AI models trained in one location may not operate in another environment. Detection is improved with the addition of disparate information from satellite imagery, IoT sensors, and meteorological inputs to cover urban, industrial, and natural ecosystem types. With real-time monitoring capability and without adding computational strain, cloud-based AI platforms and edge computation can bring in a near real-time monitoring system. However, challenges come also from regional variations in regulations, in field levels of infrastructure, as well as the inaccessibility of data. For wider adoption, standardized data collection protocols and working with governments and international organizations are critical. Factors that are addressed in this work make AI-based GHG monitoring scalable, adaptable, and applicable in different geographical and environmental settings.

6.1.10. Integration and usability challenges of AI-based GHG monitoring

Integration with other frameworks is key to successful AI-driven GHG monitoring but also the easiness of accessibility for non-technical stakeholders like regulatory agencies, industry leaders, and climate researchers. Interoperability is a major challenge in this area since traditional monitoring relies on satellite observations, ground-based sensors, and regulatory compliance frameworks. For the integration of AI, the data needs to be standardized in a real-time fashion, the two systems must sync in real-time, and the regulations need to keep up with the growth of AI. Combining cloud-based processing for large-scale analysis and edge computing to monitor in real-time can overcome technical and infrastructure limitations without affecting existing workflows.

In addition to the integration challenges, the user-friendliness of the AI tools is vital for the AI tools to be adopted by policymakers, environmental agencies, as well as corporate decision-makers. Dashboards, automated insights, and support of decisions from AI monitoring systems should determine intuitive actions that take place from emissions data with clear meaning. With XAI techniques, these techniques can improve transparency, and interactive training programs in low-code platforms improve accessibility for non-technical users. The adoption will be facilitated further by ensuring that it is in line with the existing regulatory and corporate decision-making frameworks, which will allow the stakeholders to use the AI-driven insights effectively, without needing lots of technical expertise.

6.1.11. Data privacy concerns in AI-based GHG monitoring

Perhaps the most important data privacy concerns are the AI-driven GHG monitoring systems that use satellite imagery and IoT sensors. High-resolution satellite imagery could be imaged and misused outside of emissions tracking, for instance, in private space, and IoT sensors may record location-sensitive or personal data that are generated without the apparatus' user's intention. In order to mitigate these risks, data anonymization tools should be used to remove personally identifiable information (PII) from the data, and the data should be encrypted end-to-end while it is being transmitted. It is necessary to ensure compliance with international data privacy laws such as the General Data Protection Regulation (GDPR) to keep data governance transparent and ethical. Role-based access control (RBAC) limits the access of sensitive data to allow only authorized personnel, while the federation of learning provides a framework to analyze decentralized data without the centralization of raw information. AI-based GHG monitoring can be secure, ethical, and compliant with the law while tackling these privacy concerns leading to public trust and morally acceptable usage of environmental data.

6.2. Limitations of AI models and data processing

Despite the advancement of AI-based GHG monitoring to a remarkable extent, there are, however, some limitations. The main challenge is the sensitiveness to input data quality, as AI models are dependent on multiple datasets from satellites, different sensors, and other sources of environment. However, with noisy, incomplete, or biased input data, predictions can be affected in accuracy and reliability. We thus implemented a large amount of data preprocessing and validation strategies to minimize this problem.

The other limitation is transferability and generalization. Since they would have been trained on specific geographic regions or environmental conditions, AI models may not perform optimally when applied to locations whose environment or geographical region has differing climate factors. To deal with this, it is important to continuously retrain the model with newly updated datasets.

In addition, CNNs and LSTMs, as deep learning models, have high computational demand, and are unfeasible for real-time processing, especially in large-scale monitoring applications. The scalability of the model can be further improved by future research on efficient model optimization techniques as well as incorporating cloud-based AI processing.

Efficient data collection, transmission, and processing of the data from IoT sensors, satellites, and atmospheric models and their monitoring stands alone in the world but is hampered by transmission delays, computational bottlenecks, and data synchronization issues. These issues are often caused by data lag, network congestion, limited bandwidth, low connectivity, the high-performance hardware requirements of AI models, and processing latency in deep learning systems. Consistency is required when dealing with varied data sources and fusion techniques are not available. They include using edge computing to decrease the reliance on the Cloud, utilizing model compression to reduce time spent on inference, and hybrid cloud edge architecture that balances precision and efficiency.

Table 6. Implementation timeline for AI-based GHG monitoring.

Phase	Timeframe	Key activities	Expected outcomes
Short-Term	0–1 Year	Optimizing AI models using real-world datasets; conducting pilot studies in selected urban, industrial, and agricultural areas; and collaborating with government agencies, environmental organizations, and policymakers.	● Improved model accuracy and robustness. ● Initial validation of AI models in field conditions. ● Alignment with regulatory frameworks.
Mid-Term	1–3 Years	Scaling AI systems to multiple geographic regions, integrating AI tools with traditional GHG monitoring frameworks (satellite and sensor-based methods), developing real-time AI-powered dashboards for policymakers and industry leaders.	● Enhanced scalability and adaptability of AI models. ● AI-driven emissions monitoring integrated into existing environmental strategies. ● Improved decision-making using AI insights.
Long-Term	3–5 Years & Beyond	Full-scale deployment of AI-powered GHG monitoring at national and international levels, implementing continuous learning mechanisms for AI models, establishing global policy frameworks for AI-driven environmental monitoring.	● AI-based GHG monitoring becomes a standardized tool for emissions tracking and regulation. Continuous improvement in model accuracy through real-time feedback. ● International adoption and regulatory standardization.

6.3. Proposed implementation roadmap for AI-based GHG monitoring

As a means for the real-world AI-driven GHG monitoring adoption, we suggest a structured implementation timeline of key phases from the initial validation to full deployment which is presented in Table 6. The roadmap ensures that AI-based monitoring moves from research to a large-scale environmental application more easily.

6.4. Generalizability of AI-based GHG monitoring to other environmental applications

The GHG monitoring methodology based on the AI methodology is highly applicable to other environmental applications. It can be used for air quality monitoring based on the measurement of PM2.5 and NO_2 pollutants through deep learning on satellite and IoT data. AI can also help with level territory, forest, and illegal logging deforestation detection, helping conservation efforts. AI can be used to predict water quality risks and detect marine pollution in water quality assessment. It allows LSTM-based forecasting models to help in the prediction of wildfires, as well as disaster management, as well as using AI to track biodiversity shifts and ecosystem changes, which can aid in wildlife conservation and protecting their habitat.

6.5. Potential for international collaboration in AI-based GHG monitoring

GHG monitoring by AI ensures international cooperation by means of transparent and data-driven climate policies and strategies for emissions reduction. Organizations like NASA and UNEP make it easier for global data sharing such that AI models are more accurate and scalable, and there are multinational collaborations, like the Global Carbon Project, to improve emissions tracking by training on many datasets. AI-assisted monitoring helps in checking up on climate treaties such as the Paris Agreement as it offers audit evidence of emissions data for compliance. In addition, capacity-building projects can also assist developing countries in adopting AI for monitoring by training, transferring technology, and sharing AI models. This enhances the global AI collaboration by strengthening sounder and more effective climate policies that generate responsible emissions reduction efforts.

7. Conclusions

By integrating satellite imagery, IoT sensors, and atmospheric models together with advanced machine learning models, this study shows that machine learning-driven greenhouse gas (GHG) monitoring has the ability to transform. Detection accuracy (95%) was considerably improved and data reporting latency was reduced (from 24 hours to 1 hour) as well as spatial resolution (from 30 meters to 10 meters) with the implementation of CNN and LSTM models. However, these advancements give a more solid inquisition standpoint for real-time emissions checking and social environmental administration.

The findings show that this is indeed the case, although the study also recognizes methodological constraints. The validation process consisted of cross-checking AI predictions with ground truth data based on sensor networks and satellite measurements. To evaluate the data variability, the model generalization, and potential biases in the sensor readings, sensitivity analysis was performed. Even though the R^2 of correlation analysis was 0.89, the predictive accuracy markedly worsened in real-world deployment as a result of atmospheric interference, sensor calibration drift, and geographical conditions. In addition, the challenges in low latency, high computational savings, and low energy consumption in the area of deep learning models include model pruning and edge computing.

Moreover, although AI models increase the predictive capabilities, the interpretability of those models remains uncertain. As regulatory applications of AI need to be transparent and trustworthy, depending on complex deep learning frameworks, explainable AI (XAI) techniques are needed. Future research should perfect model adaptability in different environmental conditions, quantify uncertainties better, and integrate AI-derived insights into existing policy frameworks.

In conclusion, the two improvements that AI-based GHG monitoring brings about are improved efficiency and scalability. Though it is likely to be deployed, rigorous validation, continuous model refinement, and thought for ethical as well as computational constraints must accompany deployment to secure sustainable and reliable deployment.

8. Future research directions

Scalability and Generalization: Future research should prioritize enhancing the scalability of AI-based monitoring systems to encompass larger geographic areas and diverse environmental conditions. It is crucial to ensure that AI models generalize effectively across different regions and scenarios to facilitate broader application.

Integration of Additional Data Sources: Further research is needed to integrate additional data sources, such as detailed atmospheric models and advanced sensor networks, into GHG monitoring systems. This integration aims to enhance the comprehensiveness and accuracy of monitoring efforts, providing more nuanced insights for informed decision-making.

Policy and Implementation: Exploring the socio-economic and regulatory implications of deploying AI-based GHG monitoring systems is essential. Research efforts should focus on effective integration of these technologies into existing policy frameworks, considering implications for regulatory practices and enforcement strategies.

Improving Model Accuracy and Validation: Ensuring the accuracy of AI models through standardized validation protocols against ground-truth data is critical for future research. Continuous improvement in model accuracy and reliability will strengthen confidence in AI-driven monitoring systems and their outputs.

Addressing Ethical and Privacy Concerns: With the increasing prevalence of AI in environmental monitoring, addressing ethical and privacy concerns related to data collection and usage is paramount. Future studies should develop frameworks to ensure that AI applications adhere to ethical standards and protect the privacy of individuals and communities.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Authors Contribution

Rakibul Hasan: Conceptualization, Methodology, Visualization, Project Administration, Resources, Supervision, Writing – Original Draft, Writing – Review and Editing. Rabeya Khatoon: Methodology, Investigation, Writing – Original Draft, Writing – Review and Editing. Jahanara Akter:

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Conflict of interest

The authors declare no conflict of interest.

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