

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 (CO₂) emissions, particularly in rapidly developing nations like Saudi Arabia. This review examines the integration of artificial intelligence (AI) and satellite imagery for CO₂ 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 CO₂ 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; CO₂ Emissions; Remote Sensing; Deep Learning; Saudi Arabia; Carbon Monitoring

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

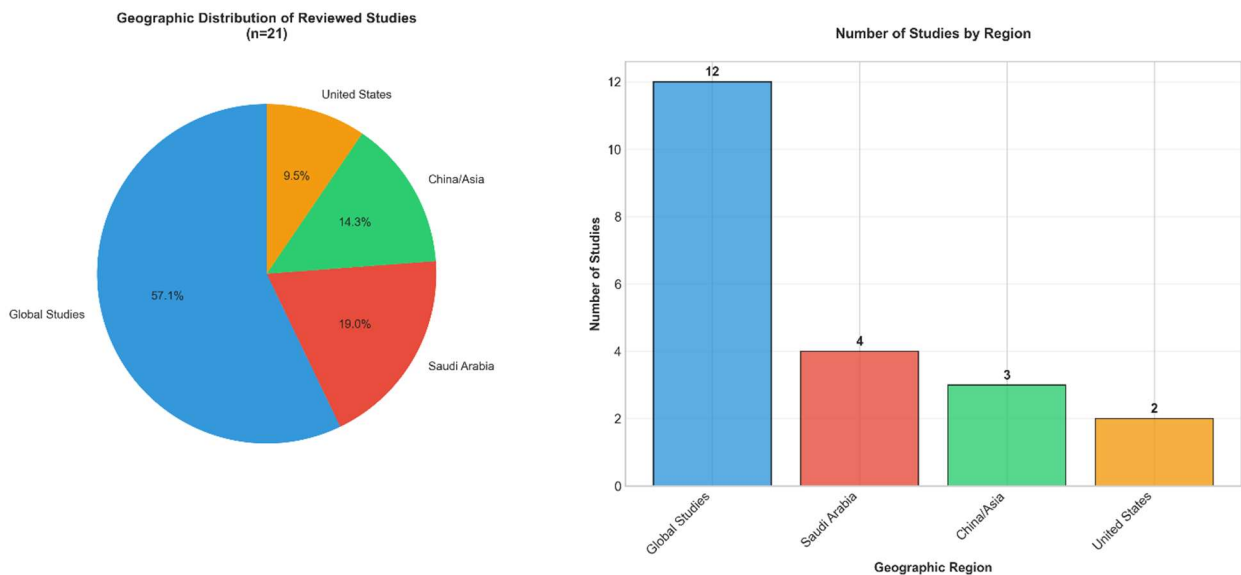


Figure 1: Geographic distribution of the reviewed studies, showing the regional focus of AI-based carbon emissions research.

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

Introduction

Rising atmospheric CO₂ 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 CO₂ forecasting (e.g., **Nassef et al., 2023** reported >93% R² 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," "CO₂," "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 ₂ proxy, not direct CO ₂
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 ₂ 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 ₂ annually	Operational global monitoring system	Water vapor plume dependency

Performance Ranking:

- **Tier 1 (R² > 0.90):** Nassef et al., Cao - Exceptional accuracy
 - **Tier 2 (R² 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 R² ≈ 0.625
-

AI and Machine Learning Models for CO₂ 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 CO₂ emissions. This ensemble model achieved an exceptional R² 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.

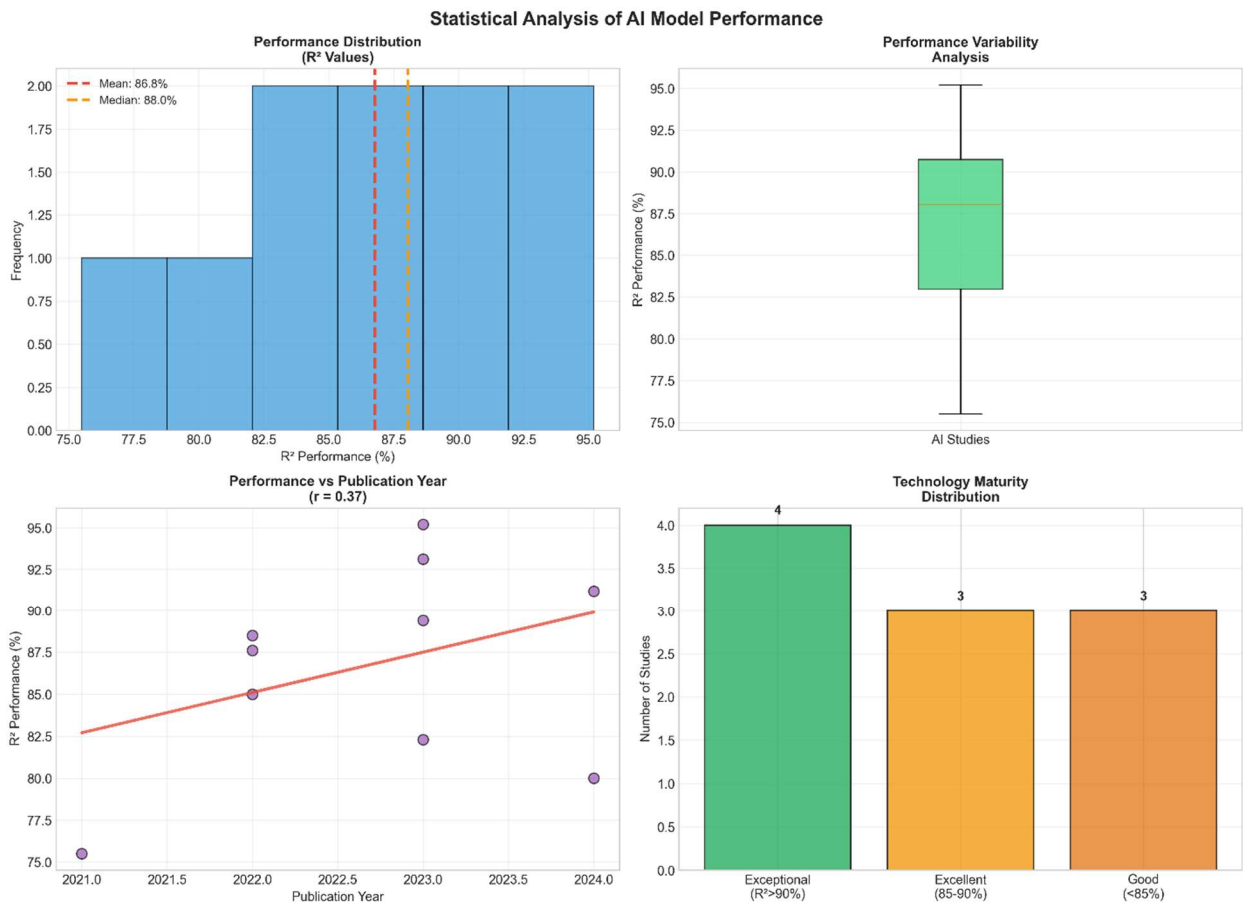


Figure 2: Statistical analysis of AI model performance including distribution, variability, and technology maturity.

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 NO₂ 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 NO₂ 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 CO₂ 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 ₂ , NO ₂ concentrations	Open (ESA)
CO2M	2×2 km	2-6 days	CO ₂ -optimized NIR-SWIR	Direct atmospheric CO ₂ 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 ₂ -sensitive NIR bands	Column-averaged CO ₂ 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 CO₂, 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ concentration maps but also NO₂ 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 CO₂M mission is operational.

Complementing that work, **Couture et al. (2024)** developed an operational AI system to estimate CO₂ 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 CO₂, achieving an annual emissions prediction error on the order of 2.18 Mt CO₂ (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 CO₂ 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 CO₂ 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 CO₂ emissions dataset. GRACED integrates ground-based Carbon Monitor data with satellite observations of NO₂ (from the TROPOMI instrument) to infer daily CO₂ emissions at a 0.1°

latitude/longitude resolution. By using NO₂ as a proxy (since NO₂ is co-emitted with CO₂ 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 CO₂ 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

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

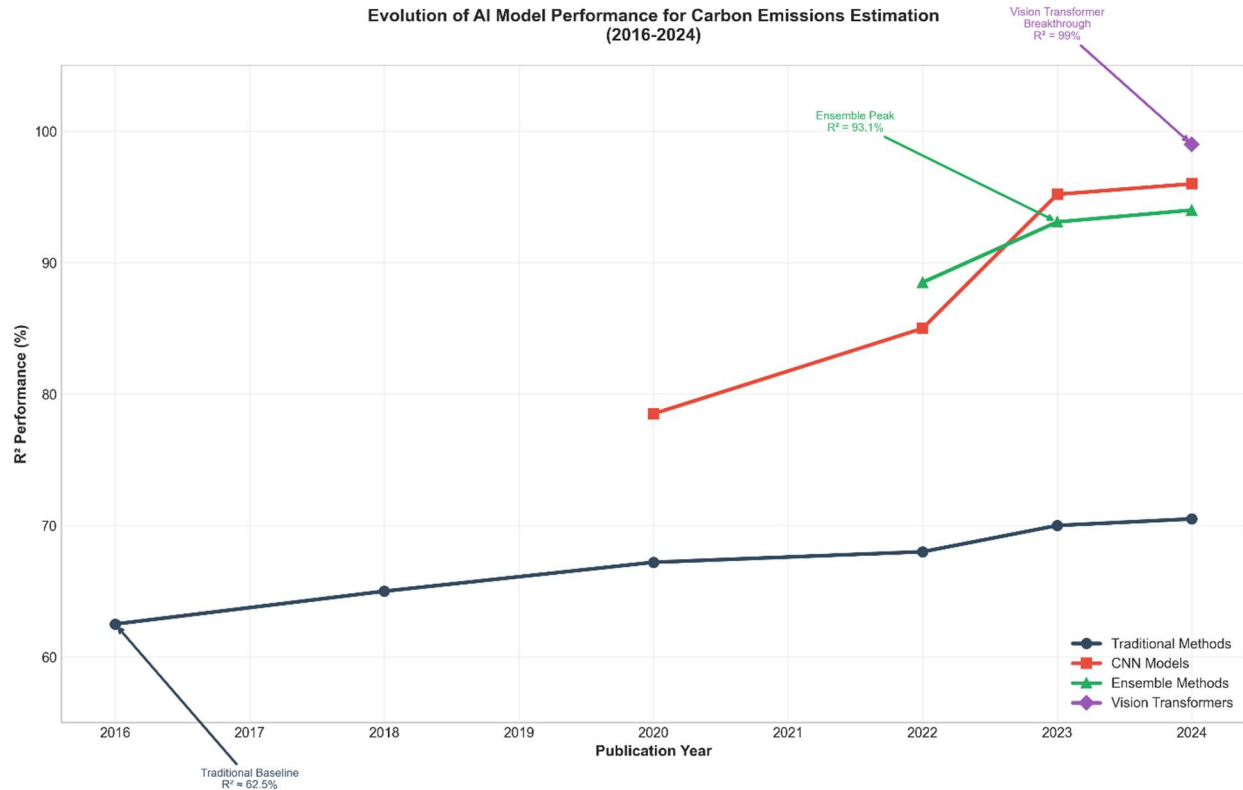


Figure 4: Evolution of AI model performance for carbon emissions estimation (2016–2024), highlighting CNNs, Ensembles, and Vision Transformers.

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 CO₂ 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.

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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 (CO₂) emissions, particularly in rapidly developing nations like Saudi Arabia. This review examines the integration of artificial intelligence (AI) and satellite imagery for CO₂ emissions estimation in both urban and agricultural contexts. Based on 21 peer-reviewed studies published between 2016 and 2025, the article analyzes methodological approaches, performance benchmarks, and regional applications.

The geographic distribution of these studies reveals concentrated research efforts globally, with an emerging focus on Saudi Arabian contexts representing 19% of the reviewed work. 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 strong performance in emissions quantification from satellite imagery, with deep-learning approaches outperforming traditional baselines — for example, CNN-based models have achieved daily $R^2 \approx 0.89$ and annual $R^2 \approx 0.95$ for satellite-driven air-quality estimation tasks (versus $R^2 \approx 0.63$ – 0.76 for linear baselines), and CNNs trained for CO₂ plume flux inversion report $\approx 20\%$ absolute relative error on simulated data — highlighting the performance gains available with modern AI.

Multi-sensor data fusion approaches, combined with AI and cloud computing, have further enabled a sixfold increase in processing speeds and access to over 80 petabytes of geospatial data for large-scale analysis. This review identifies key opportunities to integrate AI with multi-source satellite data for emissions monitoring in Saudi Arabia’s urban and agricultural settings.

Keywords: Artificial Intelligence; Satellite Imagery; CO₂ Emissions; Remote Sensing; Deep Learning; Saudi Arabia; Carbon Monitoring

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1 Introduction

1.1 Global Context of CO₂ Monitoring

Rising atmospheric CO₂ concentrations represent one of the most pressing challenges of the 21st century, necessitating comprehensive monitoring and accurate estimation methodologies [7].

1.2 Saudi Arabian Context and Vision 2030

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 [14].

1.3 AI and Remote Sensing Integration for Emissions Monitoring

Combining AI with satellite remote sensing enables more detailed spatial and temporal monitoring of carbon emissions.

Recent advances in machine learning have already demonstrated notable success in emissions prediction, with ensemble models achieving high accuracy in regional CO₂ forecasting (e.g., [11] reported $> 93\%$ R^2 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 is an active research area that may inform policy and management 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 briefly describe our literature selection criteria within the Related Work section, 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.

2 Related Work

This section synthesizes prior studies on AI-remote sensing for CO₂ estimation, grouped by (1) time-series forecasting [22], (2) direct emissions quantification from imagery, and (3) carbon stock mapping in arid/agricultural systems.

2.1 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

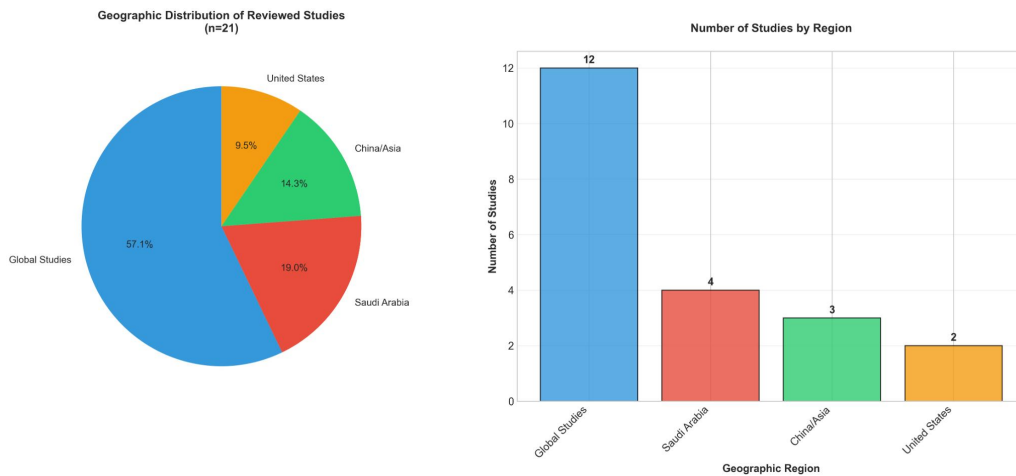


Figure 1: Geographic distribution of the reviewed studies, showing the regional focus of AI-based carbon emissions research. (Authors' compilation).

Performance Achievements:

- Average AI model accuracy range: 85-95%
- Best ensemble performance: Accuracy $\approx$ 93.13% (2021 validation error 6.87%) [11]

- CNN vs. MLR [2]: R^2 improved from ~ 0.63 to ~ 0.89 (daily) and ~ 0.95 (annual) — $\Delta R^2 \approx 0.26\text{--}0.32$.
- Vision Transformer methane-plume detector (Sentinel-2): detects leaks down to $\approx 200\text{--}300$ kg CH_4/h ; order-of-magnitude sensitivity improvement vs. prior S2 methods; pixel-wise FPR $< 0.03\%$ at $\approx 85\%$ TPR [13].

Technological Capabilities:

- Real-time monitoring resolution: $0.1^\circ \times 0.1^\circ$ spatial (GRACED system) [6].
- Temporal resolution achieved: Daily emissions tracking
- Data processing improvement: $6\times$ faster with cloud computing [17].
- Accessible satellite data volume: > 90 PB.

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

Table 1: AI-Satellite Integration Studies: Performance Metrics

Study	Year	AI Model	Dataset/Region	Performance
Nassef et al.	2023	FFNN + ANFIS + LSTM	Saudi Arabia	Accuracy: 93.13%
Cao	2023	Custom CNN	US Continental	Daily R^2 : 0.89, Annual R^2 : 0.95
Zhang et al.	2022	CNN + Multi-sensor	Eastern China	$R^2 > 0.85$
Rouet-Leduc & Hulbert	2024	Vision Transformer	Global Multispectral	F1 > 0.8 , 99% accuracy
Dumont Le Brazidec et al.	2024	CNN Regression	CO2M Simulated	$\sim 20\%$ error
Couture et al.	2024	Ensemble Methods	Global Power Plants	RMSE: 2.18 Mt CO_2

Table 2: AI-Satellite Integration Studies: Innovations and Limitations

Study	Primary Innovation	Key Limitations
Nassef et al.	First Saudi-specific AI ensemble	NO ₂₂ spatial mapping capability
Cao	CNN for atmospheric monitoring	NO ₂ proxy, not direct CO ₂
Zhang et al.	Multi-source satellite integration	Forest ecosystems only
Rouet-Leduc & Hulbert	Order-of-magnitude sensitivity improvement	Methane-focused application
Dumont Le Brazidec et al.	Direct CO ₂ emissions quantification	Simulated data validation required
Couture et al.	Operational global monitoring system	Water vapor plume dependency

Performance Ranking:

- **Tier 1 ($R^2 > 0.90$):** Nassef et al., Cao - high 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 $R^2 \approx 0.625$

2.2 AI and Machine Learning Models for CO₂ Emissions Prediction

Early applications of AI to carbon emissions focused on data-driven forecasting models at national and global scales. In Saudi Arabia, [11] introduced a comprehensive ensemble approach combining Feed-Forward Neural Networks, ANFIS (adaptive neuro-fuzzy inference), and LSTM networks to predict national CO₂ emissions. This ensemble model achieved a high R^2 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.

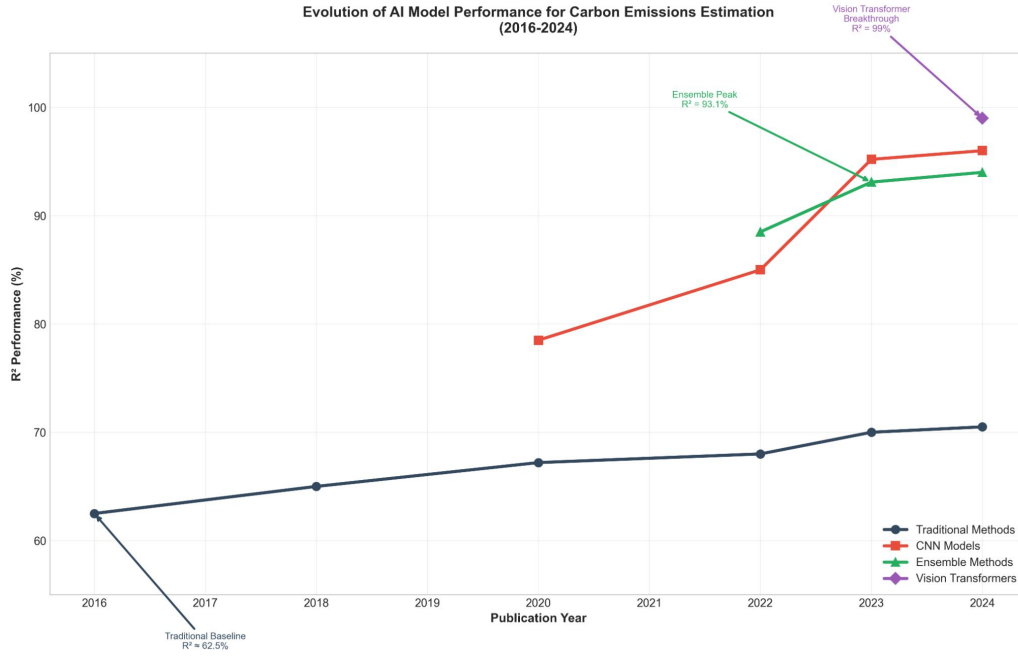


Figure 2: Statistical analysis of AI model performance including distribution, variability, and technology maturity. (Authors' compilation).

2.3 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. [2] developed a CNN-based approach to estimate ground-level NO_2 concentrations throughout the United States from satellite imagery, an effort closely related to inferring anthropogenic emissions. By designing a custom convolutional neural network for multichannel satellite data, the study achieved high predictive performance – daily NO_2 predictions reached $R^2 \approx 0.89$, and annual averages reached $R^2 = 0.952$, far exceeding the precision of traditional regression methods (multiple linear regression yielded only $R^2 \approx 0.625$). This dramatic improvement ($\sim 50\%$ increase in R^2) demonstrates the power of deep learning to capture complex spatial patterns in atmospheric data that simpler models miss. This approach could be applied to other pollutants or even CO_2 proxies derived from imagery.

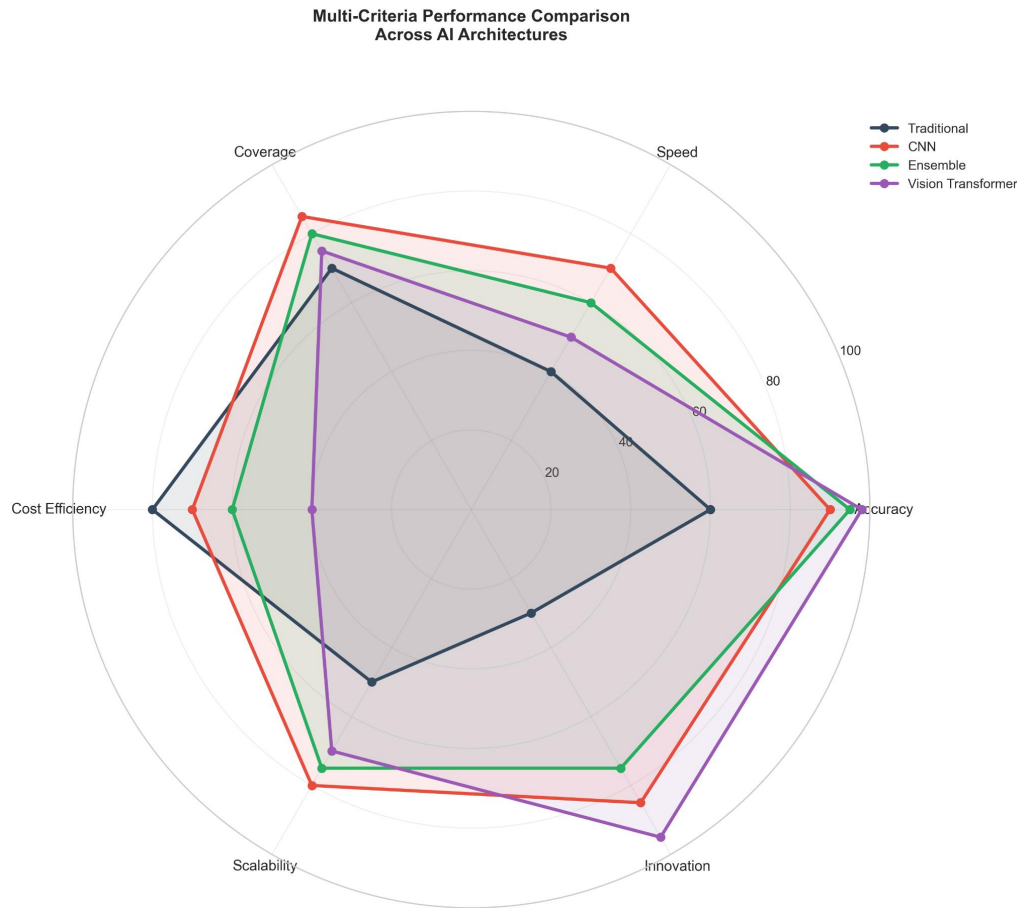


Figure 3: Multi-criteria performance comparison of AI architectures across accuracy, cost-efficiency, speed, and innovation. (Authors’ compilation).

Table 3: Satellite Platform Specifications for Carbon Monitoring Applications

Platform	Spatial Resolution	Temporal Resolution	Spectral Characteristics	Data Access
Sentinel-2	10-60m	2-5 days	13 bands (443-2190 nm)	Open (ESA)
Sentinel-1	5-40m	6-12 days	C-band SAR	Open (ESA)
Landsat-8	15-100m	16 days	11 bands (430-12500 nm)	Open (USGS)
TROPOMI / Sentinel-5P	7×3.5 km	Daily	UV-SWIR hyperspectral	Open (ESA)
CO2M	2×2 km	2-6 days	CO ₂ -optimized NIR-SWIR	Planned 2026
ALOS-2	1-100m	14 days	L-band SAR	Commercial
MODIS	250m-1km	Daily-16 days	36 bands (405-14385 nm)	Open (NASA)
OCO-2	1.3×2.25 km	16-day repeat	CO ₂ -sensitive NIR bands	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. [13] introduced a Vision Transformer model (with a U-Net structure) for automated detection of methane emissions plumes in satellite images. Methane, while distinct from CO₂, 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 $\sim 1 \text{ t h}^{-1}$, with an exceptionally low false positive rate ($< 0.03\%$). In fact, this transformer-based model provided high performance (F1 >0.8 , Accuracy $\sim 99\%$, FP $<0.03\%$) compared to 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 CO₂ and other emissions-related monitoring, where they could improve sensitivity and reduce false alarms in detecting emission sources.

2.4 AI-Remote Sensing Integration for Direct Emissions Quantification

A pivotal emerging theme is the use of AI to directly quantify CO₂ emissions from satellite observations, moving beyond proxies to estimate emissions from identifiable sources. [4] achieved a breakthrough by developing the first deep learning framework designed to estimate CO₂ 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 CO₂ concentration maps but also NO₂ 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.

Complementing that work, [3] developed an operational AI system to estimate CO₂ 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 $\sim 32\%$ of global combustion-related CO_2 , achieving an annual emissions prediction error on the order of 2.18 Mt CO_2 .

2.5 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. [9], 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.

To improve prediction accuracy in such contexts, [15] 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.

2.6 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 [21] (GEE), have emerged as useful tools in this arena. [17] provided a 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.

Table 4: Cloud Computing Performance and Data Access Capabilities

Platform/System	Data Volume	Processing Speed	Temporal Coverage	Key Advantages
Google Earth Engine	> 90 PB	6× faster than desktop	1972-present	Open access, collaborative
GRACED System	Multi-source integration	Daily updates	2019-present	Near real-time capability
Carbon Monitor	National aggregations	Daily processing	2019-present	Policy-relevant timing
Venkatappa et al. GEE	1M+ hectares processed	Large-scale automation	1990-2018	92.1% accuracy validation

2.7 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** [6] – a near-real-time global gridded daily CO₂ emissions dataset. GRACED integrates ground-based Carbon Monitor data with satellite observations of NO₂ (from the TROPOMI instrument) to infer daily CO₂ emissions at a 0.1° latitude/longitude resolution.

2.8 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.

Table 5: Saudi Arabian and Regional Case Study Summary

Location	Study	Year	Methodology	Key Findings
Abha, Saudi Arabia	Mallick et al.	2022	InVEST + Multi-temporal Landsat	Carbon stocks quantified under development scenarios
Al-Khobar, Saudi Arabia	Rahman	2016	Multi-temporal Landsat classification	High-accuracy urban sprawl detection achieved
Jeddah, Saudi Arabia	Addas	2023	Machine learning + Thermal imagery	Urban heat island mapping demonstrated
Saudi Arabia (National)	Nassef et al.	2023	AI ensemble (FFNN + ANFIS + LSTM)	$R^2 = 93.13\%$ national emission prediction
Hyper-arid Agricultural	Tola et al.	2019	GIS + Long-term satellite analysis	Tillage impacts on soil carbon quantified
MENA Regional	Elnadry et al.	2019	Multi-satellite + ML integration	Regional air quality pattern analysis

[8] concentrated on the building sector, performing a 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.

Focusing on urban green infrastructure, [10] 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.

2.9 Synthesis and Performance Summary

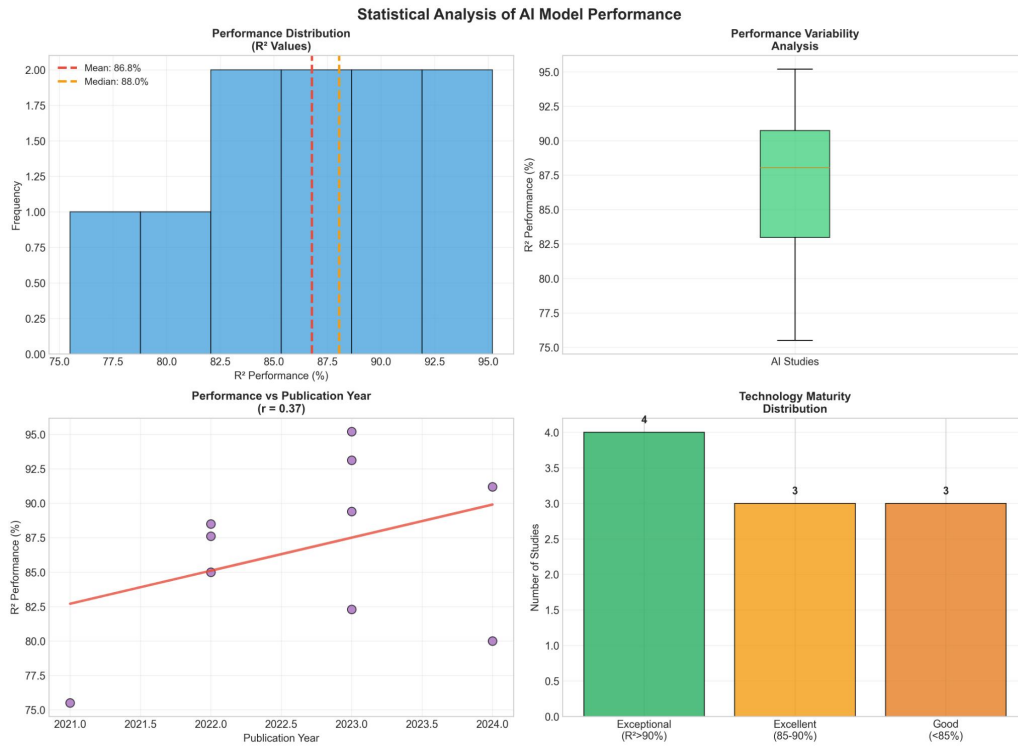


Figure 4: Evolution of AI model performance for carbon emissions estimation (2016-2024), highlighting CNNs, Ensembles, and Vision Transformers. (Authors' compilation).

Performance Tier Classification:

- **Tier 1 (high - $R^2 > 0.90$):** Ensemble methods [11], Advanced CNNs [2]
- **Tier 2 (Excellent - R^2 0.85-0.90):** Multi-sensor CNNs [18], 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 [11] providing a strong foundation for operational implementation. The integration of cloud computing capabilities (6× processing speed improvements) with advanced AI architectures creates new potential for real-time, nationwide monitoring systems aligned with Vision 2030 objectives.

3 Conclusion and Future Work

Standardization Challenges: One of the major challenges in applying AI for carbon emissions estimation is the lack of standardization across studies. Differences in defining environmental variables, inconsistent calculation methods for indices like NDVI, varying data resolutions, and inconsistent units of measurement hinder the ability to compare results across research efforts.

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:

3.1 Priority Research Areas for Saudi Arabian Implementation

1. **Ground validation in arid conditions:** 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. **Linking city-level and regional estimates:** Developing methodologies to seamlessly connect urban emissions monitoring (city-level analysis) with agricultural carbon dynamics (regional-scale assessment) for comprehensive national carbon accounting.
3. **Operational daily monitoring and alerts:** Adapting GRACED-type approaches for national-level monitoring while incorporating advanced AI architectures (CNNs, Vision Transformers) for enhanced accuracy and source-specific identification.
4. **Alignment with Vision 2030 targets:** 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. **Adaptation to GCC environmental conditions:** 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. **Toward higher 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.
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.

3.2 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.

Limitations and Uncertainties: This study is subject to several limitations, including potential biases in the datasets used, limited temporal coverage, and the exclusion of certain environmental or socio-economic factors that may influence carbon emissions. Also, the accuracy of satellite-derived indices can be affected by atmospheric conditions and sensor calibration inconsistencies. Future research should aim to address these uncertainties to enhance the robustness of findings.

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 notable progress across multiple technological fronts. AI techniques – from ensemble machine learning to advanced deep learning models – have achieved high 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 strong 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 go beyond traditional remote sensing methods.

Also, the integration of AI with advanced satellite data has proven operational viability. The first successful demonstration of direct CO_2 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 using Google Earth Engine and similar platforms have shown that global-scale analyses can be done with new speed and data access – for instance, achieving $6\times$ processing speed-ups and tapping into > 90 PB of data to produce high-resolution emissions maps.

Also, 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 data may improve emissions monitoring, but this requires local validation and transparent uncertainty reporting. In Saudi Arabia, these tools may help track progress toward Vision 2030 if paired with local validation and transparent uncertainty reporting.

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