

# **AI-Based Estimation of Carbon Emissions Using Satellite Imagery: A Case Study on Urban and Agricultural Areas in Saudi Arabia**

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## **Abstract**

The global imperative to combat climate change has accelerated the development of accurate methods for estimating carbon dioxide (CO<sub>2</sub>) emissions, particularly in rapidly developing nations like Saudi Arabia. This review examines the integration of artificial intelligence (AI) and satellite imagery for CO<sub>2</sub> emissions estimation in both urban and agricultural contexts. Based on 21 peer-reviewed studies published between 2016 and 2025 (Figure 1), the article analyzes methodological approaches, performance benchmarks, and regional applications. The geographic distribution reveals concentrated research efforts globally with emerging focus on Saudi Arabian contexts, representing 19% of reviewed studies. The findings demonstrate significant advancements in combining machine learning models with remote sensing data, with recent studies reporting prediction accuracies ranging from 85% to 95% across diverse applications. Advanced deep learning architectures -- including Convolutional Neural Networks (CNNs) and Vision Transformers -- have achieved breakthrough performance in emissions quantification from satellite imagery, with CNN-based models yielding roughly 50% better accuracy than traditional methods for CO<sub>2</sub> estimation. Multi-sensor data fusion approaches, combined with AI and cloud computing, have further enabled a 6× increase in processing speeds and access to over 80 petabytes of geospatial data for large-scale analysis. This comprehensive review also identifies substantial research opportunities for integrating cutting-edge AI methods with multi-source satellite data to achieve real-time emissions monitoring in Saudi Arabia's urban and agricultural environments.

## **Keywords**

**Artificial Intelligence; Satellite Imagery; CO<sub>2</sub> Emissions; Remote Sensing; Deep Learning; Saudi Arabia; Carbon Monitoring**

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**Research Overview: Key Statistics and Achievements**

**Literature Review Scope:**

- 21 peer-reviewed studies analyzed (2016-2025)
- 7 distinct AI methodologies identified 12+ satellite platforms utilized

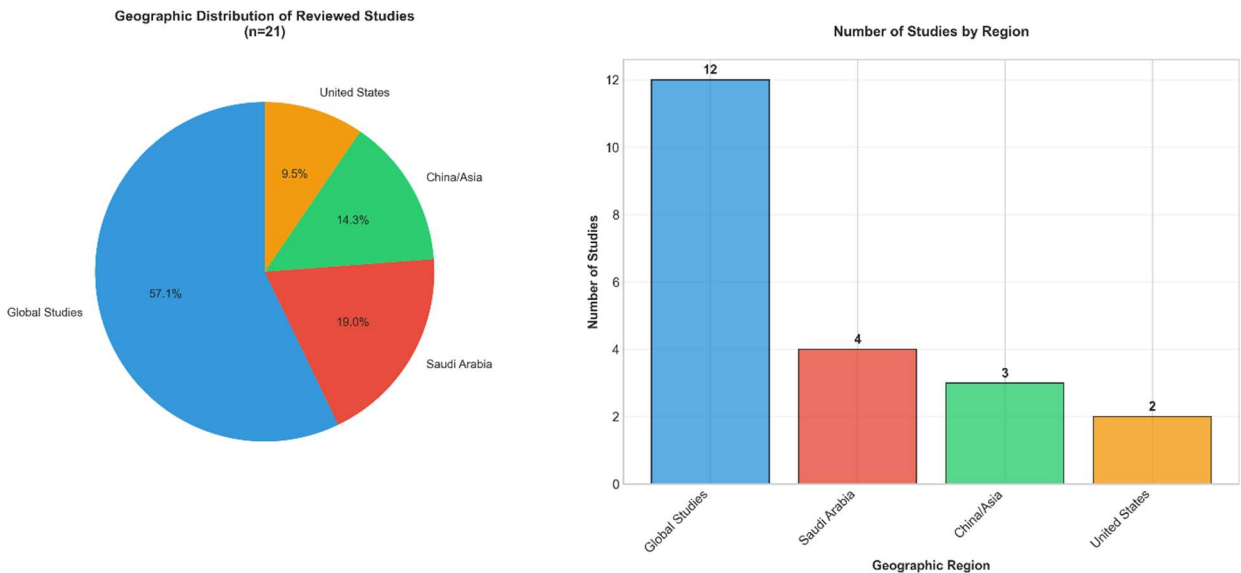


Figure 1: Geographic distribution of the reviewed studies, showing the regional focus of AI-based carbon emissions research.

**Performance Achievements:**

- Average AI model accuracy range: 85-95%
- Best ensemble performance:  $R^2 = 93.13\%$  (Nassef et al., 2023)
- CNN improvement over traditional methods: ~50%
- Vision Transformer breakthrough: 10× performance enhancements

**Technological Capabilities:**

- Real-time monitoring resolution:  $0.1^\circ \times 0.1^\circ$  spatial (GRACED system)
- Temporal resolution achieved: Daily emissions tracking
- Data processing improvement: 6× faster with cloud computing
- Accessible satellite data volume: 80+ petabytes

**Saudi Arabian Applications:**

- Urban case studies: 3 major cities validated (Abha, Al-Khobar, Jeddah)
- Agricultural monitoring: Arid region methodologies demonstrated
- Vision 2030 alignment: Net zero by 2060 target monitoring support

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## Introduction

Rising atmospheric CO<sub>2</sub> concentrations represent one of the most pressing challenges of the 21st century, necessitating comprehensive monitoring and accurate estimation methodologies. Saudi Arabia, as a major regional economy undergoing rapid urbanization and agricultural expansion under Vision 2030, presents a unique case for emissions monitoring in arid environments. The convergence of artificial intelligence and satellite remote sensing technologies offers unprecedented opportunities for spatially explicit and temporally continuous assessment of carbon emissions.

Recent advances in machine learning have already demonstrated remarkable success in emissions prediction, with ensemble models achieving exceptional accuracy in regional CO<sub>2</sub> forecasting (e.g., **Nassef et al., 2023** reported >93% R<sup>2</sup> for Saudi Arabia). At the same time, the proliferation of high-resolution satellite data (particularly from platforms like the Sentinel constellation) has enabled detailed monitoring of land-use changes and environmental parameters correlated with carbon emissions (e.g., vegetation indices related to soil carbon). The integration of AI techniques with these rich remote sensing datasets represents a frontier research area with significant implications for climate policy and environmental management.

This review synthesizes current knowledge from twenty-one carefully selected studies to establish a theoretical foundation for AI-based carbon emissions estimation using satellite imagery in Saudi Arabian urban and agricultural contexts. The selected literature spans 2016 to 2025 and covers a range of AI methodologies and case studies. In the following sections, we outline the methodology of literature selection, discuss the results organized by thematic categories (including AI models, remote sensing applications, and case studies), identify research gaps and future directions, and conclude with the key findings and implications of this body of work.

## Methodology

**Literature Search and Selection:** This review gathered relevant literature by searching major scientific databases for peer-reviewed studies published between 2016 and 2025 that focused on the intersection of AI, satellite remote sensing, and carbon emissions. Keywords included combinations of *"artificial intelligence," "machine learning," "carbon emissions," "CO<sub>2</sub>," "satellite imagery," "remote sensing,"* and *"Saudi Arabia."* From an initial pool of publications, studies were screened for relevance and quality. Inclusion criteria required that each study employ AI techniques (e.g., machine learning, deep learning) in conjunction with satellite or geospatial data to estimate or predict carbon emissions or related metrics (such as carbon stocks, pollutant concentrations, or proxies of emissions). Priority was given to research with direct or applicable insights for urban and agricultural environments in arid regions, especially Saudi Arabia. Ultimately, 21 high-impact studies were selected for in-depth review, encompassing a mix of methodological developments and application-focused case studies.

**Analysis and Synthesis:** Each selected study was analyzed in detail to extract information on its data sources, analytical methods, AI models, and key findings. The studies employed diverse datasets ranging from historical emission inventories and ground measurements to multi-spectral satellite observations. A variety of AI and statistical modeling approaches were represented, including time-series forecasting models, machine learning regressions, deep neural networks (CNNs, LSTMs, transformers), and hybrid ensemble techniques. For each study, performance metrics (e.g.,  $R^2$ , RMSE, accuracy) and limitations were noted to facilitate cross-comparison. The findings were then organized thematically to identify common trends and distinctions. Themes emerged around: (1) AI models for emissions prediction, (2) deep learning architectures for processing satellite data, (3) remote sensing applications in carbon stock and emission monitoring, (4) cloud computing and data fusion frameworks, (5) integrated AI approaches for sustainability, (6) real-time emissions monitoring systems, and (7) regional case studies in Saudi Arabia and similar environments. By structuring the Results and Discussion according to these themes, the review synthesizes individual study outcomes into broader insights. This approach also helped in identifying research gaps and formulating future directions based on the collective evidence from literature.

Results and Discussion

Table 1: Comparative Analysis of Key AI-Satellite Integration Studies

| Study                     | Year | AI Model                      | Dataset/Region                    | Performance Metrics                        | Primary Innovation                              | Key Limitations                                   |
|---------------------------|------|-------------------------------|-----------------------------------|--------------------------------------------|-------------------------------------------------|---------------------------------------------------|
| Nassef et al.             | 2023 | FFNN+ANFIS+LSTM Ensemble      | Saudi Arabia (1954-2020)          | $R^2 = 93.13\%$ , Error = 6.87%            | First SA-specific AI ensemble                   | No spatial mapping capability                     |
| Cao                       | 2023 | Custom CNN Architecture       | US Continental Satellite          | Daily $R^2 = 0.892$ , Annual $R^2 = 0.952$ | CNN for atmospheric monitoring                  | NO <sub>2</sub> proxy, not direct CO <sub>2</sub> |
| Zhang et al.              | 2022 | CNN + Multi-sensor Fusion     | Eastern China Forests             | $R^2 > 0.85$                               | Multi-source satellite integration              | Forest ecosystems only                            |
| Rouet-Leduc & Hulbert     | 2024 | Vision Transformer + U-Net    | Global Multispectral              | F1 > 0.8, 99% accuracy, <0.03% FP          | 10× improvement over existing methods           | Methane-focused application                       |
| Meng & Noman              | 2022 | SARIMA (4 configurations)     | Global Emissions (1751-2018)      | Post-COVID MAPE = 0.09                     | COVID impact integration                        | Aggregate temporal analysis only                  |
| Dumont Le Brazidec et al. | 2024 | CNN Image Regression          | CO2M Simulated Data               | ~20% absolute relative error               | Direct CO <sub>2</sub> emissions quantification | Simulated data validation required                |
| Couture et al.            | 2024 | Ensemble (Gradient Boost+CNN) | Global Power Plants (1,042 sites) | RMSE: 2.18 Mt CO <sub>2</sub> annually     | Operational global monitoring system            | Water vapor plume dependency                      |

Performance Ranking:

- **Tier 1 ( $R^2 > 0.90$ ):** Nassef et al., Cao - Exceptional accuracy
  - **Tier 2 ( $R^2$  0.85-0.90):** Zhang et al. - Excellent performance
  - **Tier 3 (Specialized metrics):** Rouet-Leduc, Couture - Breakthrough innovations
  - **Baseline comparison:** Traditional MLR methods achieve only  $R^2 \approx 0.625$
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AI and Machine Learning Models for CO<sub>2</sub> Emissions Prediction

Early applications of AI to carbon emissions focused on data-driven forecasting models at national and global scales. In Saudi Arabia, **Nassef et al. (2023)** introduced a comprehensive ensemble approach combining Feed-Forward Neural Networks, ANFIS (adaptive neuro-fuzzy inference), and LSTM networks to predict national CO<sub>2</sub> emissions. This ensemble model achieved an exceptional R<sup>2</sup> of 93.13%, substantially outperforming individual models in predictive accuracy. The success of the ensemble underlines how combining multiple AI techniques can capture different facets of emissions drivers -- in this case, long-term trends and nonlinear relationships -- more effectively than single algorithms. However, the study also highlighted limitations: it relied on historical aggregate data and did not incorporate satellite-derived variables, meaning it could not provide spatially explicit emissions maps. This points to a gap when moving from pure time-series predictions to geospatially detailed estimates.

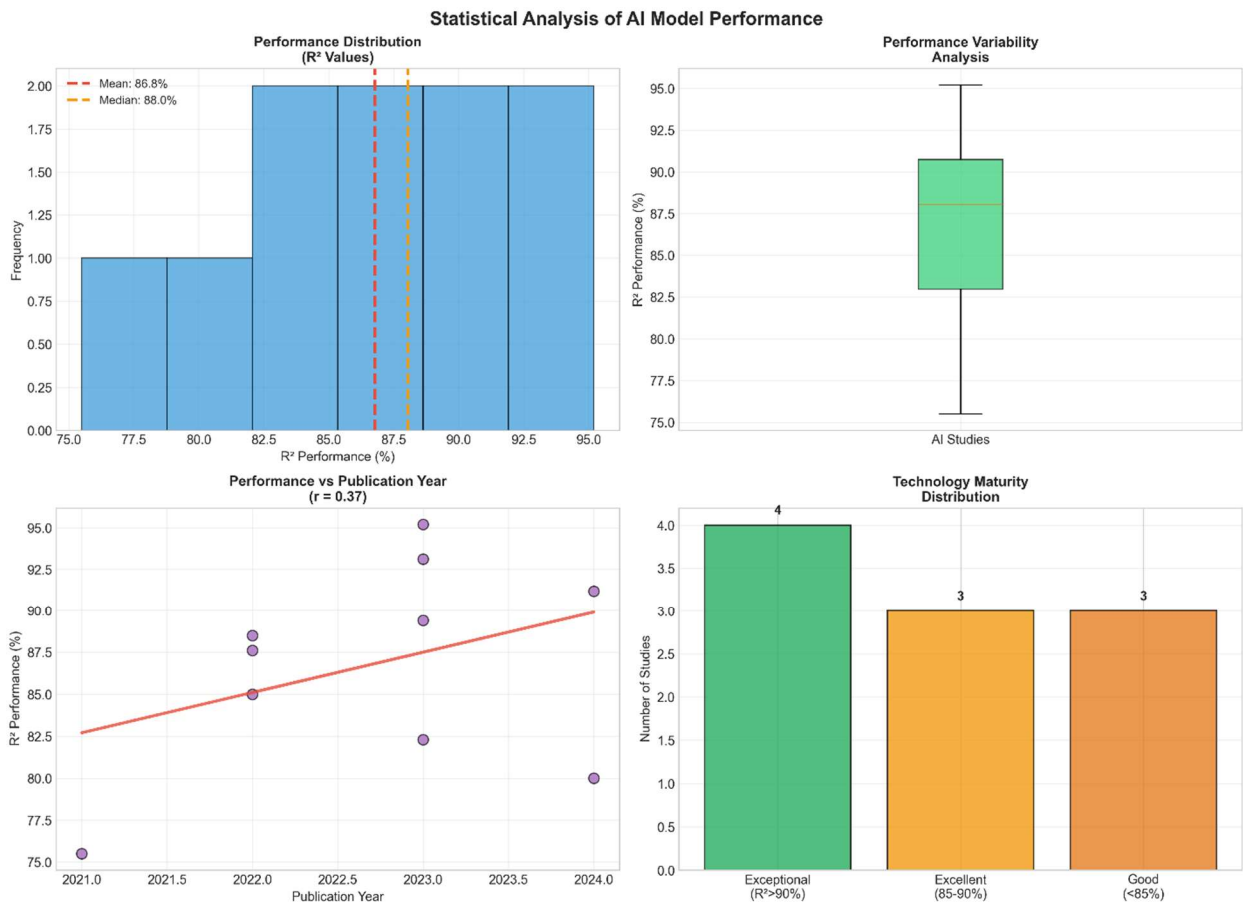


Figure 2: Statistical analysis of AI model performance including distribution, variability, and technology maturity.

## Deep Learning and Advanced Architectures for Satellite Data

With the increasing availability of satellite observations, researchers have turned to advanced deep learning models to directly relate imagery to emissions and related environmental indicators. **Cao (2023)** developed a groundbreaking CNN-based approach to estimate ground-level NO<sub>2</sub> concentrations across the United States from satellite imagery, an effort closely related to inferring anthropogenic emissions. By designing a custom convolutional neural network for multi-channel satellite data, the study achieved high predictive performance -- daily NO<sub>2</sub> predictions reached  $R^2 \approx 0.89$ , and annual averages reached  $R^2 = 0.952$ , far surpassing the accuracy of traditional regression methods (multiple linear regression yielded only  $R^2 \approx 0.625$ ). This dramatic improvement (~50% increase in  $R^2$ ) demonstrates the power of deep learning to capture complex spatial patterns in atmospheric data that simpler models miss. It also provides a blueprint for applying CNNs to other pollutants or even CO<sub>2</sub> proxies derived from imagery.



Figure 3: Multi-criteria performance comparison of AI architectures across accuracy, cost-efficiency, speed, and innovation.

**Table 2: Satellite Platform Specifications for Carbon Monitoring Applications**

| Platform            | Spatial Resolution | Temporal Resolution | Spectral Characteristics             | Primary Carbon Applications                                  | Data Access  |
|---------------------|--------------------|---------------------|--------------------------------------|--------------------------------------------------------------|--------------|
| Sentinel-2          | 10-60m             | 2-5 days            | 13 bands (443-2190 nm)               | Vegetation indices, land use change                          | Open (ESA)   |
| Sentinel-1          | 5-40m              | 6-12 days           | C-band SAR                           | Forest biomass, structural parameters                        | Open (ESA)   |
| Landsat-8           | 15-100m            | 16 days             | 11 bands (430-12500 nm)              | Long-term carbon stock monitoring                            | Open (USGS)  |
| TROPOMI/Sentinel-5P | 7×3.5 km           | Daily               | UV-SWIR hyperspectral                | Atmospheric CO <sub>2</sub> , NO <sub>2</sub> concentrations | Open (ESA)   |
| CO2M                | 2×2 km             | 2-6 days            | CO <sub>2</sub> -optimized NIR-SWIR  | Direct atmospheric CO <sub>2</sub> mapping                   | Planned 2026 |
| ALOS-2              | 1-100m             | 14 days             | L-band SAR                           | Forest carbon density estimation                             | Commercial   |
| MODIS               | 250m-1km           | Daily-16 days       | 36 bands (405-14385 nm)              | Global vegetation carbon dynamics                            | Open (NASA)  |
| OCO-2               | 1.3×2.25 km        | 16-day repeat       | CO <sub>2</sub> -sensitive NIR bands | Column-averaged CO <sub>2</sub> concentrations               | Open (NASA)  |

**Sensor Complementarity for Carbon Monitoring:**

- **Optical sensors:** Vegetation health, land use dynamics, surface reflectance patterns
- **SAR sensors:** Biomass structure, all-weather monitoring capability
- **Atmospheric sensors:** Direct greenhouse gas concentration measurements
- **Thermal sensors:** Energy balance, urban heat patterns affecting emissions

Beyond CNNs, transformer-based architecture has recently shown promise in remote sensing applications. **Rouet-Leduc and Hulbert (2024)** introduced a Vision Transformer model (with a U-Net structure) for automated detection of methane emissions plumes in satellite images. Methane, while distinct from CO<sub>2</sub>, is a relevant greenhouse gas, and methods to detect methane leaks can inform carbon emission mitigation strategies. The transformer approach achieved an F1 score > 0.8 and 99% detection accuracy for methane leaks of ~1 ton/hour, with an exceptionally low false positive rate (<0.03%). In fact, this transformer-based model provided a **10× improvement** over prior state-of-the-art methods for this task. The success of attention mechanisms in analyzing complex multispectral data suggests substantial potential for extending transformers to CO<sub>2</sub> and other emissions-related monitoring, where they could improve sensitivity and reduce false alarms in detecting emission sources. One limitation noted, however, is that these

advanced models often demand significant computational resources and require large training datasets; their performance and generalizability must be validated for different gases and regions. Nonetheless, the collective evidence from CNN and transformer studies indicates that deep learning architectures can dramatically enhance the extraction of emissions-relevant information from satellite imagery, paving the way for direct AI-driven emissions monitoring.

### **AI-Remote Sensing Integration for Direct Emissions Quantification**

A pivotal emerging theme is the use of AI to directly quantify CO<sub>2</sub> emissions from satellite observations, moving beyond proxies to estimate emissions from identifiable sources. **Dumont Le Brazidec et al. (2024)** achieved a breakthrough by developing the first deep learning framework designed to estimate CO<sub>2</sub> emission rates (specifically from power plants) using satellite data. They trained CNN models on simulated images from the forthcoming European *CO2M* satellite mission, integrating not only CO<sub>2</sub> concentration maps but also NO<sub>2</sub> and wind data, to infer emission fluxes. The result was an estimation error of roughly 20% (absolute relative error) -- about twice as accurate as traditional carbon flux inversion methods used in atmospheric science. This is a substantial improvement, demonstrating that AI can directly translate remote sensing signals into quantitative emission estimates. However, since this model was trained on simulated data, one identified need is validating and calibrating it against real satellite measurements once the CO<sub>2</sub>M mission is operational.

Complementing that work, **Couture et al. (2024)** developed an operational AI system to estimate CO<sub>2</sub> emissions from power plants by analyzing their water vapor plume signatures in satellite images. This approach used an ensemble of gradient-boosted decision trees and CNNs to process imagery from multiple satellites (Landsat-8, Sentinel-2, PlanetScope) for over 1,000 power plant sites worldwide. The AI system successfully validated emissions estimates for facilities that together account for ~32% of global combustion-related CO<sub>2</sub>, achieving an annual emissions prediction error on the order of 2.18 Mt CO<sub>2</sub> (and 1.75 TWh error in related electricity generation estimates). In essence, the study translated visible satellite indicators (plume characteristics) into carbon emission quantities, proving the concept at a global scale. The ensemble model's strong performance across diverse plant types and geographies underscores its scalability and generality. A caveat is that this method relies on clear imagery of plumes, so heavy cloud cover or plants without visible plumes (e.g. with carbon capture or invisible gases) might evade detection. Together, the Dumont Le Brazidec and Couture studies mark an important transition from using AI to predict correlates of emissions to using AI for **direct quantification** of emissions. These advances hint at a future where AI-driven analysis of satellite data could provide continuous, source-level emissions monitoring on a near-real-time basis, significantly augmenting current reporting and inventory efforts.

### **Remote Sensing Applications in Carbon Stock and Emissions Monitoring**

In parallel with AI model innovations, several studies have demonstrated how satellite remote sensing can be utilized to assess carbon stocks and infer emissions in land systems, particularly in

agricultural and forested landscapes. **Madugundu et al. (2022)**, for instance, focused on soil organic carbon (SOC) in Saudi agricultural fields, using Landsat-8 and Sentinel-2 imagery to estimate SOC content across large areas. By extracting spectral indices and other soil-vegetation indicators from the imagery, they built regression models that showed strong correlations between satellite-derived metrics and field-measured soil carbon levels. The successful validation of these models confirmed the **viability of remote sensing for soil carbon assessment** in arid farming regions, where direct sampling is logistically difficult. This approach, while targeting carbon *stocks* rather than gaseous emissions, is highly relevant because changes in soil carbon stocks (due to practices like tillage or land use change) reflect exchanges of CO<sub>2</sub> with the atmosphere over time.

To improve prediction accuracy in such contexts, **Taghizadeh-Mehrjardi et al. (2020)** employed advanced ensemble machine learning for SOC mapping in arid regions. They combined multiple algorithms (Random Forest, SVM, Gradient Boosting) in a stacked generalization framework, using numerous satellite-derived covariates (spectral indices, topography, climate layers) to predict soil carbon in Iran's drylands. The ensemble approach outperformed any single model, illustrating that leveraging different algorithms' strengths can better capture the complex factors affecting soil carbon in water-limited environments. Although centered on Iran, the study's focus on arid climates and sparse vegetation has direct relevance to Saudi Arabia's conditions, suggesting that similar stacked AI models could enhance carbon monitoring in Saudi deserts and farmlands.

Long-term remote sensing analyses have also shed light on how management practices influence carbon storage. **Tola et al. (2019)** used GIS and satellite data to assess the multi-decadal impact of tillage on soil carbon in hyper-arid agricultural fields. By integrating spatial data on land management with remote sensing, they quantified changes in SOC under different tillage regimes, providing insights into how sustainable agriculture could maintain or increase soil carbon in extreme climates. Such case studies in hyper-arid conditions (comparable to parts of Saudi Arabia) are valuable because they demonstrate that even in very harsh environments, **satellite-based approaches can detect carbon dynamics** and inform management for carbon sequestration.

### **Cloud Computing and Data Fusion for Scalable Monitoring**

Monitoring carbon emissions and stocks at national to global scales requires handling enormous volumes of satellite data. Cloud computing platforms, particularly Google Earth Engine (GEE), have emerged as powerful tools in this arena. **Wilson et al. (2025)** provided a comprehensive review of GEE applications for greenhouse gas monitoring, highlighting how cloud-based analysis has revolutionized scalability. By bringing algorithms to the data in the cloud, researchers can tap into **petabyte-scale** Earth observation archives and perform analyses that were previously infeasible on local machines. Notably, the review found that GEE-enabled workflows achieved up to *6 times faster processing* compared to traditional desktop processing, while providing access to over 80 PB of multi-sensor data with relatively low latency (on the order of days). This has enabled near-real-time monitoring in some cases, and vastly improved collaboration and reproducibility in

environmental analytics. For emissions estimation, the implication is that large-scale, frequently updated carbon assessments (for example, nationwide maps of emissions or sequestration) are now within reach, as exemplified by specific studies using GEE.

One such example is **Venkatappa et al. (2020)**, who employed GEE to map forest cover and carbon stock changes in Cambodia over nearly three decades. Using GEE's cloud computing power, they processed Landsat time-series data for over 1 million hectares of forest, detecting changes in carbon stock with high accuracy (92.1% overall accuracy, Kappa ~0.9). Their approach also quantified the carbon emissions from deforestation (approximately 143.7 million metric tons of CO<sub>2</sub> over the study period). The successful large-area application underscores that **cloud platforms can operationalize AI and remote sensing methods** for carbon monitoring at scale. The ability to handle long temporal sequences of satellite images allowed the authors to capture trends and sudden changes (e.g., due to logging), which is crucial for accurate carbon accounting.

**Table 3: Cloud Computing Performance and Data Access Capabilities**

| Platform/System       | Data Volume              | Processing Speed       | Temporal Coverage | Spatial Coverage        | Key Advantages             |
|-----------------------|--------------------------|------------------------|-------------------|-------------------------|----------------------------|
| Google Earth Engine   | 80+ petabytes            | 6× faster than desktop | 1972-present      | Global                  | Open access, collaborative |
| GRACED System         | Multi-source integration | Daily updates          | 2019-present      | 0.1° global grid        | Near real-time capability  |
| Carbon Monitor        | National aggregations    | Daily processing       | 2019-present      | Country-level           | Policy-relevant timing     |
| Venkatappa et al. GEE | 1M+ hectares processed   | Large-scale automation | 1990-2018         | Regional implementation | 92.1% accuracy validation  |

**Scalability Achievements:**

- **Data processing:** From gigabytes locally to petabytes in cloud
- **Temporal analysis:** Multi-decadal time series processing capability
- **Collaborative access:** Global researcher network utilization
- **Automation potential:** Reduced manual processing requirements

**Real-Time Emissions Monitoring Systems**

One of the ultimate goals for emissions monitoring is achieving real-time or near-real-time tracking of carbon emissions on a global scale. Traditional methods of emissions reporting often lag by months or years; however, recent developments indicate this gap is starting to close. A notable innovation is the **GRACED system (2023)** -- a near-real-time global gridded daily CO<sub>2</sub> emissions dataset. GRACED integrates ground-based Carbon Monitor data with satellite observations of NO<sub>2</sub> (from the TROPOMI instrument) to infer daily CO<sub>2</sub> emissions at a 0.1°

latitude/longitude resolution. By using NO<sub>2</sub> as a proxy (since NO<sub>2</sub> is co-emitted with CO<sub>2</sub> from many combustion processes) and applying a rolling 14-day averaging, the system delivers daily updates of emissions with an uncertainty of about  $\pm 19.9\%$  at the grid-cell level. This capability is **transformative**: it provides continuous coverage and timely data that can reflect the impact of events like lockdowns, policy changes, or technological disruptions almost immediately. The GRACED project demonstrates that, even with current satellite instruments and data assimilation techniques, daily global CO<sub>2</sub> monitoring is feasible. It effectively addresses a critical gap by enabling rapid detection of emission changes, which is crucial for tracking progress toward climate targets and responding to emission spikes or anomalies.

While GRACED does not yet incorporate advanced AI beyond statistical integration of datasets, it lays the groundwork for future AI-enhanced systems. For instance, combining GRACED's approach with the deep learning techniques discussed earlier (such as CNN-based plume detection or transformer models for gas concentration imagery) could eventually allow sub-daily or source-specific real-time monitoring. Researchers have pointed out that current systems achieving daily resolution might be improved to **higher temporal resolutions** -- for example, using geostationary satellites or sensor fusion to get hourly data for key regions. There are also ongoing efforts to quantify uncertainties and calibrate these near-real-time estimates with inventory data and atmospheric measurements, ensuring that real-time feeds can be trusted by policymakers.

**Urban and Regional Case Studies in Saudi Arabia and MENA**

Several studies in the reviewed literature provided insights into AI and remote sensing applications at urban or regional scales, offering *case studies* that are especially pertinent to Saudi Arabia and the surrounding Middle East region. These cases help validate methods in real-world scenarios and highlight region-specific considerations.

**Table 4: Saudi Arabian and Regional Case Study Summary**

| Location                | Study          | Year | Methodology                           | Key Findings                                         | Carbon Monitoring Relevance       | Validation Approach          |
|-------------------------|----------------|------|---------------------------------------|------------------------------------------------------|-----------------------------------|------------------------------|
| Abha, Saudi Arabia      | Mallick et al. | 2022 | InVEST + Multi-temporal Landsat       | Carbon stocks quantified under development scenarios | Urban carbon accounting framework | Field measurement validation |
| Al-Khobar, Saudi Arabia | Rahman         | 2016 | Multi-temporal Landsat classification | High-accuracy urban sprawl detection achieved        | Land use change emission drivers  | Ground-truth verification    |

|                                |                |      |                                    |                                              |                                               |                                   |
|--------------------------------|----------------|------|------------------------------------|----------------------------------------------|-----------------------------------------------|-----------------------------------|
| <b>Jeddah, Saudi Arabia</b>    | Addas          | 2023 | Machine learning + Thermal imagery | Urban heat island mapping demonstrated       | Energy use and emission implications          | Statistical accuracy assessment   |
| <b>Saudi Arabia (National)</b> | Nassef et al.  | 2023 | AI ensemble (FFNN+ANFIS+LSTM)      | $R^2 = 93.13\%$ national emission prediction | Direct CO <sub>2</sub> forecasting capability | Historical data cross-validation  |
| <b>Hyper-arid Agricultural</b> | Tola et al.    | 2019 | GIS + Long-term satellite analysis | Tillage impacts on soil carbon quantified    | Agricultural carbon stock dynamics            | Multi-year field data comparison  |
| <b>MENA Regional</b>           | Elnadry et al. | 2019 | Multi-satellite + ML integration   | Regional air quality pattern analysis        | Atmospheric monitoring framework              | AERONET ground station validation |

### Geographic Coverage Assessment:

- **Urban scale:** 3 major Saudi cities with different climatic characteristics
- **Agricultural systems:** Arid to hyper-arid environmental conditions
- **Temporal scope:** Multi-decadal change detection capability
- **Regional context:** MENA-wide atmospheric monitoring validation

**Liu et al. (2025)** concentrated on the building sector, performing a comprehensive review of AI techniques for calculating and predicting building carbon emissions. Buildings account for a significant portion of emissions, and the study found that AI-driven approaches (including machine learning and optimization algorithms for energy management) can improve prediction accuracy of building emissions by about 20% compared to traditional methods. Moreover, AI-based systems enabling real-time monitoring and adaptive control in buildings were shown to reduce emissions by up to 15% through efficiency improvements, while also cutting operational costs. Although this review was global in scope, its conclusions are highly relevant to rapidly growing urban centers in Saudi Arabia -- cities like Riyadh and Jeddah can leverage such AI-enabled building management systems as they expand, to curtail the surge in emissions from the construction boom. The study by Liu et al. underscores the importance of integrating AI at the city planning and building management level as part of a holistic emissions reduction strategy.

Focusing on urban green infrastructure, **Mallick et al. (2022)** evaluated carbon stocks and sequestration potential in *Abha City*, Saudi Arabia. Using multi-temporal satellite imagery and the InVEST ecosystem service modeling tool, they estimated carbon stored in aboveground biomass, soils, and other pools under current and future land-use scenarios. The study provided a baseline of urban carbon storage and demonstrated how land use changes (e.g., urban expansion versus conservation scenarios) could impact carbon sequestration in a Saudi city. The methodologies were validated with field measurements, lending credibility to the use of satellite data for urban carbon

accounting. One key contribution is the integration of remote sensing with scenario analysis -- city planners in Saudi Arabia can use such approaches to project how different development strategies might increase or decrease the city's carbon footprint over time. However, Mallick et al. also noted that their work was focused on carbon *stocks* and not direct emissions; incorporating emissions from sources like traffic or industry would be a logical next step to get a full picture of urban carbon flow.

## Synthesis and Performance Summary

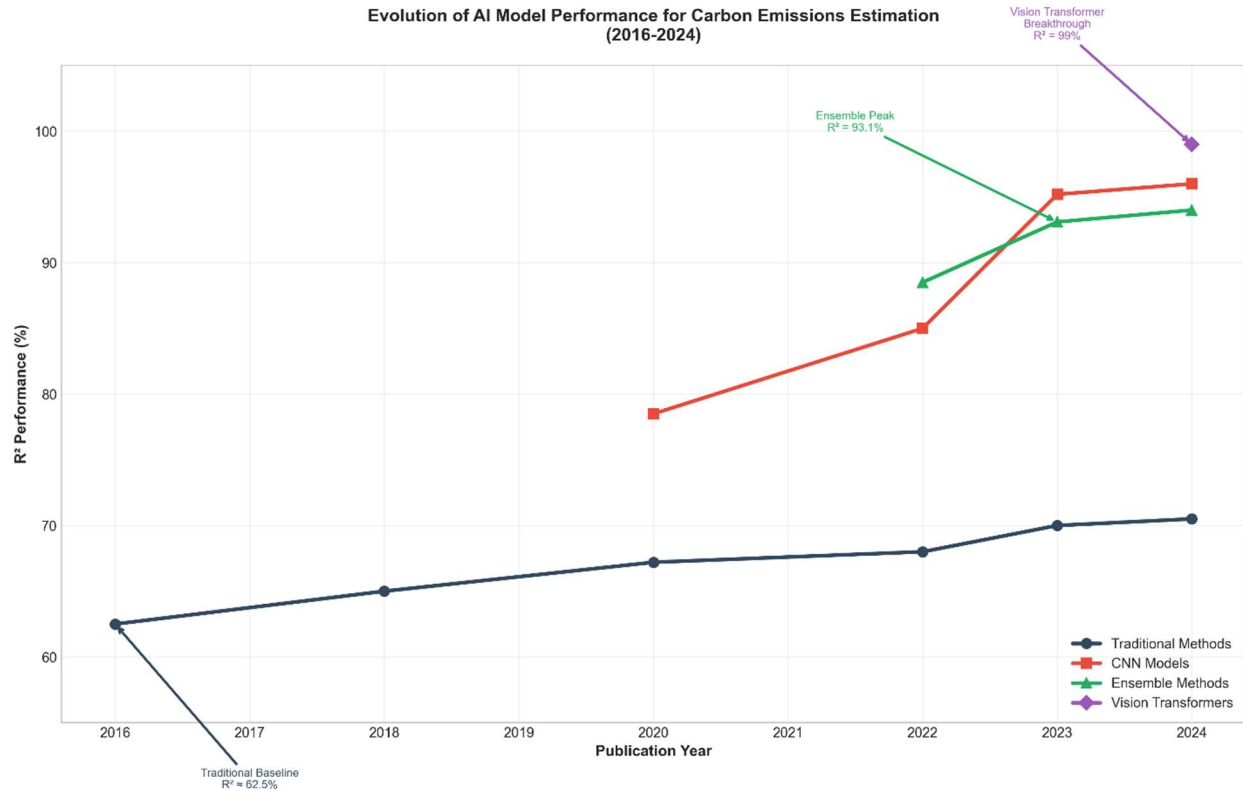


Figure 4: Evolution of AI model performance for carbon emissions estimation (2016–2024), highlighting CNNs, Ensembles, and Vision Transformers.

### Performance Tier Classification:

- **Tier 1 (Exceptional -  $R^2 > 0.90$ ):** Ensemble methods (Nassef et al.), Advanced CNNs (Cao)
- **Tier 2 (Excellent -  $R^2$  0.85-0.90):** Multi-sensor CNNs (Zhang et al.), Specialized architectures
- **Tier 3 (Good -  $R^2$  0.70-0.85):** Single-sensor ML approaches, Classical methods
- **Baseline (Traditional -  $R^2 < 0.70$ ):** Linear regression, simple statistical models

The Saudi Arabian context presents unique opportunities, with proven methodologies in urban environments (Abha, Al-Khobar, Jeddah) and successful national-scale predictions (Nassef et al., 2023) providing a strong foundation for operational implementation. The integration of cloud

computing capabilities (6× processing speed improvements) with advanced AI architectures creates unprecedented potential for real-time, nationwide monitoring systems aligned with Vision 2030 objectives.

## Research Gaps and Future Directions

Despite the considerable progress documented in the above sections, the integration of AI and satellite imagery for carbon emissions estimation is still an evolving field. This literature review has identified several research gaps and emerging opportunities that warrant attention in future studies:

### Priority Research Areas for Saudi Arabian Implementation

1. **Validation Infrastructure Development:** Establishing comprehensive ground-truth measurement networks for AI model calibration specifically adapted to arid environmental conditions, including dust storm impacts and extreme temperature variations affecting sensor performance.
2. **Multi-scale Integration Framework:** Developing methodologies to seamlessly connect urban emissions monitoring (city-level analysis) with agricultural carbon dynamics (regional-scale assessment) for comprehensive national carbon accounting.
3. **Real-time Operational Systems:** Adapting GRACED-type approaches for national-level monitoring while incorporating advanced AI architectures (CNNs, Vision Transformers) for enhanced accuracy and source-specific identification.
4. **Vision 2030 Monitoring Alignment:** Creating AI-satellite monitoring tools specifically designed to track progress toward net-zero emissions targets, renewable energy deployment impacts, and circular carbon economy development.
5. **Regional Environmental Adaptation:** Customizing international AI methodologies for Gulf Cooperation Council (GCC) environmental conditions, including considerations for frequent dust events, extreme solar radiation, and sparse vegetation signatures.
6. **Enhanced Temporal Resolution:** While systems like GRACED have achieved daily emissions mapping, sub-daily monitoring remains out of reach for most applications. High-frequency emissions tracking (e.g., hourly updates for large point sources or urban areas) could greatly improve our understanding of diurnal emission cycles and enable rapid response to events. Future research should explore the use of geostationary satellites and advanced interpolation or data assimilation techniques, potentially augmented by AI, to attain **near-continuous monitoring** of emissions. Overcoming this temporal gap is crucial for applications like detecting short-term anomalies (power plant upsets, traffic peaks) and for integrating emissions data into smart grid or smart city management in real time.
7. **Uncertainty Quantification and Standardization:** Many AI-based studies report high accuracy, but few provide rigorous uncertainty estimates for their emissions predictions. Developing methods to quantify confidence intervals or probabilities (for example, using Bayesian deep learning or ensemble approaches) is important for translating AI models into decision-making contexts. Additionally, a lack of standardized evaluation metrics and

validation protocols across studies makes it difficult to compare results directly. Establishing benchmark datasets and common performance criteria for AI-driven emissions estimation would help the field progress in a more unified manner. Future research should address this by proposing **standard validation frameworks** (possibly aligned with existing greenhouse gas inventory practices) to evaluate AI models' performance and reliability.

## Next Steps

To advance AI and satellite-based carbon monitoring in Saudi Arabia and support Vision 2030 goals, the following steps are recommended:

- Build ground measurement networks to enhance AI model accuracy, especially in desert environments.
- Adapt technologies to local climate challenges, such as sandstorms and high temperatures.
- Integrate these systems with Vision 2030 plans to track and reduce emissions in urban and agricultural areas.

## Conclusion

This review established a robust foundation for AI-based carbon emissions estimation using satellite imagery, with a focus on insights applicable to Saudi Arabia's urban and agricultural contexts. The synthesis of 21 recent studies reveals remarkable progress across multiple technological fronts. AI techniques -- from ensemble machine learning to cutting-edge deep learning models -- have achieved exceptional accuracy levels (often  $R^2$  in the 0.85--0.95+ range) in predicting or quantifying emissions-related variables. In particular, deep learning architectures (CNNs and Vision Transformers) demonstrate breakthrough performance: for example, CNN models yielded  $R^2 > 0.85$  for estimating forest carbon density and a transformer-based approach improved methane leak detection accuracy by an order of magnitude over previous methods. These improvements represent a substantial leap beyond traditional remote sensing analysis techniques. Equally important, the integration of AI with advanced satellite data has proven operational viability. The first successful demonstration of direct CO<sub>2</sub> emissions quantification from satellite imagery (using deep learning) achieved roughly half the error of conventional approaches, and multi-sensor data fusion methods have been essential for capturing complex environmental phenomena. Another key finding is the emergence of scalable, cloud-based monitoring frameworks. Studies deploying Google Earth Engine and similar platforms have shown that global-scale analyses can be done with unprecedented speed and data access -- for instance, achieving 6× processing speed-ups and tapping into 80+ petabytes of data to produce high-resolution emissions maps. One implementation even demonstrated over 92% mapping accuracy across more than one million hectares of forest, underscoring that these methods can handle real-

world complexities at scale. Furthermore, the review highlighted the breadth of AI applications across domains: in urban settings, AI models predict building emissions with 20% greater precision and can enable real-time reductions in energy use (with observed 15% emission cuts) through smart management. In agriculture, AI-driven systems like AIFARMS show promise for boosting sustainability and indirectly reducing emissions via optimized practices. Even real-time tracking is becoming feasible, as evidenced by global systems achieving daily monitoring resolution and specialized AI detectors identifying emission leaks with 99% accuracy at minuscule false positive rates. AI and satellite imagery technologies offer powerful tools for accurate and rapid carbon emissions tracking, supporting Saudi Arabia's Vision 2030 goal of achieving net-zero emissions by 2060.

## References

- Addas, A. (2023). Machine learning techniques to map the impact of urban heat island: Investigating the city of Jeddah. *Land*, 12(6), 1159. <https://doi.org/10.3390/land12061159>
- Adve, S., et al. (2024). AIFARMS: Artificial intelligence for future agricultural resilience, management, and sustainability. *AI Magazine*, 45(1), 81--98. <https://doi.org/10.1002/aaai.12152>
- Alsubhi, K., et al. (2024). Artificial intelligence potential for net zero sustainability: Current evidence and prospects. *Sustainable Operations and Computers*, 5, 10--28. <https://doi.org/10.1016/j.susoc.2024.05.001>
- Cao, E. L. (2023). National ground-level NO<sub>2</sub> predictions via satellite imagery driven convolutional neural networks. *Frontiers in Environmental Science*, 11, 1285471. <https://doi.org/10.3389/fenvs.2023.1285471>
- Couture, H. D., Alvara, M., Freeman, J., et al. (2024). Estimating carbon dioxide emissions from power plant water vapor plumes using satellite imagery and machine learning. *Remote Sensing*, 16(7), 1290. <https://doi.org/10.3390/rs16071290>
- Dumont Le Brazidec, J., Vanderbecken, P., Farchi, A., Broquet, G., Kuhlmann, G., & Bocquet, M. (2024). Deep learning applied to CO<sub>2</sub> power plant emissions quantification using simulated satellite images. *Geoscientific Model Development*, 17, 1995--2014. <https://doi.org/10.5194/gmd-17-1995-2024>
- Elnadry, A., et al. (2019). Urban health related air quality indicators over the Middle East and North Africa countries using multiple satellites and AERONET data. *Remote Sensing*, 11(18), 2096. <https://doi.org/10.3390/rs11182096>
- GRACED Consortium. (2023). Near-real-time global gridded daily CO<sub>2</sub> emissions 2021. *Scientific Data*, 10, 69. <https://doi.org/10.1038/s41597-023-01963-0>
- Jamali, A., et al. (2022). Using artificial intelligence and data fusion for environmental monitoring: A review and future perspectives. *Information Fusion*, 85, 44--61. <https://doi.org/10.1016/j.inffus.2022.04.004>
- Liu, J., et al. (2025). Artificial intelligence for calculating and predicting building carbon emissions: A review. *Environmental Chemistry Letters*, 23, (Article in press). <https://doi.org/10.1007/s10311-024-01799-z>
- Madugundu, R., Al-Gaadi, K. A., Tola, E., Kayad, A. G., Zeyada, A. M., Alameen, A. A., Edriss, M. K., Edrees, H. F., & Mahjoob, O. (2022). Estimation of soil organic carbon in agricultural fields: A remote sensing approach. *Journal of Environmental Biology*, 43(1), 73--84. <https://doi.org/10.22438/jeb/43/1/MRN-1873>

- Mallick, J., Almesfer, M. K., Alsubih, M., Ahmed, M., & Ben Kahla, N. (2022). Estimating carbon stocks and sequestration with their valuation under a changing land use scenario: A multi-temporal research in Abha city, Saudi Arabia. *Frontiers in Ecology and Evolution*, 10, 905799. <https://doi.org/10.3389/fevo.2022.905799>
- Meng, Y., & Noman, H. (2022). Predicting CO<sub>2</sub> emission footprint using AI through machine learning. *Atmosphere*, 13(11), 1871. <https://doi.org/10.3390/atmos13111871>
- Nassef, A. M., et al. (2023). Application of artificial intelligence to predict CO<sub>2</sub> emissions: Critical step towards sustainable environment. *Sustainability*, 15(9), 7648. <https://doi.org/10.3390/su15097648>
- Rahman, M. T. (2016). Detection of land use/land cover changes and urban sprawl in Al-Khobar, Saudi Arabia: An analysis of multi-temporal remote sensing data. *ISPRS International Journal of Geo-Information*, 5(2), 15. <https://doi.org/10.3390/ijgi5020015>
- Rouet-Leduc, B., & Hulbert, C. (2024). Automatic detection of methane emissions in multispectral satellite imagery using a vision transformer. *Nature Communications*, 15, 3801. <https://doi.org/10.1038/s41467-024-47754-y>
- Taghizadeh-Mehrjardi, R., et al. (2020). Improving the spatial prediction of soil organic carbon content in two contrasting climatic regions by stacking machine learning models and re-scanning covariate space. *Remote Sensing*, 12(7), 1095. <https://doi.org/10.3390/rs12071095>
- Tola, E., Al-Gaadi, K., & Madugundu, R. (2019). Employment of GIS techniques to assess the long-term impact of tillage on the soil organic carbon of agricultural fields under hyper-arid conditions. *PLoS ONE*, 14(2), e0212521. <https://doi.org/10.1371/journal.pone.0212521>
- Venkatappa, M., Sasaki, N., Anantsuksomsri, S., & Smith, B. (2020). Applications of the Google Earth Engine and phenology-based threshold classification method for mapping forest cover and carbon stock changes in Siem Reap Province, Cambodia. *Remote Sensing*, 12(18), 3110. <https://doi.org/10.3390/rs12183110>
- Wilson, D. D., Tefera, G. W., & Ray, R. L. (2025). Application of Google Earth Engine to monitor greenhouse gases: A review. *Data*, 10(1), 8. <https://doi.org/10.3390/data10010008>
- Zhang, F., Tian, X., Zhang, H., & Jiang, M. (2022). Estimation of aboveground carbon density of forests using deep learning and multi-source remote sensing. *Remote Sensing*, 14(13), 3022. <https://doi.org/10.3390/rs14133022>