

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

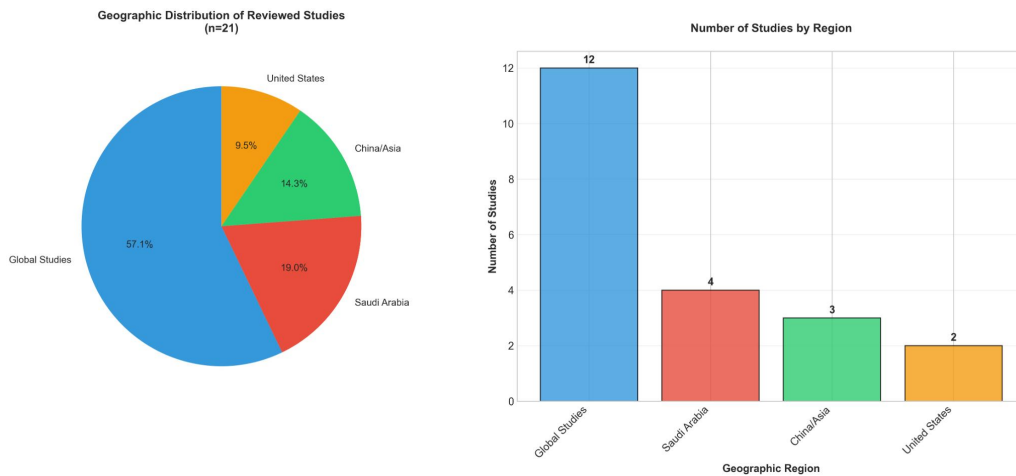


Figure 1: Geographic distribution of the reviewed studies, showing the regional focus of AI-based carbon emissions research. (Authors' compilation).

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.

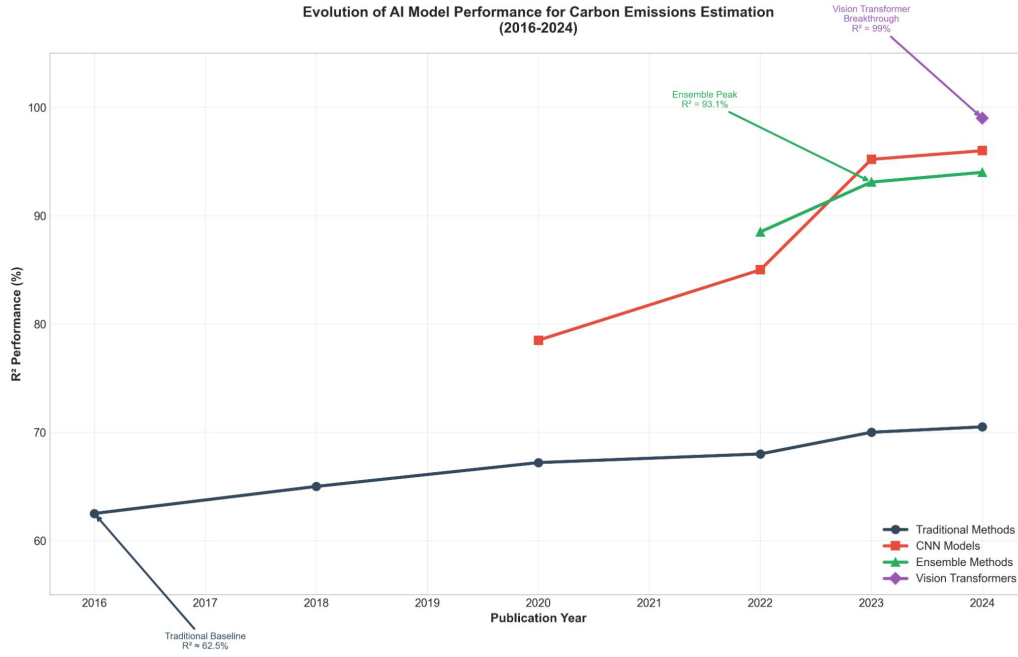


Figure 2: Statistical analysis of AI model performance including distribution, variability, and technology maturity. (Authors' compilation).

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.

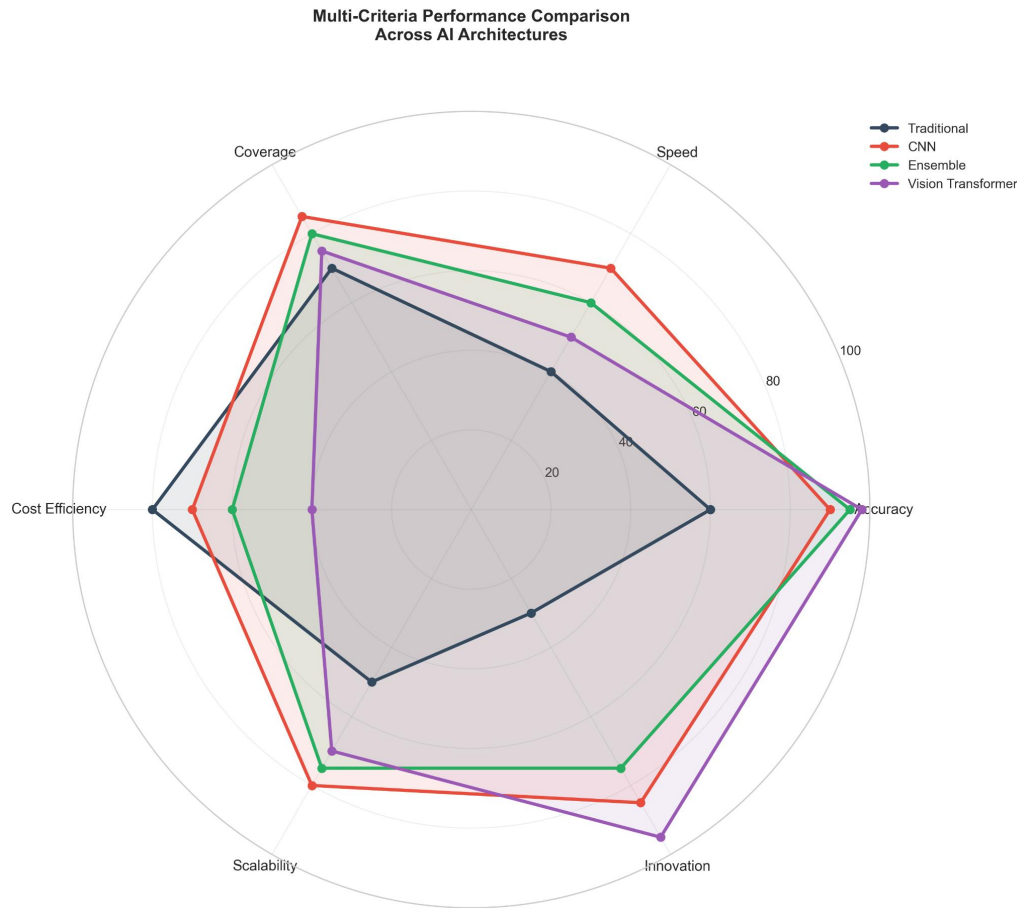


Figure 3: Multi-criteria performance comparison of AI architectures across accuracy, cost-efficiency, speed, and innovation. (Authors’ compilation).

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

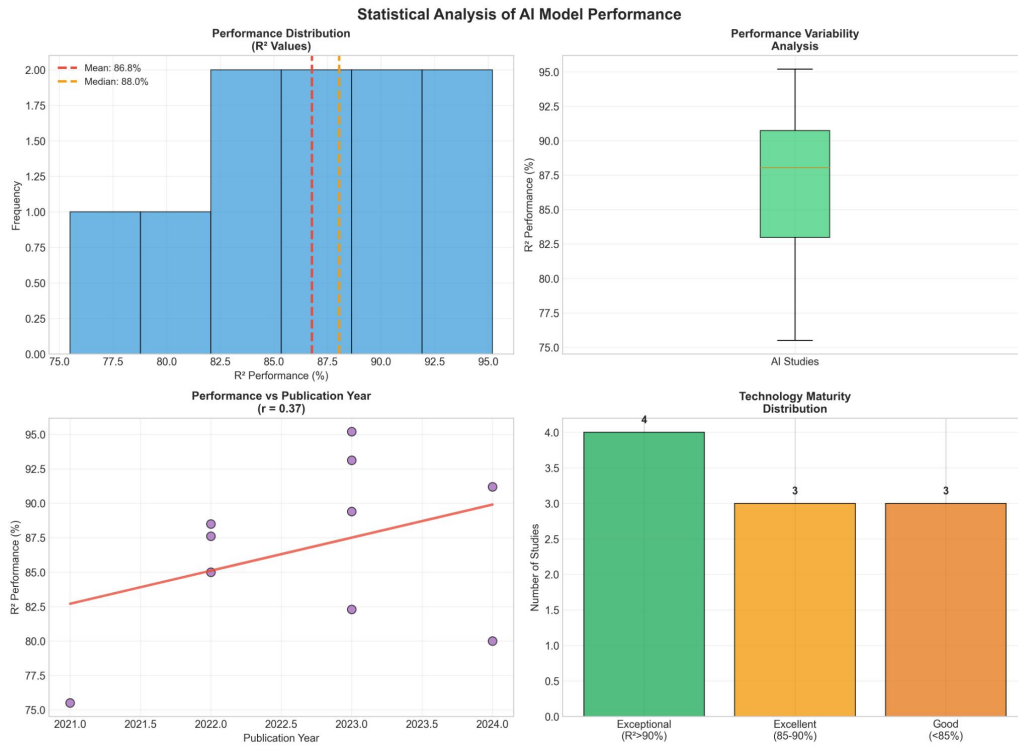


Figure 4: Evolution of AI model performance for carbon emissions estimation (2016-2024), highlighting CNNs, Ensembles, and Vision Transformers. (Authors' compilation).

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.

References

- [1] 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>
- [2] Cao, E. L. (2023). National ground-level NO₂ predictions via satellite imagery driven convolutional neural networks. *Frontiers in Environmental Science*, 11, 1285471. <https://doi.org/10.3389/fenvs.2023.1285471>
- [3] 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>
- [4] Dumont Le Brazidec, J., Vanderbecken, P., Farchi, A., Broquet, G., Kuhlmann, G., & Bocquet, M. (2024). Deep learning applied to CO₂ power plant emissions quantification using simulated satellite images. *Geoscientific Model Development*, 17, 1995–2014. <https://doi.org/10.5194/gmd-17-1995-2024>
- [5] 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>
- [6] Dou, X., et al. (2023). Near-real-time global gridded daily CO₂ emissions 2021. *Scientific Data*, 10, 69. <https://doi.org/10.1038/s41597-023-01963-0>
- [7] IPCC. (2023). *Climate Change 2023: Synthesis Report. Summary for Policymakers*. Intergovernmental Panel on Climate Change. <https://www.ipcc.ch/report/ar6/syr/>
- [8] Hua, J., et al. (2025). Artificial intelligence for calculating and predicting building carbon emissions: A review. *Environmental Chemistry Letters*. <https://doi.org/10.1007/s10311-024-01799-z>
- [9] 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>
- [10] 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>
- [11] Nassef, A. M., et al. (2023). Application of artificial intelligence to predict CO₂ emissions: Critical step towards sustainable environment. *Sustainability*, 15(9), 7648. <https://doi.org/10.3390/su15097648>
- [12] 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>
- [13] 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>
- [14] Saudi Green Initiative (SGI). (2021). Saudi Arabia to achieve net zero emissions by 2060. <https://www.saudigreeninitiative.org>
- [15] 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>
- [16] 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>

- [17] 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>
- [18] 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>
- [19] Meng, Y., & Noman, H. (2022). Predicting CO₂ emission footprint using AI through machine learning. *Atmosphere*, 13(11), 1871. <https://doi.org/10.3390/atmos13111871>
- [20] 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>
- [21] 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>
- [22] Himeur, Y., Rimal, B., Tiwary, A., & Amira, A. (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.2022.06.003>
- [23] Olawade, D. B., 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>